Final report

The effects of inflation on insurers' performance and value*

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Executive summary

The aim of this study is to analyze the impact of inflation risk on the financial performance of insurers in each of the two main sectors of the US insurance industry: P&C and Life. Very few contributions have analyzed the effect of inflation on the insurance industry. A literature review is presented in Section 1 of the report.

Section 2 describes the evolution of inflation measured by the *Inflation rate*[1], with a special attention on our period of analysis, 1973 to 2023. The United States has experienced three inflationary shocks since 1973. The first shock started in 1974 and was linked to an oil shock as for the second one that started in 1979. A third shock was linked to the *COVID-19* pandemic. The *Inflation rate* exhibited an overall downward trend from 1990 to 2020. It oscillated at below 6 % throughout this period.

The *Inflation rate*e reached a historically negative low point in 2009. It became more volatile after 1990. Finally, the *Inflation rate* and the nominal rate of LT government bonds (10-year maturity) moved in the same direction over the entire period.

The US more recent inflation period following the *COVID-19* pandemic was mainly explained by strong increases in the prices of food and energy (Bernanke and Blanchard, 2025). Supply disruptions in key sectors of the economy are also a cause. Labor supply became tight and then contributed to wage inflation.

Section 3 analyses in more detail the properties of the US *Inflation rate* series during the 1973-2023 period. Our analysis of the impulse response of inflation to 1970s oil shocks, the 1979

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[1] Variable names analysed in this report are in italics.

monetary policy reform shock and the *COVID-19* shock yielded two observations. First, all three shocks had an instantaneous impact on inflation. The instantaneous magnitude of the shock was greater with the oil shocks. Second, we observed that the oil shocks and the 1979 monetary policy reform shock had permanent consequences (lasting effect) on inflation, whereas the *COVID-19* shock had short-term consequences on inflation. The main difference of the *COVID-19* shock on inflation with respect to the oil shocks is probably explained by the early intervention of the Fed in 2020.

Section 4 presents the main insurance business indicators studied that include the *Combined ratio*, the *Operating ratio*, and the return on assets (*ROA*). Section 5 adds more structural analysis of inflation in the 1973-2023 period with the Autoregressive Distributed Lag (ARDL) model and the Error Correction Model (ECM) for long-term effect and short-term effect of inflation on financial variables in the P&C and Life sectors. We have modeled the links between the *Inflation rate* and many financial variables in each of the two insurance sectors, using the ARDL (c,q) model and the ECM model.

Our results indicate that *Premiums*, *Total expenses*, and *Net investment income* variables are positively affected by inflation, which is a quite natural result. These effects seem to compensate each other since profitability variables such as *Combined ratio*, *Operating ratio*, *Pretax operating income*, and *ROA* are not affected by inflation according to the results. These preliminary results may be explained by the implicit assumption of linearity in the stochastic inflation processes in the above models.

Section 6 studies impulse response of inflation on insurers' financial variables in the two insurance sectors using the VAR process. We confirm that the shock of the *COVID-19* pandemic in comparison to previous oil shocks had a short-term impact on inflation.

Robustness checks of VAR model are analyzed in Section 7. In this section, we revisit the impulse responses derived from the VAR estimations to investigate whether our conclusions about insurance variables' responses to inflation shocks are robust to an alternative econometric methodology, namely the Local Projection (LP) estimation. Overall, we can say that both methodologies give similar impulse responses for near forecasting horizons as predicted by the theory. However, for more distant forecasting, discrepancies between the two approaches become more apparent. Particularly, the VAR estimation depicts smoother response pattern than those of local projection (LP), which may also explain the results in Section 5.

Section 8 analyses the nonlinear stochastic processes of inflation during the 1973-2023 period. We observe that the US *Inflation rate* series are characterized by a random trend and nonlinear dynamics (asymmetry). These results led us to select the two-regime Markov model for analyzing the effect of inflation on different performance indicators of the insurance industry.

In Section 9, we confirm that the US *Inflation rate* series is characterized by a random trend and nonlinear dynamics. These characteristics led us to select the two-regime Markov-switching model over the MS-GARCH model to study the impact of inflation on various fundamental indicators of insurance industry performance. We show that performance indicators are differently affected by inflation in the Life and P&C insurance sectors according to the inflation regime considered.

Results show that both Life and P&C insurers were significantly exposed to inflation fluctuations, especially in periods of high inflation (State 2). Inflation in State 1 (low inflation) did not significantly affect the P&C underwriting variables and had a positive effect on investment income at only 5%. Results in State 2 are more significant and the negative result on *Premiums* generated a negative performance overall in the P&C sector. The positive result on investment did not create a significant hedging effect in this sector.

Results also indicate that the impact of inflation on *ROA* in the Life sector was not significant, in State 2. Other factors than the *Operating ratio* seem to have affected the *ROA*. The impact of inflation on Life insurers performance indicators in State 1 was negative for the underwriting activities, but the good performance of investment created a net positive effect on profitability.

The P&C sector seems to have been more affected by inflation during our period of analysis. The negative effect on *Premiums* in State 2, probably explained by a reduction in purchasing power of clients, affected insurance demand and the higher interest rates did not compensate for the negative underwriting results. In the Life sector, the hedging effect of investment was efficient in State 1 and neutral in State 2.

Section 10 evaluates the impact of inflation—both observed and expected—on *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* for P&C US insurers from 1993 to 2023, with particular attention to differences across firm size. The analysis distinguishes between lagged observed *Inflation rate* and inflation forecasts made one and three years prior, capturing how insurers react to realized inflation and how prior expectations shape current outcomes.

For *Reinsurance demand*, the findings reveal a clear positive relationship with lagged observed inflation, suggesting that insurers react to actual inflation through reinsurance protection. In contrast, long-term inflation expectations formed three years earlier are negatively associated with current *Reinsurance demand*. This implies that when insurers anticipated prolonged inflation in the past, they likely adopted more conservative strategies which manifest in more stable financial positions. Short-term forecasts, however, show no significant impact on *Reinsurance demand* across the full sample, indicating that recent expectations may have had a limited influence on current decisions. Short-term forecasts may be too volatile, particularly those following the *COVID-19* pandemic.

Liquidity creation ratio demonstrates a time-sensitive dynamic. Insurers increase liquidity creation in response to realized inflation and short-term forecasts, likely as a response to manage near-term uncertainty in bond values. Conversely, long-term inflation forecasts are associated with decreasing liquidity creation in the economy and investing more in liquid assets. These patterns are more pronounced among small insurers, who are more exposed to inflationary risks and show clearer adjustments. Large insurers, by contrast, do exhibit less significant changes in *Liquidity creation ratio*, likely due to their greater diversification, stronger asset-liability matching, and broader access to financial instruments.

Regarding profitability, *ROA* improves with prior inflation expectations, a surprising result obtained, particularly with lagged one- and three-year-ahead forecasts, suggesting that insurers who planned for inflation were better positioned to adjust pricing, reallocate investments, or take advantage of higher interest rates. In contrast, realized inflation does not significantly affect *ROA* at the industry level. Firm-level differences are notable.

We also examined the direct effects of inflation on six key financial indicators in the P&C sector: *Premiums to Total assets*, *Losses incurred to Total assets*, *Net gain from operations to Total assets*, *Net investment income to Total assets*, *Net realized capital gains to Total assets*, and *Capital ratio*. Findings indicate that large insurers adapt more quickly and systematically to inflation.

These findings highlight the importance of robust inflation risk management—incorporating forward-looking pricing, disciplined underwriting, proactive capital planning, and dynamic investment strategies tailored to evolving macroeconomic conditions.

The *COVID-19* pandemic posed several challenges for the estimation and analysis of multivariate macroeconomic time-series. Particularly, estimated models may become unstable and generate unlikely forecasts with the inclusion of the pandemic extreme observations. We tackle these methodological challenges in Section 11 by using a flexible Bayesian VAR (BVAR) framework allowing for heavy tails and stochastic volatility for innovations to appropriately treat these extreme observations as suggested in the literature. We find empirical evidence that *COVID-19* pandemic created outliers for main US macroeconomic variables as the degrees of freedom of the student *t*-distributions of residuals became lower with the inclusion of post-pandemic observations. The simultaneous shifts in the tail fatness of macro-variables could create macroeconomic tail risk. Hence, our analysis shows that macroeconomic transmission channels were highly altered by the pandemic shock.

In Section 12 we pose the question of whether the US property and casualty insurance industry is subject to social inflation and to what extent. Social inflation, characterized by the increasing costs of insurance claims due to societal and legal shifts, constitutes a major issue for policyholders, insurers and reinsurers. This phenomenon, which originated in the 1970s and has resurfaced over the past five years, is particularly driven by the growing use of third-party ligation funding and contingency-fees, higher jury awards and punitive damages, increasingly assertive legal strategies by plaintiff lawyers, plaintiff-friendly legislation and the expansion of liability through new legal doctrines.

Considering the unpredictable nature and the growing importance of social inflation in the present era, the necessity to find mitigating measures to control the risks implied by this phenomenon becomes crucial to ensure the long-term profitability and stability of insurance operations.

Sections 9 to 12 represent the main contributions of this report. They are written for publication in academic journals. They can be read separately.

Introduction

Our goal is to study the effect of inflation on the insurance industry. This research subject is very important because the new generations of actuaries and insurers' managers, including CEOs and CFOs, do not have strong experience with inflation. In the beginning of the 1980's they were too young to be motivated by inflation and since the end of the 1980's inflation was almost absent in industrial countries (Lowe and Warren, 2010), if we exclude the recent post-*COVID-19*[2] period. Our results will provide information permitting insurers to react appropriately to this important insurance risk. Crowley (2011) reports that for certain CEOs, inflation could be a greater risk than an earthquake or a tsunami!

As said, insurers have limited experience with inflation risk and their models are often not adapted to inflation even if some stress tests may consider different inflation scenarios on regulatory capital like a 10% inflation shock over the next three years results. Very few academic and non-academic studies have been published during the last ten years on inflation in the insurance sector although some recent non-academic contributions started to consider inflation (Swiss Re, 2010; EIOPA, 2023; Geneva Association, 2023). However, these well documented studies on potential effects of inflation on the insurance industry do not provide empirical evidence with appropriate methodologies on the real effects of inflation on this industry.

The main objective of the research is to measure the effect of inflation on the insurance industry. Does inflation reduce firms' performance and value or do insurers manage this risk efficiently? If

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[2] Variable names analysed in this report are in italics.

so, to what extent? Do they hedge inflation risk? How does inflation affect underwriting activities, *Reinsurance demand*, investment strategies, and financial performance?

The first section of the report proposes a literature review on the effect of inflation on the insurance industry. We discuss academic and non-academic main contributions in detail.

The second section compares different inflation periods in the United States over time with aggregated data. This data started in 1915, so we can compare the post-*COVID-19* inflationary period with those of the beginning of the 1970s (73-75) and 1980s (79-81) and those of the two great wars where inflation was very high. Inflation had a downward trend from 1990 to 2020 after the two oil shocks of 1973 and 1979. A third important shock started in 2020 with the *COVID-19* pandemic. This last inflation period was short, probably explained by the active monetary policy of the Fed.

We then study in more detail, in Section 3, the characteristics of inflation during our period of analysis with aggregate data from 1973 to 2023. We first present the nature of the Vector Autogressive (VAR) model during this time-period. The VAR model is a linear global approximation of the data generating process to represent the dynamics between dependent variables and to derive impulse responses. We focus on inflation impulse response functions following the two 1970s oil shocks, the Fed1979 monetary policy reform shock, and the *COVID-19* shock. We also look at the forecast error variance decomposition of the different models. These two analyses allow us to synthesize the essential information contained in the dynamics of the estimated VAR system. The variance decomposition allows us to isolate the relative importance of each shock in explaining inflation fluctuations during the studied period. Section 4 is devoted to the description of the main financial indicators analyzed in this study.

Section 5 focuses on the impact of inflation shocks from linear models on different financial variables of P&C and Life insurers, including the *Combined Ratio* and the *ROA*. To analyze the specific relationship between inflation and financial data, we used the annual series of the *Inflation rate* over the 1973 to 2023 period. We determine the impact of inflation shocks on the future values of each financial variable. We apply the Autoregressive Distributive Lagged Model (ARDL) and the Error Correction Model (ECM), as these models allow us to measure the long-term or short-term effect of a shock to inflation on a given financial variable. The ARDL model is a time series model that includes the past values of both the studied financial variable and inflation while the ECM model is more related to cointegration in the data.

In Section 6, we used again the VAR model to obtain more detailed results of the impulse function results relating, this time, inflation to the different financial variables. Here we focus on the impulse functions of the different financial variables following an inflation shock, instead of the impulse function of different macroeconomic shocks on inflation as presented in Section 3.

This standard procedure to recover impulse responses of insurance variables to inflation shocks consists of a two-step procedure: 1) Estimate the stable long-term relationship between the studied variables; 2) Choose the best VAR (c) model by estimating the optimal lag *c*. This estimation procedure is theoretically justified when the model coincides with the underlined data. The linear approximation of the data generating process enables the VAR to produce optimal and robust one-period ahead forecasting even when the model is misspecified.

However, impulse responses are usually function of forecasts at ever-increasing horizons for which a VAR may provide a poor approximation due to recursiveness. In Section 7 we propose a robustness of the results of Section 6 by applying the Local Projection (LP) model. Local projections have numerous advantages: (1) they can be estimated by simple OLS regression; (2) they are more robust to misspecification of the true data generating process; (3) joint or point-wise analytic inference is simple; and (4) they can be easily adapted to a nonlinear specification by including nonlinear regressors.

Section 8 introduces nonlinear stochastic processes of inflation during the 1973-2023 period. Nonlinearity is not rejected. We show that the two-regime Markov model is appropriate to estimate the evolution of inflation during the 1973-2023 time-period. In section 9 we estimate the effect of inflation on insurers' financial variables with the two-regime Markov model.

A third study of inflation on insurers' financial variables is realized this time with the NAIC data source having information on all individual P&C insurers in the United States from 1992 to 2023. We study the effect of inflation on different activities such as *Reinsurance demand*, investment strategies, and on different financial indicators such as the return on assets (*ROA*). Other important financial indicators are also considered. We use our data to evaluate the effect of *COVID-19* on the insurance industry during the years 2020-2023. The presentation of this analysis is in Section 10 of the report.

Knowing that hedging risks is a forward-looking activity which begins by understanding well the dynamic of the underlying risk and finishes by accurately forecasting it to be well prepared, we analyze the interconnexions between inflation and other main macroeconomics variables to accurately predict future inflation. This forecasting exercise is done with an emerging econometric framework based on Bayesian inference (BVAR) and accounting for real features of macroeconomic variables, namely heavy tails and asymmetric distributions, particularly during economic downturns periods. This is presented in Section 11.

Social inflation (or superimposed inflation) is particular to insurance. It differs from economic inflation discussed above. It is defined as excessive growth in insurance settlements or excessive inflation in claims (Lynch and Moore, 2023). It has increased auto liability claims by more than 20 billion during the period 2010-2019. It is also important in other liability markets including medical malpractice. Social inflation is covered in detail in the last section of this report. We then conclude the report by reporting the main results of the study.

Sections 9 to 12 represent the main contributions of this report. They are written for publication in academic journals. They can be read separately.

1 Literature review

1.1 Economic inflation

Economic inflation is the loss of purchasing power that results in a general and sustainable increase in prices. The *Inflation rate* is the percentage change of a price index during a period, usually a year. Inflation can affect the real economy and the monetary policy.

There are two kinds of inflation originating from the real economy (Sowell, 2004). Demand pull inflation where workers with higher wages increase their demand for goods and services. Supply push inflation from natural resources exogenous shocks or other material supply shocks and labor shortage as we particularly observed in 2020 to 2023. The observed oil price shock explained by the war in Ukraine is an example of such inflation driver. It is also associated with the post *COVID-19* economic environment.

A poor local currency may create inflation in an open economy as imported goods and services will become more expensive (demand pull) while imported natural resources for production push prices (supply push). Finally, inflation can be caused by monetary policy, the other main causality link. A central bank may increase the money supply without having a corresponding increase in real output. This increase in money supply may then devaluate the local currency and increase prices of imported goods and services.

Deflation is another issue that must be considered. Deflation is a decline in the general price index explained by a lack of aggregate demand. Suppliers of goods and services must cut their selling prices and wages because demand is low. Deflation can induce unemployment and even a recession. Deflation may also be caused by a drop in the aggregate supply of money. On the converse we can have hyperinflation often explained by a large supply of money in the economy following important government deficits.

Social inflation is particular to insurance. It is defined as excessive growth in insurance settlements of claims often established by courts (Lynch and Moore, 2023). We do not analyze in detail social inflation in this report. We propose a literature review of the main contributions in the last section of the report.

The price index the most often used is the Consumer Price Index (*CPI*) of a large basket of goods and services (Bureau of Labor Statistics, BLS). Keeping a constant basket over the years may create a bias, because some goods may become less important for consumption and new goods from innovations may turn into high demand. Moreover, during an inflation period, customers may substitute goods with high inflation in the general basket and consume other goods with lower *Inflation rate*. A US Senate committee concluded that the *CPI* overstated inflation by 1.1% in 1996 (Boskin et al., 1996; see also Gordon 2006). Since 1999, the BLS updates the index. We do not consider other measures of inflation in this study.

1.2 Causes of recent inflation

Inflation was not important over the 1983-2019 period. The 2007-2009 financial crisis did not accentuate price variations significantly although it affected financial markets. Particularly it increased default and liquidity risks in the banking sector.

The *COVID-19* crisis had a different pattern on prices stability by creating shortage in many markets and inciting governments to inject money into the economy. Following the recent *COVID-19* pandemic, inflation became an international growing concern. The BLS reported that the *CPI* for all items in the US rose 7% from December 2020 to December 2021, the largest annual percent change since 1981. The annual *Inflation rate* was 8.3% in April 2022 (6% in December 2022 and 3.3% in May 2024). The European Union annual *Inflation rate* was 5.3% in December 2021 and 7.4% in April 2022 (10.4% in December 2022 and 2.4% in April 2024).

Many sources of the recent inflation are reported. Labor shortage in about all sectors is often mentioned as a primary source. The pandemic has triggered many workers to re-evaluate their priorities and discouraged many unemployed individuals from returning to the workforce. These labor shortages have led pressure for businesses and caused operational delays. Some employers had to increase their compensation packages to retain or attract workers. Such trends have increased overall labor costs. Supply chain disruptions represent another source of inflation during this period. They caused production slowdowns during pandemic-related closures and created scarcity. Finally, the Russia-Ukraine war is view as another cause of inflation for energy and food prices.

Used cars, houses replacement prices and skilled workers wages were particularly affected, values that are directly related to the severity of insurance claims. Moreover, the economic activity was restarting in the third quarter of 2021 which may have increased road accidents frequency and severity. Inflation also affected interest rates and consequently investments decisions and asset-liability risk management activities.

Bernanke and Blanchard (2025) analyze the causes of the post *COVID-19* inflation. They show that, for the US, the recent inflation period was explained by strong increases in the prices of food and energy. Supply disruptions in key sectors is also a cause, as well labor supply became tight and contributed to wage inflation. They conclude that, for the United States, returning to price inflation target may require higher unemployment.

They estimate the relationships between four endogenous variables: wage inflation, price inflation, short-run inflation expectations, and long-run inflation expectations. Lag explanatory variables such as price inflation, wage inflation, commodity price shocks, sectoral shortages, and labor market tightness were used as explanatory variables over the period from 1990 to the start of the pandemic[3]. They then used their estimates to simulate the inflationary effects of the various shocks that affected the US economy from the beginning of 2020 to early 2023. Quarterly data was used for the period 1990Q1 to 2023Q2.

They find that energy prices, food prices, and price spikes due to shortages were the significant drivers of inflation in its early stages, although the second-round effects of these factors, through their effects on other prices and through higher inflation expectations were limited. The contribution of labor market conditions to inflation was initially modest. But as product market shocks became less significant over time, the labor market conditions and the persistence in nominal wage increases have become the main factors behind wage and price inflation. These sources of inflation were unlikely to depart without macroeconomic policy intervention from the Fed.

The US response to the *COVID-19* pandemic included a series of federal intervention plans which caused roughly $5 trillion in government spending. These programs contributed to

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[3] For example, wage inflation is function of lag of wage inflation, and lagged values of other determinants such as ratio of vacancies and the number of unemployed persons. Price inflation is function of wage inflation and generic price shocks. Short-run inflation expectations are a weighted average of long-term inflation expectations and realized inflation. Long-run inflation expectations evolve as a weighted average of the previous link of long-run expectations and actual inflation. Different additional lags were added in the applications.

strong consumer and business demand, which affected labor markets in mid-2021 and early 2022, causing upward pressure on wages and prices.

In summary, rising commodity prices and supply chain disruptions were the principal triggers of the recent inflation. But when these factors became less significant, labor market conditions and wage increases became the main drivers of the rate of price increase.

1.3 Historical effect of inflation on the insurance industry

1.3.1 Some general results

The main reference for this section is the excellent survey prepared by Ahlgrim and D'Arcy (2012) for the Casualty Actuary Society, the Canadian Institute of Actuaries, and the Society of Actuaries. Additional recent documents are also discussed although they are few because inflation has not been a popular research subject over the recent years. We also present recent industry documents.

The effect of inflation on the real economy depends on the fact that it was anticipated or not. For example, workers may ask for higher wages when they anticipate inflation. Not anticipated inflation by workers may cause increases in prices higher than wage increases and reduce the aggregate demand in the economy. Inflation could create a number of concerns for insurance policyholders and insurers. Inflation may also have redistributive effects (Blanchard, 1987).

Insurers should be proactive in managing inflation to keep profitability and reserves in adequate real values. Reinsurers must also be proactive in insulating their portfolios by conditioning and managing their treaty features in relation to inflation. Different financial hedging instruments (T-Bills and ETFs) can be used but the literature is very scarce on this subject.

During the 1951-1976 period, inflation had a negative correlation with underwriting margin profits and investment returns in the P&C insurance industry (D'Arcy, 1982). No significant correlation between the levels of underwriting profits and inflation was observed during the 1977-2006 period. A negative and significant correlation was observed between inflation and investment returns during that period (Krivo, 2009).

Masterson (1968) measures the impact of inflation on insurers by isolating components that are related to inflation by line of business. Inflation did not have an isolated impact on insurer global performance. While high inflation by itself may increase claim costs of insurers, the interaction with other economic and financial variables may lead to a more complex risk assessment. When an insurer may be experiencing higher automobile claims caused by inflation, these effects may be offset by lower employment which might influence negatively workers compensation claims.

A positive relationship between T-Bill yields and inflation was estimated in the two 1951-1976 and 1977-2006 periods. In fact, D'Arcy (1981) recommends using T-Bills to immunize deteriorations in underwriting profit margins due to inflation. There is a trade-off here between return and coverage, and T-Bills represent a form of risk management during inflation period because of their very short duration.

Lowe and Warren (2010) describe the negative impact of inflation on property-casualty insurers' claim costs, loss reserves and asset portfolios. However, the document does not mention if the effects are statistically significant or not. The authors express concern that most current actuaries, underwriters and claim staff have never experienced severe inflation, so could be slow to adapt to any change in the economic environment.

In general, medical cost inflation for property-casualty insurers tends to exceed the general *Inflation rate*. The Milliman Medical Index shows that the healthcare costs for workers and their Health insurance companies have increased at a rate significantly in excess of the rate of inflation (Mayne et al, 2011).

Another major component of claim costs for property-casualty insurers is with liability claims for damage to property or injury to a person caused by an insured. In these cases, the claimant has little incentive to control costs when they will be paid by the party's insurer responsible. In fact, there is the perverse incentive to increase the cost of such items as medical care or loss of wages, to generate a larger settlement for non-economic losses such as pain-and-suffering (ex-post moral hazard, Dionne and St-Michel, 1991). As noted by Lowe and Warren (2010), when inflation spiked in the 1980s, a liability insurance crisis erupted, with claims costs increasing well in excess of the general *Inflation rate*. Insurers are also likely to experience adverse development on loss reserves if inflation increases. As explained in D'Arcy et al. (2009), loss reserves are commonly set based on the inherent assumption that the *Inflation rate* experienced in the recent past will continue until these claims are closed. For some liability insurance lines, it can take a decade for these losses to close.

An increase in interest rates reduces the value of long-term fixed income holdings, which make up a significant proportion of investments for property-casualty insurers. Short-run insurance investment returns were significantly negatively correlated with inflation during the period 1933-1981 (D'Arcy, 1982) and that of 1977-2006 (Krivo, 2009). In addition, stock returns were significantly negatively correlated with inflation during the period 1933-1981 (D'Arcy, 1982), although not during the period 1977-2006 (Krivo, 2009). This discrepancy may be due to the level of inflation and whether it was expected.

Bruneau (2010) studied the impact of inflation on P&C and Life insurance *Premiums* over the period 1965-2007 in six countries of the G7. She found a long-run relationship between inflation and *Premiums*. Over the 1986-2007 period she observed an overreaction of premium growth rate to inflation, as a result of transitory and persistent effects of inflation around 1985. For the P&C sector, the results were relatively uniform for all countries studied except for Japan and Italy. In the Life insurance sector, the findings of persistent inflation were also comparable between the countries except for Canada where inflation had no impact at all in the short term and the long term on *Premiums*.

Blondeau (2001) shows that the *Combined ratio* was related to inflation in the P&C insurance sector in France during the 1963-1999 period. Bruneau and Sghaier (2014) analyzed the causes of underwriting cycles of the *Combined ratio* and the capacity ratio in the French P&C insurance market during the period 1963-2008. They verify that inflation affected the capacity ratio and the *Combined ratio* of insurance firms, meaning that capital regulation should take into account market conditions when evaluating the solvability of insurance firms.

Life insurers are less affected by claims inflation since many products have policy payouts that are fixed in amount. Also, inflation-indexed Life insurance products are available, Brown et al. (2000) point out that sales of these products have not been very important. Instead, Life insurers have promoted variable products (mainly annuities) to tie values of stock market performance for policyholders who are concerned about the erosion of value due to inflation (Rejda, 2011). However, high inflation reduces the current value of fixed future payments creating a disincentive for Life insurance purchases. Li et al. (2007) provides empirical evidence for the negative impact of inflation on Life insurance demand and sales.

Browne et al. (2001) show that the financial performance measures such as return on equity (ROE) and return on assets (ROA) are significantly negatively affected by unanticipated inflation, likely driven by the significant leverage of Life insurers.

On the asset side of the balance sheet, understanding exposure to inflation risk requires some knowledge on the relation between inflation and asset returns. The Fisher hypothesis suggests a direct link between nominal asset returns and expected inflation. There are contradictory empirical results on this relationship, however (Titman and Warga, 1989, and Stock and Watson, 2003). The solution in the understanding of the differences revolve around the investment horizon and the type of investment. Swiss Re (2010) reports correlations between inflation and annual returns in various asset classes. They document a high positive correlation for real estate, commodities, and Treasury bills, while the correlation between inflation and longer-term bonds is predictably negative. They find no statistical significance between equities and inflation. Boudoukh and Richardson (1993) extend the short-term results of Fama and Schwert (1977) and find that while stock returns are slightly uncorrelated with inflation in the short-term, at longer horizons the expected Fisher relationship is stronger. Solnik and Solnik (1997) confirm the link between inflation and stock returns over longer horizons using data from eight countries and Schotman and Schweitzer (2000) find that the effectiveness of stocks as an inflation hedge depends on the investment horizon. It had been believed that since stocks are claims on real assets, monetary policy should not affect stock returns.

There is a high correlation between Treasury bills and inflation. But as longer-term interest rate securities, as yields on bonds, rise with inflation, prices move in the opposite direction to generate the negative correlation illustrated over short horizons. Bekaert and Wang (2010) report that hedging inflation risk is difficult when using securities such as stocks and bonds. They also consider and expanded the set of potential hedges including real estate and commodities with similar disappointing results. Bekaert and Wang (2010) argue that the lack of a good inflation hedge highlights the importance of inflation indexed securities such as Treasury Inflation Protected Securities (or TIPS).

1.3.2 Insurer inflation risk mitigation strategies

The first risk mitigation strategy for insurers is to prepare staff to be ready to deal with deflation or high inflation. Effective contingency planning that recognizes the negative impact that deflation or high inflation would have on insurance companies is an essential first step. This will allow companies to respond quickly when economic conditions change. Specific risk mitigation steps can be considered in at least two different areas: underwriting, risk management, and investments.

During the 1973-1982 period of high inflation, insurers found it necessary to reduce policy terms and adjust rates frequently to keep up with increasing costs. Keeping rate adjustments in line with inflation required semi-annual rate adjustments. For property-liability insurers, loss reserves were significantly affected by changes in *Inflation rate*. Most loss reserve calculations did not specifically consider inflation as a factor in setting reserves.

This is more complicated when inflation is volatile. Taylor (1977) and D'Arcy and Gorvett (2000) proposed loss reserve methods that separate out the impact of inflation from experience and then allow the actuary to incorporate a different *Inflation rate* in the reserve calculations.

For Life insurers, many policy forms have incorporated features which lessen the chance for arbitrage opportunities in products. Instead of providing policy loans at fixed rates, whole Life policies often linked loan rates to a floating index correlated with inflation. Policies that index benefits for inflation, such as inflation adjusted annuities, need to have a cap in order to avoid significant unexpected exposure in the event of sustained high inflation. Hyperinflation, although considered a remote possibility by many, is a risk that does need to be addressed. As properly pricing a policy that fully indexes inflation could be cost prohibitive if the risk of hyperinflation is reflected, this risk could be viewed as a macroeconomic problem, and not one that can be handled through insurance.

1.3.3 More recent inflation period

The resurgence of inflation in 2020 was a surprise in insurance markets (Geneva Association, 2023). The immediate impact of inflation on non-Life insurers' earnings should be negative according to the report, primarily through rising future claims costs on current insurance policies and the need to protect loss reserves with more capital. The effect on Life insurers' earnings should be more neutral. Most Life insurance products, e.g. mortality, wealth accumulation and longevity protection, offer benefits that are nominally fixed. Rising interest rates may negatively affect insurers' balance sheets. Higher interest rates, however, could have a favorable effect on the net present value of future liabilities.

According to the Geneva Association (2023), there is a wide range of management actions insurers can take to respond to the recent macroeconomic environment. In terms of product design, insurers could offer more low-cost products with an increased focus on risk and loss prevention. With tight labor markets and increasing wage pressure, insurers can also improve operational cost efficiency and overall productivity. However, these activities take a long while to realize.

One underwriting response to inflation is to reset the insurance price of risks that exhibit high claims costs. This activity depends on the competitive environment in insurance markets, insurers' anticipation about central banks' ability to reduce inflation and the degree of public policy and regulatory constraints.

In investment management, there is some possibility for inflation protection on asset allocation by moving the investment portfolio away from bonds towards commodities, equities and real estate. For many insurers, however, such potential activity is constrained by their very high solvency capital requirements.

Every insurer should monitor price developments, focusing on insurance exposure, such as repair costs, construction prices or medical cost inflation. Insurers must react to anticipated cost increases by adjusting *Premiums*. Moreover, trade-off between increase in *Premiums* and potential losses of clients effects must always be considered. The same logic applies to reserving, especially in long-tail business. In this context, rising interest rates can mitigate selection issues by making it easier to finance long-term guarantees.

In general, effective insurer responses to inflation would have to occur ex-ante, rather than ex-post. So, inflation anticipation remains a key issue. Once inflation has picked up, the value of inflation-linked securities and the level of interest rates reflect capital markets' inflation expectations, which drive up the cost of any hedging strategy. This means that the insurance industry must have models to anticipate inflation.

According to EIOPA (2023), the key determinants of P&C insurers' welfare sensitivity to inflation and corresponding higher interest rates are the exposure to interest rate sensitive assets, the relative duration of liabilities and the sensitivity of claims and expenses to inflation.

Inflation may also have an impact on regulated capital. A decrease in the value of fixed income assets leads to a decrease in market risks while an increase in exposure to future *Premiums* might lead to a potential increase in underwriting risk. High inflation and interest rates could be beneficial for Life and non-Life insurers in the long run due to the reinvestment of assets at higher yields. In the short term, the impact should be negative mainly due to losses on interest rate sensitive investments.

When assessing the impact of inflation on profitability, the time horizon needs to be considered. In the short run, the impact of inflation on profitability may be negative, in particular for non-Life insurers with higher share of business in competitive lines of business such as liability insurance. The impact is reflected in higher claims for which insurers must increase their reserves. Moreover, *Premiums* need to be adjusted to maintain the equilibrium *Combined ratio*. In the short run, under market competition, underwriting profitability is usually reduced.

Another important component of profitability is investment (EIOPA, 2023). If high inflation generates high interest rates this would result in higher investment returns on the fixed income portfolios. Better investment results would allow non-Life insurers to compensate for lower premium increases and maintain overall profitability. In other words, considering that the pre-tax profitability of a non-Life insurer is the sum of the underwriting result and the investment result, then higher investment results can provide at least a partial offset for the inability to increase *Premiums* in line with inflation. This suggests that the potential partial offset from higher investment results should be significant for long-tail business.

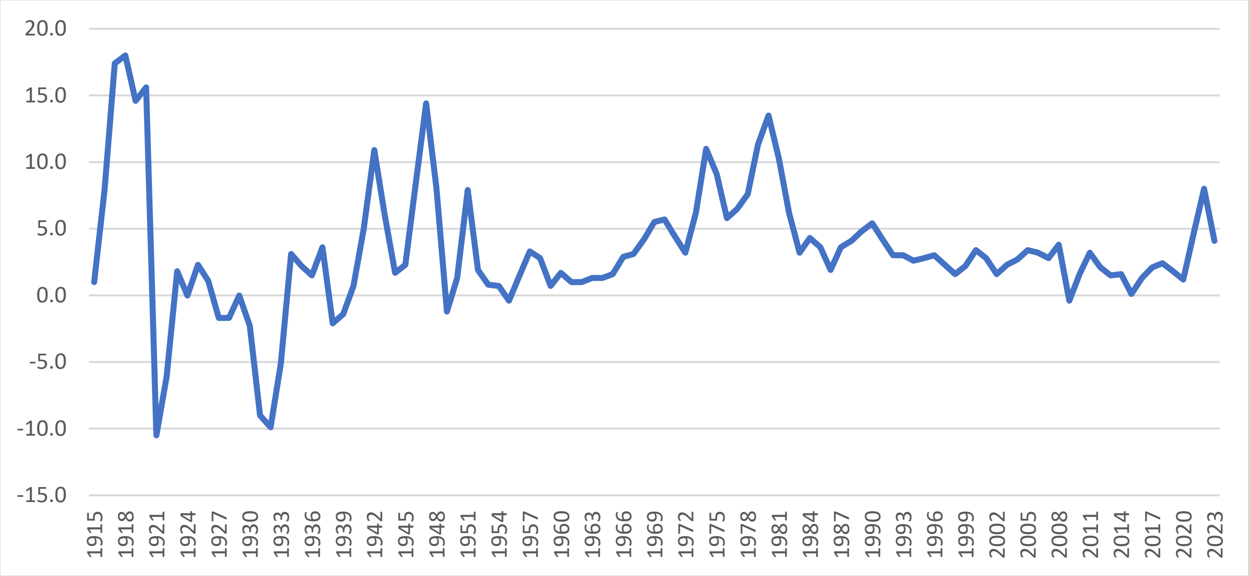
Regarding the impact of inflation on insurance asset values, according to Swiss Re (2010, 2022), the impact of inflation on asset prices depends on time horizon. Insurers must consider short and long-term effects of inflation separately. Insurers can substitute bonds to commodities, equities, and real estate. In investigating the correlation between different asset classes returns and *CPI* in the US market between 1998 and 2009, the study showed that treasury bills and real estate were positively correlated while long-term bonds were negatively correlated.

2 Inflation in the US during the 1915-2023 period

2.1 *Inflation rate* as a measure of inflation

US *Inflation rate*, as measured by the change in the Consumer Price Index (*CPI*), is shown in Figure 2.1.

Figure 2.1: *Inflation rate* in the US during the 1915-2023 period



Source: US Bureau of Labor Statistics.

Periods of high inflation, moderate inflation and deflation can be observed in these data. The two periods of high inflation, 1917-1920 and 1941-1947, correspond to wars while the 1974-1980 period is linked to oil prices shocks. Deflationary periods occurred from 1927 to 1933 and in 1938. After 1983, inflation was quite stable. In Table 2.1, we separate the three types of inflation in the US. We observe that moderate inflation periods dominate in frequency.

Table 2.1: Periods of high inflation, moderate inflation, and stagflation in the US between 1915 and 2023

	Frequency	Mean
All Years		3.29%
Stagflation	11.93%	-3.98%
Moderate 0 to 6 %	68.80%	2.55%
High > 6%	19.27%	10.42%

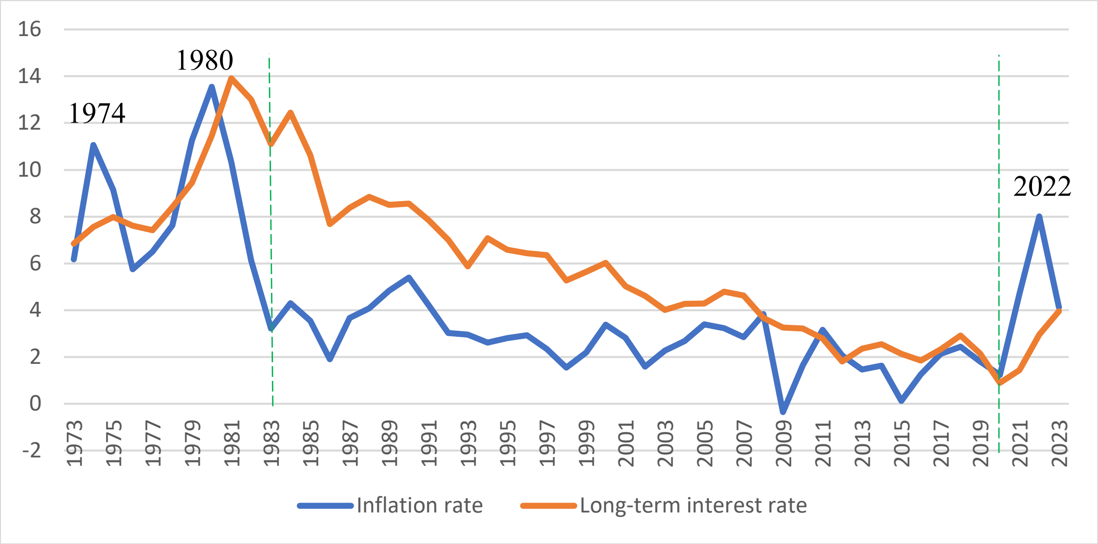
Any analysis of future *Inflation rate* effects on insurance industry should not be parameterized based solely on the levels of inflation experienced in a country over the last few years. A longer time horizon that would include the deflation periods and those of high inflation as well as consideration of developments in other countries that have faced similar economic conditions, needs to be reflected in any model for predicting inflation. Understanding historical inflation is important, but Stock and Watson (2007) show how changing economic conditions over decades have made it more difficult to accurately predict inflation.

One interpretation of these inflationary periods is that when the economy is experiencing normal economic periods, the average *Inflation rate* should be considered moderate. But two other economic regimes are possible over time. First, expansionary fiscal policy combined with accommodative monetary policy may lead to sustained inflationary pressures. In this high-inflation regime, there is a significantly higher average level of inflation than indicated from recent history. This may correspond to the post-*COVID-19* situation. It is even plausible that, in this high-inflation regime, inflation volatility was higher. Another regime is one of continued worldwide economic stagnation with moderate government spending and central bank easing. This third regime incorporated in the inflation model reflects the possibility of deflationary pressures. The average level of inflation and its volatility should be low, as observed during the years preceding the *COVID-19* pandemic.

In many countries, inflation is a major concern for politicians and decision-makers, not only because of its significant variability over time, but mainly owing to its potential adverse effects on economic stability. As the insurance industry is a key component of the economy, given the high volume of direct *Premiums* earned, claims managed, and investments made, it is worth knowing the impact inflation variability could have on the financial stability of the insurance industry. In our study, we consider the *Inflation rate*, often used by insurers as an indicator for measuring inflation. Other inflation indexes will not be considered.

2.2 US *Inflation rate* during our period of analysis

Figure 2.2: *Inflation rate* and nominal rate of LT (10-year) government bonds, 1973 to 2023 period

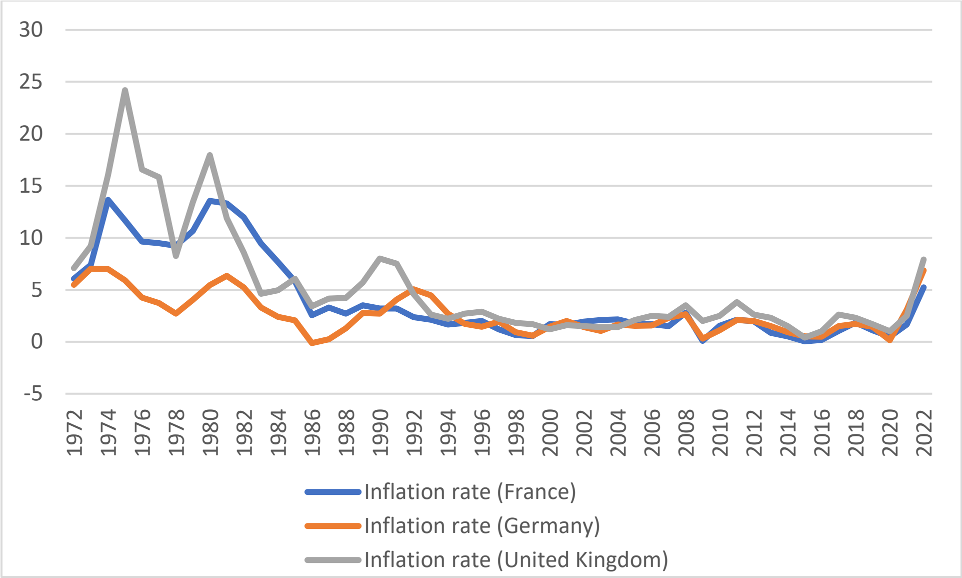


Source: World Bank.

Figure 2.2 shows that *Inflation rate* exhibits an overall downward trend from 1990 to 2020. It also indicates that the United States has experienced three inflationary shocks since 1973. The first shock started in 1974. It was linked to a first oil shock. The second shock, the biggest in this period of analysis, started in 1980. It is linked to a second oil shock. The third shock started in 2020 and is linked to the *COVID-19* pandemic.

Three other observations can be made from Figure 2.2. The first is that the *Inflation rate* has been sliding steadily since the early 1990s and reached a historically low point in 2009. It hovered below 6% throughout the 1990-2020 period. The second observation stems from the specific nature of the post-1990 period. The *Inflation rate* has also become more variable than before 1990. Protecting against the risks associated with fluctuating inflation is now becoming a necessity. Finally, Figure 2.2 shows that *Inflation rate* and the nominal rate of LT government bonds (10-year maturity) moved in the same direction over the entire period. We can clearly see that the steady slide in *Inflation rate* observed since the early 1990s has led to a reduction in the interest rates on LT (10-year maturity) government bonds in which insurers, especially Life insurers, invest. Figure 2.3 presents the variation of inflation in three European countries over the same period.

Figure 2.3: *Inflation rate* in France, Germany and England, 1973 to 2023 period



Source: World Bank.

The comparison between Figures 2.2 and 2.3 permits to observe two results. First, inflation varies strongly between the European countries over time before 1990. Germany was less affected by the inflation shocks of these years. Second, inflation rates in the three European countries are more similar to those in US after 1990. Notice that the European Central Bank was established in 1999, following the decision of building the Economic and Monetary Union taken in 1988.

3 Properties of the US *Inflation rate* series

In this section we review some empirical regularities in the US *Inflation rate* series.

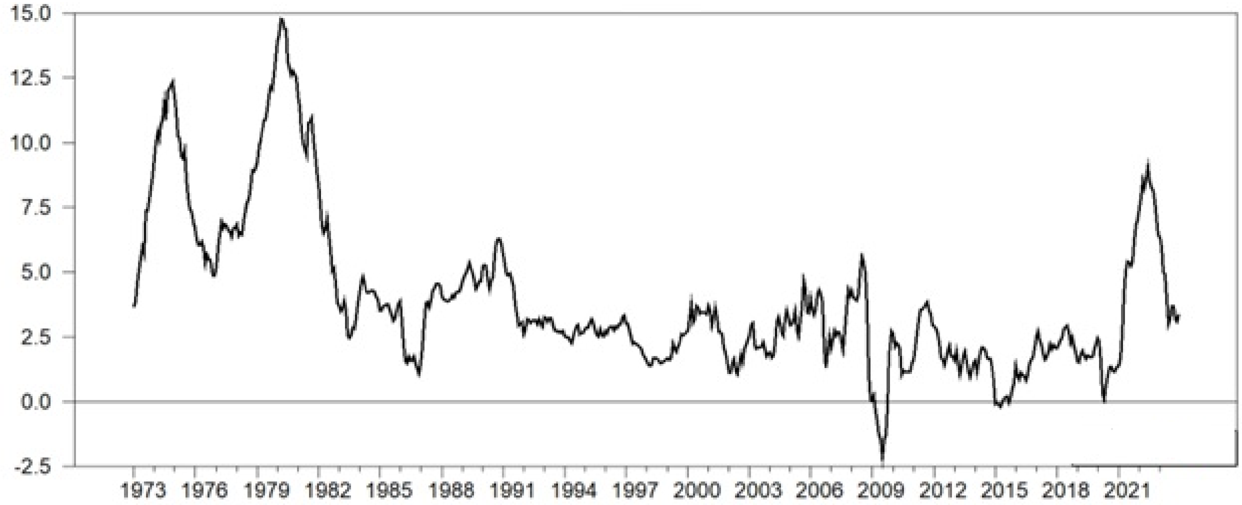
3.1 Nonstationarity

Figure 3.1 shows that the inflation annual rate series appears to be nonstationary. To verify this, we applied the Augmented Dickey-Fuller (ADF) stationarity test. We tested the null hypothesis that the *Inflation rate* variable is nonstationary against the alternative hypothesis of stationarity. Our ADF test on *Inflation rate*, using a model with a constant and trend for an optimal lag equal to 5. The hypothesis that *Inflation rate* is nonstationary was not rejected.

The no-stationary nature of the series may be linked to the presence of a deterministic linear trend or to the presence of a stochastic trend in the series. To make the series stationary, we first assumed the presence of a deterministic linear trend and performed a linear regression (OLS) of the series against a time trend variable.

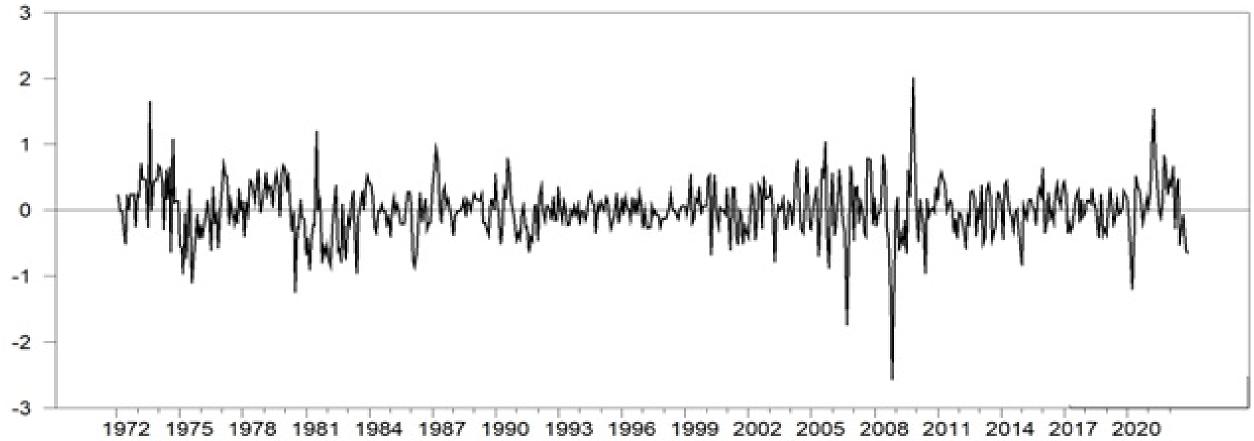
Figure 3.1 shows that the series still seems to retain its nonstationary character after the deterministic trend is extracted. This led us to suspect the presence of a stochastic trend in place of the deterministic linear trend in the US *Inflation rate* series. To verify this, we transformed the series into first-difference mode.

Figure 3.1: Evolution of the annual *Inflation rate* after purging the deterministic trend, 1973-2023 period



Source: World Bank.

Figure 3.2: Evolution of the *Inflation rate* after purging the stochastic trend, 1973-2023 period



Source: World Bank.

Figure 3.2 shows the variation of the *Inflation rate* around a mean. In some periods, the *Inflation rate* varies only slightly around its mean, while in others, the variations are large. As can be seen in Figure 3.2, the downward trend in the *Inflation rate* has been suppressed, and the series average appears to lie on a straight line parallel to the *x*-axis. In this case, the rate variable is integrated of order 1, because it is made stationary after a difference. We checked this graphical result using the

Augmented Dickey-Fuller (ADF) test. Our application of the ADF test on the rate, using a model with constant and trend for an optimal lag equal to 2, gave us a p-value $Z(t)$ equal to 0.0003, which is well below the 5% significance level. Consequently, the null hypothesis that inflation purged of the stochastic trend is nonstationary is rejected.

Our analysis enabled us to detect the presence of nonstationarity in the inflation series. In the presence of nonstationarity, a series has an infinite (long) memory or finite (short) memory depending on whether the inflation variable and the shock variable are integrated of order 1 and cointegrated or not. Consequently, a shock may have a permanent or short-term impact on the inflation series. The cases of the oil shocks of the 1970s (1973 and 1979), the 1979 monetary policy change, and *COVID-19* on the *Inflation rate* may be illustrative. To demonstrate this, we will use VAR (c) processes, where *c* denotes the number of orders. VAR (1) models were introduced by Sims (1980) as alternatives to Keynesian-inspired macro-econometric models. In empirical applications, one of the main utilities of VAR processes is to analyze impulse responses of the variables under study.

3.2 VAR (1) processes and impulse responses

3.2.1 Description of the Vector Autoregression (VAR (1)) model

VAR (1) processes are a generalization of autoregressive processes (AR) to the multivariate case (Sims, 1980). VAR (1) modeling is based on the assumption that the evolution of the economy is well described by the dynamic behavior of a vector of *N* variables that are linearly dependent on the past. The advantage of the VAR (1) model is that it is a powerful forecasting tool.

We use a VAR (l) model containing two variables, y_t and x_t. Each variable is a function of its own past values, but also of the past values of the other variable in the system of equations (3.1) and (3.2).

$$y_t = \beta_0 + \Sigma_{j=1}^{1} a_j y_{t-j} + \Sigma_{j=1}^{1} b_j x_{t-j} + u_{t,y} \tag{3.1}$$

$$x_t = \beta_0 + \Sigma_{j=1}^{1} a_j x_{t-j} + \Sigma_{j=1}^{1} b_j y_{t-j} + u_{t,y} \tag{3.2}$$

where y_t represents *Inflation rate*, x_t our shock variable, $u_{t,y}$ is the unanticipated impact of inflation (innovation) on the inflation variable and $u_{t,x}$ is the unanticipated impact of the shock variable on the shock variable.

3.2.2 Cointegration and VAR (l)

The VAR (l) model of order 1 is generally estimated on stationary variables. The VAR (l) model can also be estimated on nonstationary variables, provided they are integrated of order 1, i.e. they are nonstationary variables in the raw state that are made stationary after a difference. However, to estimate the VAR (l) model with nonstationary variables integrated of order 1, we need to distinguish between two possibilities for the VAR (l) model, depending on whether the variables y_t and x_t are cointegrated or not. The two special cases of the VAR (l) model are: 1) the VAR (l) level model, which is adapted to integrated variables of order 1 that are cointegrated, and 2), the VAR (l) difference model, which is adapted to integrated variables of order 1 that are not cointegrated.

The starting point for cointegration theory is the fact that many macroeconomic and financial series are nonstationary. Cointegration theory enables us to study nonstationary series of which one linear combination is stationary. It thus lets us specify stable long-term relationships. One of the fundamental properties of cointegration theory is that two nonstationary (I (1)) series y_t and x_t are cointegrated if there is a stationary linear combination (I (0)) of these two series.

According to Engle and Granger's (1987) approach, two nonstationary series I (1) of y_t and x_t are integrated if the residuals of the long-term relationship between these series are stationary. If two series y_t and x_t are cointegrated (stable long-term relationship between y_t and x_t), the VAR (l) model can be estimated directly on the variables y_t and x_t. We thus estimate a level VAR (l) model. However, if the two series y_t and x_t are not cointegrated (short-term dynamics between y_t and x_t), we must consider the first difference of the variables, i.e. estimate a VAR (l) model in difference. To this end, it is therefore legitimate to test for the presence of cointegration to identify whether to use a *level* VAR (l) model or a VAR (l) model for our estimation. In short, we estimate a *level* VAR (l) model when we reject the null hypothesis (H_0) of no cointegration and estimate a VAR (l) model when we do not reject the null hypothesis of no cointegration.

3.2.3 Two-step estimation method

Our approach to estimating a VAR (c) model of order *c* is based on a two-stage estimation method proposed by Engle and Granger (1987). The advantage of this approach is that it is simple to implement. The first step is to estimate the stable long-term relationship between the variables y_t and x_t. The second step consists in choosing one of the two special cases of the VAR (c) model best suited to the variables y_t and x_t.

- First step: Estimate the long-term relationship (static relationship between $\boldsymbol{y_t}$ and $\boldsymbol{x_t}$)

Let the variables y_t and x_t be two I (1) variables. We estimate the following relationship:

$$y_t = \alpha + bx_t + v_t \tag{3.3}$$

where v_t is the error term. According to this equation, $v_t = y_t - \alpha - bx_t$, i.e. the error term v_t is a linear combination of y_t and x_t. In the special case where $b = 0$, v_t is I (1), since it is the sum of a variable y_t and the constant $-\alpha$. In contrast, if $b \neq 0$, it is possible that v_t is I (0). If we estimate (3.3) by OLS and find a high R^2, this indicates the presence of a long-run equilibrium relationship between the variables y_t and x_t. This relationship is called a cointegration relationship.

- Second step: Choosing and estimating the VAR (c) model

If the variables y_t and x_t are cointegrated, i.e. if the residuals of the long-run relationship in equation (3.3) are stationary, we proceed to estimating the VAR (c) *level* model in step 2. In the opposite case, we proceed to estimating the VAR (c) model in step 2.

3.3 Estimation of the VAR (c) model between inflation and the various shocks

3.3.1 VAR process for the 1970s oil shocks events and inflation

We represent the input, which is oil shocks events of the 1970s (positive inflation shock), by the x_t variable in our VAR (c) model. The variable 1970s oil shocks and inflation takes the value of 1 for each year of the period from 1973 to 1979, a period marked by various oil shocks during which inflation rose sharply. The *Inflation rate* output rate is represented by the variable y_t in our VAR (c) model.

Since Engle and Granger's (1987), we know the method is valid only for integrated series of order 1, i.e. $I(1)$. We first need to determine the order of integration of each of our two variables: *Inflation rate* and 1970s oil shocks. We showed earlier that the *Inflation rate* series is made stationary after a difference. It is therefore integrated of order 1 (1). We will now check whether the 1970s oil shocks events is also integrated of order 1.

Table 3.1: ADF test on the 1970s oil shocks events, 1973-2023 period

$Z(t)$	Test Statistic	1% Critical value	5% Critical value	10% Critical value	p-value
1970s oil shocks	-2.407	-4.159	-3.504	-3.504	0.376
D.1970s oil shocks	-7.205	-4.159	-3.504	-3.182	0.000

Note: D stands for first difference.

Table 3.1 shows, in the first row, a p-value of $Z(t)$ = 0.376, which is above the 5% significance level. The null hypothesis that the 1970s oil shocks events are nonstationary (presence of unit root) is therefore not rejected. We took the first difference of the 1970s oil shocks events (D.1970s oil shocks) and repeated the test. The result of the Augmented Dickey-Fuller (ADF) test on D.1970s oil shocks, shown in the second row of Table 3.1, indicates a p-value of $Z(t)$ = 0.000, which is below the 1% significance level. Consequently, the null hypothesis, that D.1970s oil shocks are nonstationary, is rejected. In other words, 1970s oil shocks are stationary after a difference and therefore integrated of order 1.

We now need to determine whether there is a stable long-term relationship between these two variables. To this end, we will estimate the static relationship between 1970s oil shocks events and the *Inflation rate* variable. Next, we will recover the residuals of the static relationship and apply ADF tests on them.

Table 3.2: Estimation of the static relationship between 1970s oil shocks and *Inflation rate*, 1973-2023 period

Dependent variable	*Inflation rate*
1970s oil shocks	4.874*** (0.901)
Constant	3.342*** (0.371)
Observations	51
R-squared	0.332
Adjusted R-squared	0.319

Note: Robust standard errors in parentheses. *** p<0.01.

We mentioned that if we estimate the static relationship and $b \neq 0$, it is possible that the residuals of the static relationship v_t are I (0). This indicates the presence of a long-term equilibrium relationship between the variables y_t and x_t. The results of the estimation of the static relationship between 1970s oil shocks events and the *Inflation rate* variable presented in Table 3.2 indicate that the coefficient of 1970s oil shocks events are statistically different from zero at 1%. It is therefore possible that the residuals (v_t) of the static relationship between 1970s oil shocks and *Inflation rate* are stationary. We will check this by applying the ADF test to the residuals of the static relationship between the two variables. Table 3.3 shows the results of the ADF tests on the residuals of the static relationship.

Table 3.3: ADF test on the residuals of the static relationship between the 1970s oil shocks and *Inflation rate* variable, 1973-2023 period

$Z(t)$	Test Statistic	1% Critical value	5% Critical value	10% Critical value	p-value
RES	-2.853	-3.600	-2.938	-2.604	0.051

Note: RES stands for residuals.

Table 3.3 shows a p-value of $Z(t)$ = 0.051, which is below the 10% significance level. Consequently, the null hypothesis that the residuals of the static relationship between 1970s oil shocks and *Inflation rate* are nonstationary is rejected. Consequently, the *Inflation rate* and 1970s oil shocks series are cointegrated, i.e. there is a stable long-term relationship between these two variables. It is then possible to estimate the VAR (c) *level* model. To do this, we must first determine the order to retain. To this end, we have estimated various level VAR processes on our two *Inflation rate* and 1970s oil shocks series. For each model, we calculated the Akaike information criterion (AIC), the Schwarz Information criterion (SIC) and the LR statistic. The LR statistic technique consists in estimating a constrained VAR (c) model and an unconstrained VAR (c+1) model and computing the log likelihood ratio (LR). In other words, we can test the order *c* of the VAR model by considering the following equations:

$$H_0: \Phi_{\mathrm{c+1}} = 0\text{: VAR (c) process} \tag{3.4}$$

$$H_0: \Phi_{\mathrm{c+1}} \neq 0\text{: VAR (c+1) process} \tag{3.5}$$

where Φ is the optimal number of delays. VAR (c) represents the constrained model and VAR (c+1) the unconstrained model.

Under the null hypothesis, the LR statistic follows a chi-square distribution with q degrees of freedom. The q value is obtained by calculating the difference between the *c* of the unconstrained VAR $\left(P_{H_1}\right)$ and that of the constrained VAR $\left(P_{H_0}\right)$, which is the difference multiplied by the number of equations squared (N).

$$q = \left(P_{H_1} - P_{H_0}\right)N^2 \tag{3.6}$$

$$LR = 2\left(Log\_lik_{H_1} - Log\_lik_{H_0}\right) \tag{3.7}$$

The decision rule is as follows: If the value of the LR statistic is less than the critical value associated with a $\chi^2(q)$, H_0 is rejected (rejection of the constrained model). In this case, the LR test prefers the unconstrained model, namely the VAR (c+1) model.

We also use the BIC and the AIC criteria. This fits very well with the parsimony principle of Box and Jenkins (1970) and Box et al. (2015) in time series. According to this principle, when given a choice between two roughly equivalent models, we should choose the one involving the fewest parameters to be estimated. This is based on the principle that each parameter that we estimate represents one more possibility of making an error.

Table 3.4: Level VAR (c) model selection statistics, 1973-2023 period

VAR (c)	AIC	BIC	LR
$c = 1$	2.5518	2.7812*	-57.7943*
$c = 2$	2.4365	2.8226	-49.6951
$c = 3$	2.4007	2.9464	-43.6162
$c = 4$	2.4473	3.1558	-39.5107
$c = 5$	2.2840	3.1586	-30.5318
$c = 6$	2.1336*	3.1774	-22.0049

Note: The asterisk indicates the model to be retained according to the selected criterion.

Table 3.4 shows the different statistics of interest for the choice of *c*. The AIC chooses VAR (6) and BIC chooses VAR (1). The log-likelihood ratio statistic $LR = 2\left(Log\_lik_{H_6} - Log\_lik_{H_1}\right)$ confirms the choice with the BIC. Thus, based on the LR test, we prefer VAR (1) to VAR (6). We retain the level VAR (1) model to analyze the impulse response of inflation to 1970s oil shocks.

3.3.2 Impulse response of inflation to the shock of the 1979 monetary policy reform

- VAR process between the variable 1979 Volcker shock and inflation

We represent the input, i.e. the 1979 Volcker shock, by the variable x_t in our VAR (c) model. 1979 Volcker shock takes the value of 1 for each of the years from 1980 to 1982, the period of implementation of the 1979 monetary policy reform led by Volcker. Once again, the *Inflation rate* is represented by the variable y_t.

We have previously shown that the inflation series is nonstationary and have made it stationary after a difference. We will now check the stationarity of the variable 1979 Volcker monetary reform shock before estimating our VAR model.

Table 3.5: ADF test on the 1979 Volcker shock, 1973-2023 period

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
1979 Volcker shock	-3.262	-4.159	-3.504	-3.182	0.073
D.1979 Volcker shock	-6.788	-4.159	-3.504	-3.182	0.000

Note: D stands for first difference.

Line 2 of Table 3.5 shows a p-value of $Z(t)$= 0.000, which is below the 1% significance level. Consequently, the null hypothesis that the D.1979 Volcker shock is nonstationary is rejected. In other words, D.1979 Volcker shock is made stationary after a difference and is therefore integrated of order 1. Given that the two 1979 Volcker series and the inflation variables are integrated of order 1, we now need to check whether there is a stable long-term relationship between these two variables. To this end, we estimate the static relationship between the 1979 Volcker shock and the *Inflation rate* variable.

Table 3.6: Estimation of the static relationship between 1979 Volcker shock and *Inflation rate*, 1973-2023 period

Dependent variable	*Inflation rate*
1979 Volcker shock	6.844*** (1.409)
Constant	3.474*** (0.329)
Observations	51
Adjusted R-squared	0.388

Note: Robust standard errors in parentheses. *** p<0.01.

Table 3.6 shows that the coefficient of 1979 Volcker shock is statistically significant at 1%. It is therefore possible that the residuals of the static relationship between the 1979 Volcker shock and *Inflation rate* variable are stationary. We will check this by applying an ADF test.

Table 3.7: ADF test on the residuals of the static relationship between 1979 Volcker shock and *Inflation rate*, 1973-2023 period

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
RES	-2.954	-3.600	-2.938	-2.604	0.040

Note: RES stands for residuals.

Table 3.7 shows a p-value of $Z(t)$ = 0.040, which is below the 5% significance level. Consequently, the null hypothesis that the residuals of the static relationship between the 1979 Volcker shock and *Inflation rate* variable are nonstationary is rejected. The *Inflation rate* and 1979 Volcker shock series are therefore cointegrated. It is then possible to estimate the level VAR (c) model. To do this, we first need to determine the order c to use for our estimation. To this end, we have estimated various level VAR processes on our two-shock series, *Inflation rate* and 1979 Volcker shock.

Table 3.8: Level VAR (c) model selection statistics, 1973-2023 period

VAR (c)	AIC	BIC	LR
$c = 1$	3.3940	3.6234	-78.8499
$c = 2$	3.2463	3.6324	-69.5339
$c = 3$	3.0111	3.5569	-58.2667
$c = 4$	3.5572	3.5572	-48.9438
$c = 5$	2.5699*	3.4445*	-37.1088
$c = 6$	2.6506	3.6945	-33.6391

Note: The asterisk indicates the model to be retained according to the selected criterion.

Table 3.8 shows that there is a consensus on the AIC and BIC criteria for the choice of VAR (5). We have therefore chosen the level VAR (5) model to analyze the impulse response of inflation to the 1979 monetary policy reform shock from 1973 to 2023 (1979 Volcker shock).

- Impulse response of inflation to the *COVID-19* shock

VAR process between *COVID-19* shock and inflation

We represent the input, namely the *COVID-19* shock (positive inflation shock), by the variable x_t in our VAR (c) model. *COVID-19* shock takes the value of 1 for each year in the period from 2020 to 2023 (even if the official end date is May 2023). The output represented by the y_t variable in our VAR (c) model remains the *Inflation rate*.

We begin by checking the stationarity of the *COVID-19* shock before estimating our VAR model.

Table 3.9: ADF test on the *COVID-19* shock, 1973-2023 period

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
COVID-19 shock	-0.825	-4.159	-3.504	-3.182	0.964
D.*COVID-19* shock	-7.277	-4.159	-3.504	-3.182	0.000

Note: D stands for first difference.

Line 2 of Table 3.9 shows a p-value of $Z(t)$ = 0.000, which is below the 1% significance level. Consequently, the null hypothesis that the D.*COVID-19* shock is nonstationary is rejected.

Table 3.10: Estimation of the static relationship between *COVID-19* shock and *Inflation rate*, 1973-2023 period

Dependent variable	*Inflation rate*
COVID-19 shock	0.674
	(1.684)
Constant	3.971***
	(0.429)
Observations	51
Adjusted R-squared	-0.017

Note: Robust standard errors in parentheses. *** p<0.01.

Table 3.10 shows that the coefficient of the *COVID-19* shock is not statistically significant. The non-statistical significance of this coefficient suggests that the residuals of the static relationship between the *COVID-19* shock and *Inflation rate* variable are nonstationary. We will check this by applying the ADF test to the residuals of the static relationship between the *COVID-19* shock and *Inflation rate* variable.

Table 3.11: ADF test on the residuals of the static relationship between *COVID-19* shock and *Inflation rate*, 1973-2023 period

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
RES	-1.901	-3.600	-2.938	-2.604	0.331

Note: RES refers to residuals.

Table 3.11 shows a p-value of $Z(t)$ = 0.331, which is above the 5% significance level. Consequently, the null hypothesis that the residuals of the static relationship between the *COVID-19* shock and *Inflation rate* variable are nonstationary is not rejected. Thus, there is no stable long-term relationship between these two variables. It is then necessary to estimate the VAR (c) model. To do this, we must first determine the order *c* to retain. To this end, we have estimated various VAR processes on our two *Inflation rate* and *COVID-19 shock* series.

Table 3.12: VAR (c) difference model selection statistics,
1973-2023 period

VAR (c)	AIC	BIC	LR
$c = 1$	3.0084	3.2423*	-66.2005*
$c = 2$	2.9511*	3.3447	-59.3506
$c = 3$	3.0340	3.5170	-57.9192
$c = 4$	3.0320	3.5941	-54.2199
$c = 5$	3.1389	3.7877	-53.0567
$c = 6$	3.1363	3.8735	-49.4300

Note: The asterisk indicates the model to be retained according to the selected criterion.

Table 3.12 shows the different statistics of interest for the choice of *c*. The AIC chooses VAR (2) and the BIC chooses VAR (1). The LR value chooses VAR (1).

- Orthogonalization of shocks

Our econometric approach enabled us to retain the VAR (1) model to analyze the impulse response of inflation to 1970s oil shocks and to the *COVID-19* shock, and the VAR (5) model to analyze the impulse response of *Inflation rate* (IR_t) to the 1979 Volcker shock. We have retained the VAR (1) process to explain the notion of orthogonalization of shocks.

$$IR_t = a_{11}IR_{t-1} + a_{12}Shock_{t-1} + u_{1t} \tag{3.8}$$

$$Shock_t = a_{21}Shock_{t-1} + a_{22}IR_{t-1} + u_{2t} \tag{3.9}$$

where IR represents inflation, $Shock$ represents our shock variable, u_{1t} represents the unanticipated impact of inflation (innovation) on inflation and u_{2t} is the unanticipated impact of the $Shock$ variable on the shock. We can clearly see that a shock to u_{1t} will immediately affect the present value of inflation (IR_t). It will also affect future values of inflation and those of the shock variable, because past values of inflation are involved in both equations.

If the innovations u_{1t} and u_{2t} are uncorrelated, interpretation of the impulse response function is very straightforward. In this case, u_{1t} is the inflation innovation and u_{2t} is the innovation of the shock variable. In contrast, if the innovations u_{1t} and u_{2t} are correlated, they have a common component that cannot be associated with a specific variable. It is arbitrary to assume common effects for innovations in impulse response analysis. To put it plainly, assuming common effects between innovations leads to incorrect interpretation in impulse response analysis. The Cholesky decomposition method (Brezinski and Tournès, 2014) allows us to orthogonalize innovations u_{1t} and u_{2t} to make them uncorrelated.

Table 3.13: Calculation of innovation correlation coefficients, 1973-2023 period

	1970s oil shocks innovation	1979 Volcker shock innovation	*COVID-19* shock innovation
IR innovation	0.576***	0.431***	0.050

Note: *** p<0.01.

Table 3.13 shows a statistically significant correlation coefficient at the 1% level between IR innovation u_{1t} and innovation in 1970s oil shocks events u_{2t}. It also indicates a statistically significant correlation coefficient at the 1% level between IR innovation u_{1t} and innovation in the

1979 Volcker shock variable u_{2t}. The correlation coefficient between IR innovation u_{1t} and innovation in the *COVID-19* shock indicates a non-statistically significant relationship.

On the one hand, the results show that innovation in IR and in 1970s oil shocks events are correlated. This suggests that we need to orthogonalize innovations u_{1t} and u_{2t} to make them uncorrelated, in order to interpret the impulse response analysis correctly. The same applies to the IR and 1979 Volcker shock innovations. On the other hand, the statistical significance of the correlation coefficient between IR innovations and 1970s oil shocks events suggests that IR and 1970s oil shocks are endogenous variables in the VAR (c) model. The same is true of the IR and Volcker shock variables in VAR (5) model. The non-statistical significance of the correlation coefficient between the *CPI* and *COVID-19* shock innovations suggests that the IR variable and *COVID-19* shock are exogenous variables in the VAR (c) model. To validate these results, we used the weak exogeneity test and the strict exogeneity test of Durbin-Wu-Hausman. This test determines whether variables are endogenous or exogenous in the VAR (c) model.

- Exogeneity

The graphical representation of impulse responses differs according to whether the variables in the VAR system are exogenous or endogenous. It also depends heavily on the order in which the variables are arranged in the VAR model. A good VAR model specification requires variables to be ordered from the most exogenous to the most endogenous. This is why it is essential to test the exogeneity of our variables. To this end, we have used the weak exogeneity test for 1970s oil shocks and *COVID-19* shock. To test the endogeneity of the Volcker shock (monetary policy shock), we used the strict exogeneity test of Durbin-Wu-Hausman (with instrument) because there is a collinearity problem in the data. This result is explained by the high correlation between Volcker shock and the error term.

Table 3.14: Weak exogenous test for oil shocks and *COVID-19* shock, 1973-2023 period

Shock	(1) *Inflation rate*	(2) *Inflation rate*
1970s oil shocks	0.000	0.000
COVID-19 shock	0.887	0.001

Note: *Inflation rate* is the dependent variable and shock is the independent event.

Table 3.14 shows that the *p*-value associated with the coefficient of 1970s oil shocks is less than 1%. This indicates that the null hypothesis (H0) 1970s oil shocks events are weakly exogenous is rejected. In other words, 1970s oil shocks events are endogenous in our VAR (c) model. The *p*-value associated with the coefficient of the independent *COVID-19* shock event is greater than 10%. This indicates that the null hypothesis (H0) that the *COVID-19* shock event is weakly exogenous is not rejected. In other words, the *COVID-19* shock event is exogenous in our VAR (c) model. Column (2) of Table 3.14 shows that the independent variable *IR* is endogenous in our VAR (c) model for each of our two events: 1970s oil shocks and *COVID-19* shock. In sum, we can conclude that our two events (1970s oil shocks and *COVID-19* shock) are endogenous in our VAR (c) model, whereas the *COVID-19 shock* event is exogenous in our VAR (c) model.

We now turn to the exogeneity test for the Volcker shock. Since we will be treating the Volcker shock event as an endogenous regressor, we have used the Fed interest rate variable, which is correlated with the Volcker shock variable, but not necessarily with the error term, as the instrument for our Durbin-Wu-Hausman strict exogeneity test.

Table 3.15: Strict exogeneity test by Durbin, Wu and Hausman, 1973-2023 period

Durbin chi2(1) = 24.815 (*p* = 0.0000)	Wu-Hausman *F*(1,48) = 45.489 (*p* = 0.0000)

Note: Tests of endogeneity. H0: Variables are exogenous.

The Durbin-Wu-Hausman strict exogeneity test indicates a *p*-value of less than 1%. The null hypothesis (H0) that the *IR* variable and Volcker shock event are exogenous is therefore rejected. In other words, these two variables are endogenous in our VAR (c) model.

3.3.3 Impulse response and forecast error variance decomposition

We now present the nature of the VAR (c) models specified in the previous subsection. We will focus on the inflation impulse response functions for the 1970s oil shocks, the 1979 monetary policy reform shock, the *COVID-19* shock and on the forecast error variance decomposition. These two analyses allow us to synthesize the essential information contained in the dynamics of the estimated VAR (c) system. The variance decomposition allows us to indicate the relative importance of each shock in explaining inflation fluctuations. As for the shock reaction functions, they enable us to highlight the nature of the effects of the various shocks on inflation.

3.3.4 Impulse response of inflation to 1970s oil shocks

Figure 3.3 plots the impulse response of the inflation variable to 1970s oil shocks. The gray area represents the 95% confidence interval. The amplitude of the shock is assumed to be equal to one standard deviation, and we are interested in the effects of the shock over 15 periods (i.e. 15 years, from 1973 to 1988). This horizon represents the maximum time required for the inflation variable to return to its normal level (pre-shock level). We have shown that there is a stable long-term relationship between inflation and 1970s oil shocks. It is therefore possible to estimate the *level* VAR model. Furthermore, the Cholesky decomposition of the variance-covariance matrix of canonical innovations, advocated by Sims (1980), suggests that when the dynamics are stationary, short-run constraints should be imposed. These constraints express the absence of instantaneous response.

Figure 3.3: Inflation impulse response function to 1970s oil shocks,
1973 to 1988 period

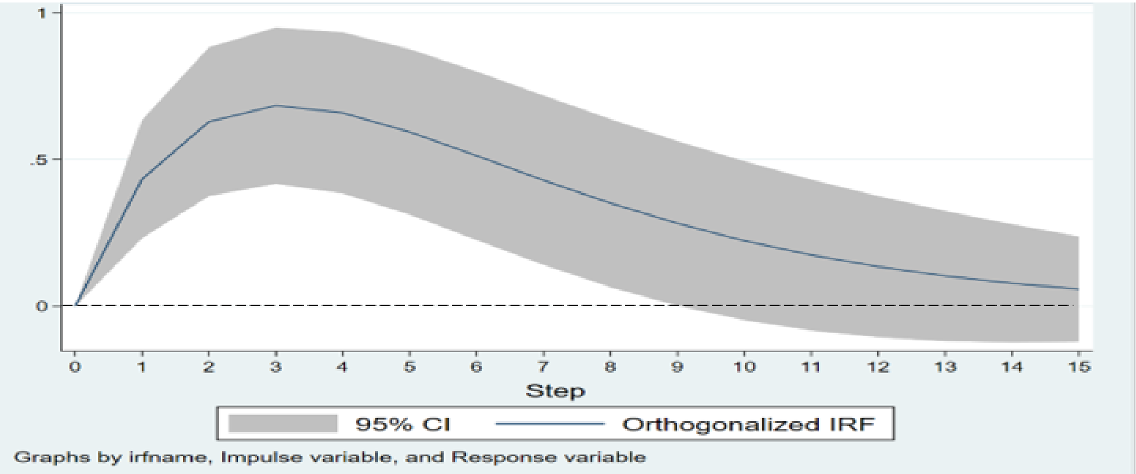


Figure 3.3 shows that 1970s oil shocks have a positive effect on inflation. 1970s oil shocks have a marked impact on inflation, resulting in a maximum increase after 3 years, before the effects gradually disappear until period 9.

Impulse response results are often interpreted in terms of the size (amplitude) of the standard deviation of the shock and the contribution of the shock to the forecast error variance of the variable responding to the shock. Table 3.16 shows that the standard deviation of 1970s oil shocks events is 12.36% (response of 1970s oil shocks events to their own innovations at time 0) and that 1970s oil shocks events has reached a maximum rise with an Oirf coefficient of 0.6839. Thus, the effects of 1970s oil shocks on annual inflation after three years can be calculated approximately as follows: 12.36% × 0.6839 = 8.45 percentage points. In other words, the positive effects of the 1970s oil shocks increased inflation by 8.45 percentage points after three years, before inflation gradually returned to its pre-shock level (convergence toward zero). Given that inflation returned to its pre-shock level after 9 periods following the 1970s oil shocks (transitory effect), it can be argued that inflation has a finite memory of the 1970s oil shocks.

To complete our analysis based on impulse response functions, we decompose the forecast error variance. The aim is to calculate the contribution of each of the innovations to the error variance. The results of the forecast error variance decomposition study are reported in Table 3.16. The results indicate that in period 3, 17.28% of the variance of the inflation forecast error is due to the innovations of 1970s oil shocks events and 82.72% to the innovations in inflation.

Table 3.16: Measuring the effect of 1970s oil shocks on inflation
and forecast error variance decomposition, 1973-2023 period

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Step	S.E.	*IR*	70s oil shocks	Lower	Oirf	Upper	Standard deviation	Amplitude of shock
0	0	0.00%	0.00%	0	0	0	12.36%	0.00%
1	0.1025	100.00%	0.00%	0.2323	0.4332	0.6340	11.23%	5.35%
2	0.1293	93.61%	6.39%	0.3758	0.6292	0.8826	9.75%	7.78%
3	0.1358	82.72%	17.28%	0.4177	0.6839	0.9501	8.20%	8.45%
4	0.1400	72.68%	27.32%	0.3847	0.6592	0.9336	6.73%	8.15%

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Step	S.E.	IR	70s oil shocks	Lower	Oirf	Upper	Standard deviation	Amplitude of shock
5	0.1439	65.64%	34.36%	0.3122	0.5942	0.8762	5.42%	7.35%
6	0.1465	61.25%	38.75%	0.2260	0.5130	0.8000	4.30%	6.34%
7	0.1472	58.65%	41.35%	0.1410	0.4295	0.7180	3.36%	5.31%
8	0.1461	57.13%	42.87%	0.0652	0.3514	0.6377	2.60%	4.34%
9	0.1430	56.25%	43.75%	0.0020	0.2823	0.5626	1.99%	3.49%
10	0.1380	55.75%	44.25%	-0.0471	0.2234	0.4939	1.51%	2.76%
11	0.1312	55.47%	44.53%	-0.0825	0.1745	0.4316	1.14%	2.16%
12	0.1227	55.31%	44.69%	-0.1056	0.1349	0.3753	0.85%	1.67%
13	0.1129	55.22%	44.78%	-0.1181	0.1032	0.3245	0.63%	1.28%
14	0.1023	55.17%	44.83%	-0.1223	0.0783	0.2789	0.47%	0.97%
15	0.0914	55.15%	44.85%	-0.1203	0.0589	0.2380	0.34%	0.73%

Note: (1) standard error; (2) impulse = IR and response = IR; (3) impulse = 1970s oil shocks, and response = IR; (4) Lower bound confidence interval; (5) IR Orthogonalized Impulse Response Functions to 1970s oil shocks; (6) Upper bound confidence interval; (7) standard deviation 1970s oil shocks; (8) amplitude of shock = (5)*(7) first line.

3.3.5 Impulse response of inflation to the 1979 Volcker monetary policy shock

Figure 3.4 traces the impulse response of the inflation variable to the 1979 monetary policy reform shock. Again, the amplitude of the shock is considered a function of the standard deviation, and we are interested in the effects of the shock over 15 periods (i.e. 15 years, from 1979 to 1994). We have shown that there is a stable long-term relationship between inflation and the 1979 Volcker shock. This is why it is possible to estimate the *level* VAR model.

Figure 3.4: Impulse response function of inflation to monetary policy reform shock (Volcker 1979), 1979 to 1994 period

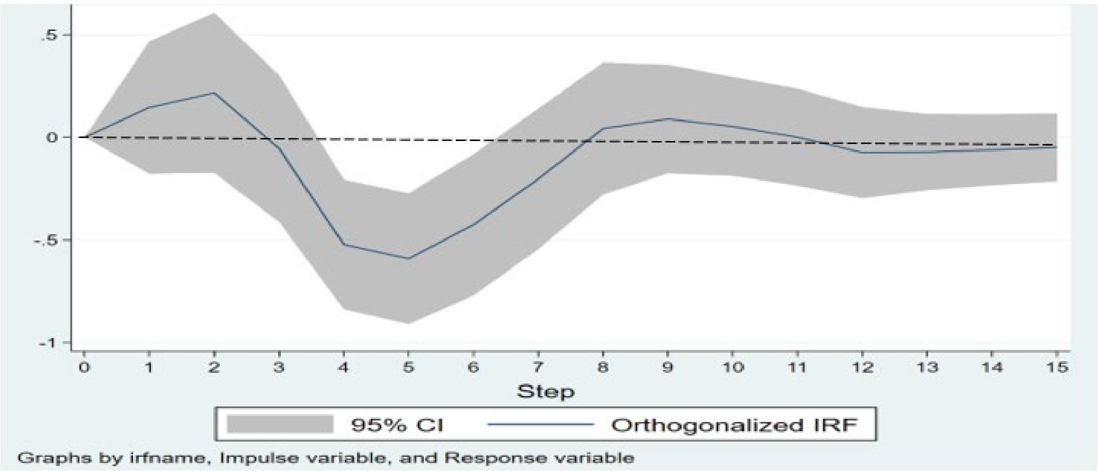


Figure 3.4 shows that a positive shock to interest rates in monetary policy (1979) has a negative effect on inflation. The Volcker shock has a marked impact on inflation, with a decline starting in the second year and peaking after five years, before the effects gradually disappear. In other words, the 1979 Volcker shock brought annual inflation down to a maximum level of -6.152 percentage points (10.40% × -0.5914) five years after the implementation of Volcker's monetary policy, before gradually returning to its pre-shock level (convergence towards zero). Since following the 1979 Volcker shock, inflation returns to its pre-shock level, it can be argued that inflation has a finite memory of the Volcker shock (transitory effect).

The results of the forecast error variance decomposition study are shown in Table 3.17. The results obtained indicate that at period 5, 11.79% of the variance of the inflation forecast error is due to the innovations of the 1979 Volcker shock event and 88.21% to the innovations in inflation.

Table 3.17: Measuring the effect of the 1979 Volcker shock on inflation and forecast error variance decompositions, 1973-2023 period

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Step	S.E.	IR	Volcker shock	Lower	Oirf	Upper	Standard deviation	Amplitude of shock
0	0	0.00%	0.00%	0	0	0	10.40%	0.000%
1	0.1647	100.00%	0.00%	-0.1772	0.1455	0.4683	4.47%	1.514%
2	0.1988	99.17%	0.83%	-0.1730	0.2166	0.6063	4.47%	2.254%
3	0.1821	97.40%	2.60%	-0.4111	-0.0542	0.3028	3.16%	-0.563%
4	0.1610	97.30%	2.70%	-0.8375	-0.5220	-0.2064	-4.63%	-5.430%
5	0.1625	88.21%	11.79%	-0.9098	-0.5914	-0.2729	-6.03%	-6.152%
6	0.1754	80.16%	19.84%	-0.7698	-0.4261	-0.0823	-7.02%	-4.432%
7	0.1745	78.09%	21.91%	-0.5448	-0.2028	0.1393	-4.69%	-2.109%
8	0.1640	78.09%	21.91%	-0.2782	0.0432	0.3646	-0.06%	0.449%
9	0.1350	78.33%	21.67%	-0.1754	0.0891	0.3537	0.54%	0.927%
10	0.1229	78.18%	21.82%	-0.1879	0.0530	0.2940	1.66%	0.552%
11	0.1204	78.13%	21.87%	-0.2354	0.0007	0.2368	1.11%	0.007%
12	0.1132	78.14%	21.86%	-0.2961	-0.0742	0.1476	-0.60%	-0.772%
13	0.0944	78.05%	21.95%	-0.2569	-0.0720	0.1130	-0.37%	-0.749%
14	0.0879	78.00%	22.00%	-0.2335	-0.0612	0.1111	-0.98%	-0.636%
15	0.0844	77.97%	22.03%	-0.2140	-0.0486	0.1167	-0.83%	-0.506%

Note: (1) standard error; (2) impulse = IR, and response = IR; (3) impulse = Volcker shock, and response = IR; (4) Lower bound confidence interval; (5) IR Orthogonalized Impulse Response Functions to Volcker shock; (6) Upper bound confidence interval; (7) standard deviation Volcker shock; (8) amplitude of shock = (5)*(7) first line.

3.3.6 Impulse response of inflation to the *COVID-19* shock

Figure 3.5 plots the impulse response of the inflation variable to the *COVID-19* shock. We have shown that there is a *short-term* relationship between inflation and the *COVID-19* shock event. We then need to impose long-term constraints, which express the presence of an instantaneous response.

Figure 3.5: *IR* impulse response function to *COVID-19* shock, 2020 to 2035 period

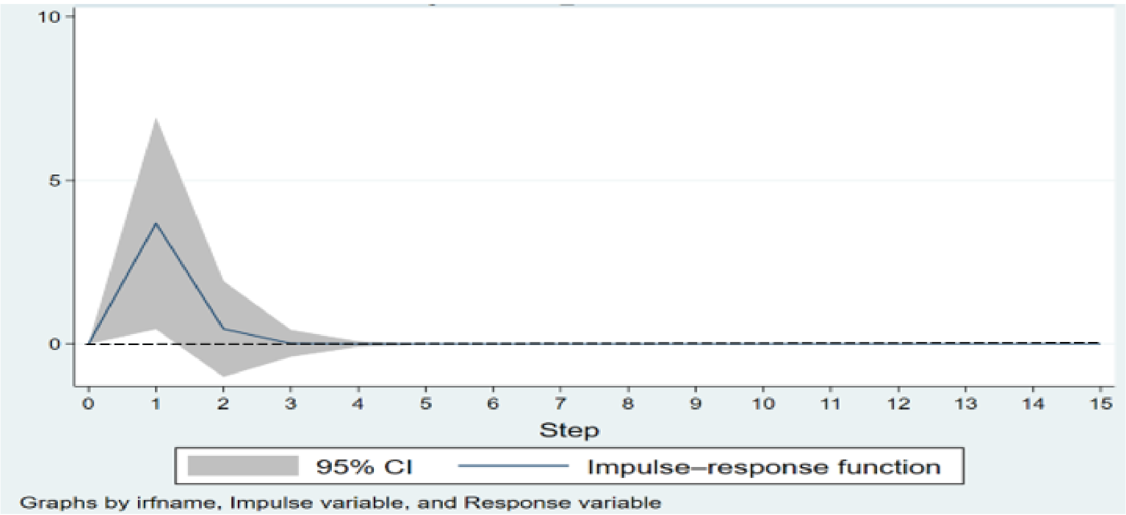


Figure 3.5 shows that the *COVID-19* shock had a positive effect on inflation. The *COVID-19* shock had a marked impact on inflation, resulting in a maximum increase after one year, before rapidly returning to its pre-shock level (convergence toward zero). In other words, the positive effects of the *COVID-19* shock caused inflation to rise to a maximum level of 3.7 percentage points (3.69 × 1%) after one year, before returning abruptly to its pre-shock level (transitory effect). In statistical terms, we can see that the *COVID-19* shock had a significant positive *short-term* impact on inflation, since the positive and significant effects of the *COVID-19* shock on annual inflation lasted at most 15 months, i.e. ending in 2021. Unlike the 1970s oil shocks and the 1979 Volcker shock, where the significant effect observed was long-lasting, the effect of the *COVID-19* shock was rather *short-lived*, as inflation responses became statistically insignificant after 1 year.

The results of the forecast error variance decomposition study are shown in Table 3.18. The results indicate that at period 2, 0.20% of the variance in the inflation forecast error is due to innovations in the *COVID-19* shock event and 99.80% to its own innovations.

Table 3.18: Measuring the effect of the *COVID-19* shock on inflation and forecast error variance decomposition, 1973-2023 analysis

Step	(1) S.E.	(2) *IR*	(3) *COVID-19* shock	(4) Lower	(5) irf	(6) Upper	(7) Standard deviation	(8) Amplitude of shock
0	0	0.00%	0.00%	0	0	0	1%	0
1	0.0090	100.00%	0.00%	0.4512	3.6854	6.9197	-2.35%	3.69%
2	0.0780	99.80%	0.20%	-1.0052	0.4571	1.9194	-1.38%	0.46%
3	0.0789	99.80%	0.20%	-0.3921	0.0164	0.4249	-0.15%	0.02%
4	0.0789	99.80%	0.20%	-0.0840	-0.0030	0.0781	0.00%	0.00%
5	0.0789	99.80%	0.20%	-0.0090	-0.0005	0.0079	0.00%	0.00%
6	0.0789	99.80%	0.20%	-0.0007	0.0000	0.0006	0.00%	0.00%
7	0.0789	99.80%	0.20%	-0.0002	0.0000	0.0002	0.00%	0.00%
8	0.0789	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%
9	0.0789	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%
10	0.0789	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%
11	0.07897	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%
12	0.0789	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%
13	0.0789	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%
14	0.0789	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%
15	0.0789	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%

Note: (1) standard error; (2) impulse = *IR*, and response = *IR*; (3) impulse = *COVID-19* shock, and response = *IR*; (4) Lower bound confidence interval; (5) *IR* Orthogonalized Impulse Response Functions to *COVID-19* shock; (6) Upper bound confidence interval; (7) standard deviation *COVID-19* shock; (8) amplitude of shock = (5)*(7) first line.

Our analysis of the impulse response of inflation to 1970s oil shocks, the 1979 monetary policy reform shock and the *COVID-19* shock has yielded a number of observations. First, all three shocks have an instantaneous impact on inflation because the beginning is not at origin 0, as shown in figures 3.3, 3.4 and 3.5. The instantaneous magnitude of the shock is greater with oil shocks. Second, we observed that oil shocks and the 1979 monetary policy reform shock have permanent consequences (lasting effect) on inflation, whereas the *COVID-19* shock has *short-term* consequences on inflation. Third, according to our forecast based on the *COVID-19* shock, we should expect the decline in inflation observed in 2022 to continue in 2023 and 2024. The main difference of the *COVID-19* shock on inflation with respect to oil shocks is probably explained by the early intervention of the Fed in 2020.

3.4 Serial correlation of *Inflation rate*

Empirical studies have shown that when serial correlation is present, financial series are frequently modeled using an ARMA (AutoRegressive Moving Average) model. The class of ARMA (1,q) processes includes the first-order autoregressive process, AR (l), and the *q*-order moving average process, MA (q). ARMA (l,q) processes are a natural extension of AR (l) and MA (q) processes. They are mixed processes in the sense that they simultaneously incorporate AR (l) and MA (q) components.

When serial correlation is present, financial series are frequently analyzed using a model of the three categories of the ARMA class (AR, MA and ARMA). To do this, we will first check whether serial correlation is present in our *Inflation rate* data.

Table 3.19: Serial correlation of *Inflation rate*,
1973-2023 period

Variable	*Inflation rate*
(1) IR_t	1.000
(2) L.1.IR_t	0.787*** (0.000)
(3) L.2.IR_t	0.567*** (0.000)
(4) L.3.IR_t	0.468*** (0.001)
(5) L.4.IR_t	0.441*** (0.002)

Note: L.i.IR_t means *IR* lagged *i* periods. Robust standard errors in parentheses. *** p<0.01.

Table 3.19 shows a strong presence of serial correlation between IR and IR lagged one period (L.1.IR), IR lagged 2 periods (L.2.IR), IR lagged 3 periods (L.3.IR) and IR lagged 4 periods (L.4.IR). This result suggests that we can use the ARMA (l,q) to model the inflation series and apply the characteristics of the error term of the ARMA (l,q) IR model as those of IR_t.

3.5 Serial dependency of the *Inflation rate* series

Table 3.20 shows that IR_t^2 depends positively and strongly on its one-year and two-year lagged values. IR_t^2 is an approximation of the variance of the IR. This suggests that strong variations tend to be followed by strong variations, and weak variations by weak variations. Thus, the variance of IR_t conditional on known events at time *t*-1 is not constant and depends on its past values. This points to a phenomenon of persistence in the variance of the conditional IR_t variance. ARCH-type models take this phenomenon into account.

Table 3.20: Serial dependency of the IR^2 series, 1973-2023 period

Variable	IR^2
L.1.IR_t^2	1.276*** (0.343)
L.2.IR_t^2	-0.868** (0.400)
L.3.IR_t^2	0.384 (0.389)
L.4.IR_t^2	0.008 (0.245)
Constant	3.222 (2.311)
Observations	47
R-squared	0.711
Adjusted R-squared	0.684

Note: L.i.IR_t^2 means IR^2 lagged *i* periods. Robust standard errors in parentheses. *** p<0.01, ** p<0.05.

3.6 Distribution of the US inflation series

Table 3.21: Descriptive statistics for inflation
and Skewness/Kurtosis tests for normality, 1973-2023 period

	Mean	Median	Std.-dev.	Skewness	Kurtosis	*p*-value
Inflation rate	4.0107	3.1568	2.9388	1.4437	4.7359	0.0006

Table 3.21 gives rise to several comments. First, the skewness coefficient is different from 0 and positive. This illustrates the presence of asymmetry, which may be an indicator of nonlinearity, since we know that linear Gaussian models are necessarily symmetrical. The positive skewness coefficient suggests that the distribution is skewed to the right: Inflation thus reacts more to a positive shock than to a negative one. Second, the kurtosis coefficient is high, i.e. above 3. This excess kurtosis indicates a high probability of extreme points occurring. In other words, the distribution of the inflation series has thicker tails than the N (0,1). Lastly, the *p*-value of the normality test is 0.0006. This indicates that the inflation series follows a normal distribution at the 5% threshold is rejected. To summarize, the inflation series is characterized by nonlinear dynamics and a stochastic trend.

In the literature, stochastic nonlinear processes take two forms: nonlinear stochastic processes in variance (GARCH models) and nonlinearity stochastic processes in the mean (regime-switching models such the Markov regime-switching model). We have just shown that the US *Inflation rate* series is characterized, on the one hand, by a stochastic trend dynamic and, on the other hand, by a nonlinear dynamic (high amplitude or low amplitude breaks). To take into account the presence of the stochastic (or random) trend and the presence of the nonlinearity detected in our *Inflation rate* data, we use nonlinear stochastic processes in variance and nonlinear stochastic processes in the mean to analyze the behavior of inflation.

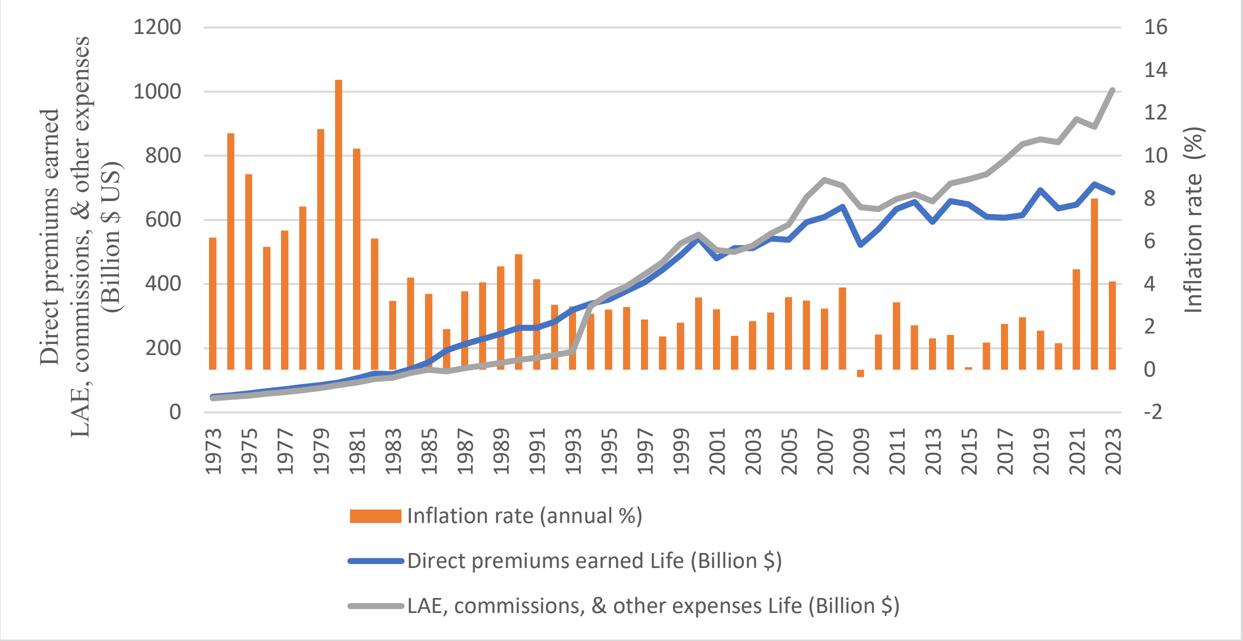
4 Insurance business performance indicators

Two accounting indicators are often used by insurance professionals to measure insurance companies' performance: the *Combined ratio* (indicator of efficiency in managing the operating costs of the insurance business) and the *Operating ratio* (indicator of efficiency in managing the operating costs of the insurance business and investments). These two indicators, also known as loss ratios, are widely used in the insurance industry. In addition to these indicators of operating cost management efficiency, there is another indicator traditionally used in the literature to measure the performance of insurance companies: the *ROA*, which measures the accounting profitability of insurers (Dionne and Harrington, 2014). Finally, insurers' capital and investment levels are indicators of their ability to cover more or less anticipated risks.

4.1 Influence of inflation on the *Combined ratio*

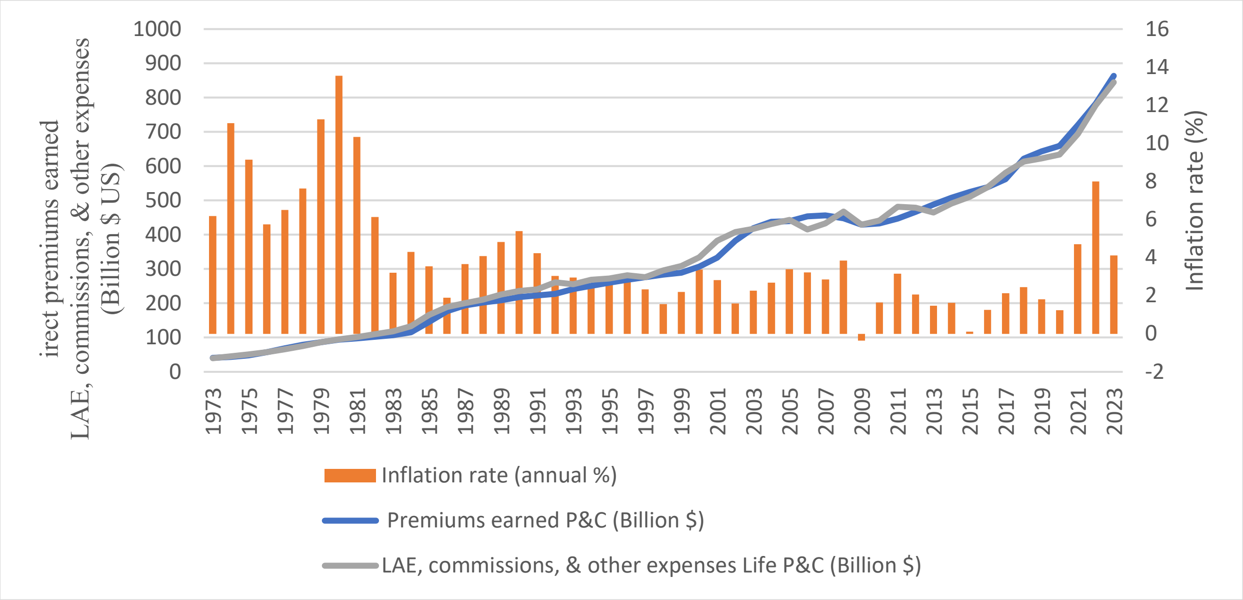
The *Combined ratio* is measured by the ratio of *Total expenses* (claims paid + management expenses) to *Premiums* collected (insurance policies sold). This indicator shows whether *Premiums* collected are sufficient to cover all operating expenses. Clearly, the most obvious risk for the insurer is that *Premiums* collected are insufficient to pay policyholder claims and cover management expenses. The less sufficient *Premiums* are to cover claims paid and management expenses, the higher the *Combined ratio* will be, and the more the insurer will experience financial difficulties. Consequently, a high *Combined ratio* will have a negative influence on the profitability of insurers' insurance business. A *Combined ratio* below 100% means that the insurance company is in a profitable situation.

Figure 4.1: Trends in inflation, *Premiums* collected
and *Total expenses* in the Life sector, 1973-2023 period



Source: American Council of Life Insurers (ACLI).

Figure 4.2: Trends in inflation, *Premiums* collected
and *Total expenses* in the P&C sector, 1973-2023 period



Source: AM-Best.

Generally speaking, the two determinants of the *Combined ratio*—*Total expenses* (claims paid + management expenses) and *Premiums* collected—follow the same trend, as shown in figures 4.1 and 4.2. Figure 4.2, however, points to some difficulties in the Life insurance sector since the financial crisis of 2007-2009, despite the fact that inflation was at a low level before 2021. Inflation can affect each of the two determinants of the *Combined ratio*. In fact, it is difficult to detect the precise influence of inflation on the *Combined ratio*.

The P&C sector appears more stable than the Life sector over the same period, as shown in Figure 4.2. This difference can be explained by low interest rates, such as those observed in Dionne et al. (2024). The Life insurance sector has been more affected by the low interest rate policy of the Fed after the 2007-2009 financial crisis, a policy not related to inflation but to the lack of liquidity in different markets.

4.2 Influence of inflation on the *Operating ratio*

According to Ahlgrim and D'Arcy (2012), an insurance company has two main sources of revenue, namely *Premiums* and net investment income, and two main sources of costs, namely claims paid and operating expenses (commissions and management fees or operating expenses). These two main sources of income and two main sources of costs (LAE)[4] are used to determine the *Operating ratio* (Hull, 2018).

An insurance company can be profitable even with a *Combined ratio* of over 100%. This is because the *Combined ratio* does not consider the second source of income for insurance companies: net investment income, which comes from income earned on *Premiums* invested in bonds, equities or

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[4] Losses and adjustment expenses.

other forms of longer-term investment. The inclusion of net investment income should reduce the level of the *Operating ratio* in periods of high financial profitability, often associated with high inflation.

In the remainder of our analysis, we have chosen the *Operating ratio* as the most reliable indicator for measuring the efficiency of operating cost management in the insurance business, since it considers the total level of revenue and the total level of operating expenses. As the *Operating ratio* is an increasing function of the *Combined ratio*, we can deduce that inflation can have a positive or negative influence on the operating ratio.

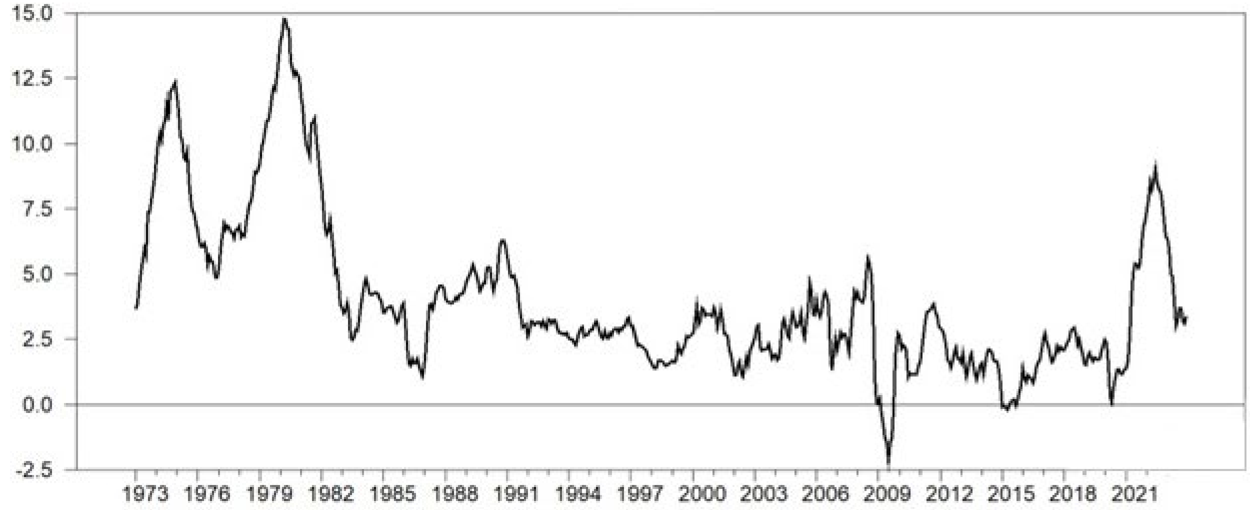
4.3 Financial performance indicator for the insurance business

Until now, we have analyzed the performance of insurance companies simply by considering their operating activity, i.e. the net profit generated by their commercial activity, without considering the capital invested by shareholders and creditors to finance this activity. In fact, an insurer's real performance lies in its ability to create value or wealth for the shareholders and creditors who finance its activity. The impact of capital invested by shareholders and creditors on profitability can be measured by the *ROA* indicator. *ROA* is obtained by taking the ratio between net income and total assets. This accounting measure indicates profitability per dollar invested. In other words, the financial performance of the insurance business (*ROA*) is an increasing function of the profitability of the insurance business. We have just mentioned that inflation can exert a positive or negative influence on the profitability of the insurance business and that *ROA* is an increasing function of the profitability of the insurance business. It can then be argued that inflation can exert positive or negative effects on the performance of the insurance business.

5 Modeling the links between inflation variability and different financial variables in the US P&C and Life insurance sectors using ARDL models

Below we first examine the relationship between inflation and the components of the *Combined ratio*, using Autoregressive Distributed Lag (ARDL) model. The two components of the *Combined ratio* are *Premiums* earned and *Total expenses*, including claims payments. We also analyze the effect of inflation on *Combined ratio*, *Net investment income*, *Operating ratio*, *Pretax operating income*, and *ROA*. The data are annual and cover the period from 1973 to 2023. In line with our analysis, we consider the basic input to be the *Inflation rate* as shown in Figure 5.1.

Figure 5.1: *Inflation rate* trends from 1973 to 2023 period



Source: US Bureau of Labor Statistics

5.1 Inflation series and its features

To analyze the specific characteristics of inflation on financial data, we used the annual series of the *Inflation rate* over the 1973 to 2023 period.

Figure 5.1 shows that the *Inflation rate* series exhibit an overall downward trend over the period of 1980 to 2020. We then observe an upward trend following *COVID-19*. It appears to be nonstationary. To verify this, we perform a stationarity test using the Augmented Dickey-Fuller (ADF) test. For this exercise, we test the null hypothesis that the inflation variable is nonstationary (it contains at least one unit root) against the alternative hypothesis of stationarity.

To apply the Dickey-Fuller test, we first need to select the optimal number c of lags for the test. To do this, we use three selection criteria: two information criteria, i.e. the Akaike (1969) Information criterion, the Bayesian information criterion (Stone, 1977) or the Schwarz Information criterion (Schwarz, 1978), and a criterion based on the statistical test of the Likelihood ratio (LR).

Table 5.1 shows that two of the four criteria consensually choose the optimal number of lags $c = 3$ (LR and AIC). The BIC chooses $c = 1$. There is therefore a conflict. Given that there is a consensus with two criteria for an optimal number of lags $c = 3$, we retain this number of lags for our Augmented Dickey-Fuller (ADF) test.

Table 5.1: Choice of the number of delays with the inflation series, 1973 to 2023 period

c	LL	LR	AIC	BIC
0	-113.375		4.86701	4.90638
1	-90.2537	46.242	3.92569	4.00442*
2	-89.3468	1.8137	3.92965	4.04775
3	-87.2862	4.1213*	3.88452*	4.04198
4	-87.2495	0.07341	3.92551	4.12233

Note: LL: Log likelihood; LR: Likelihood ratio; AIC: Akaike information criterion; BIC: Bayesian information criterion or Schwarz Information criterion.

Table 5.2: ADF test on *Inflation rate*, model with constant and trend, 1973 to 2023 period

	Interpolated Dickey-Fuller test			
	Test statistic	1% critical value	5% critical value	10% critical value
$Z(t)$	-2.241	-4.178	-3.512	-3.187

Note: MacKinnon approximate p-value for $Z(t)$ = 0.4666.

Table 5.2 shows a p-value $Z(t)$ = 0.4666, which is above the 5% significance level, so the null hypothesis that *Inflation rate* is nonstationary (presence of at least a unit root) is not rejected. In this case, the usual asymptotic properties are no longer valid. The nonstationary nature of our series may be linked to the presence of a deterministic linear trend or to the presence of a stochastic trend in the inflation series. To make our inflation series stationary, we first hypothesize the presence of a deterministic linear trend. We perform an OLS regression of the series against the trend variable (time), extracted the trend and recovered the residuals.

Figure 5.2: Changes in *Inflation rate* after purging the deterministic trend, 1973 to 2023 period

Figure 5.2 shows that the series still retains its nonstationary character after extraction of the deterministic trend. This leads us to suspect the presence of a stochastic trend instead of the deterministic linear trend in the inflation series. To verify this, we transform our series into a first

difference. This enables us to purge the stochastic trend and make our series stationary, so that we could use the usual asymptotic properties often considered in time series analysis.

Figure 5.3: Changes in *Inflation rate* after purging the stochastic trend, 1973 to 2023 period

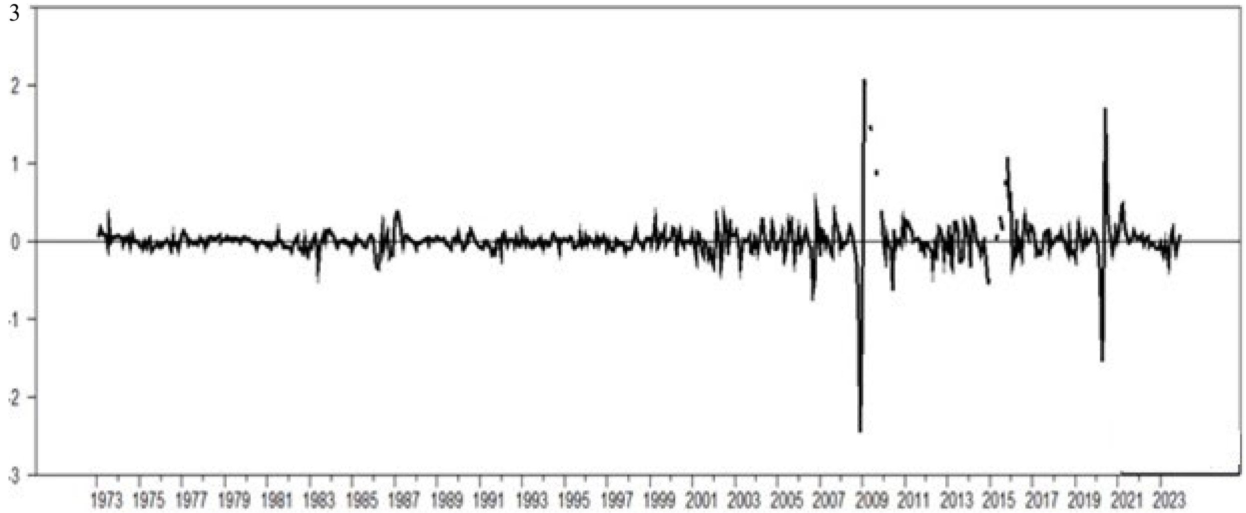


Figure 5.3 shows that the downward trend in inflation has been suppressed, and the series average appears to lie on a straight line parallel to the *x*-axis. Our inflation series thus became stationary after we transformed our series into a first difference. In this case, we can say that the *Inflation rate* variable is integrated of order 1 since it is stationary after a difference. We will check this graphical result using the Augmented Dickey-Fuller (ADF) test. We first determine the optimal number of delays to use for the test.

Table 5.3: Choice of number of delays with the integrated 1st-order inflation series, 1973 to 2023 period

c	LL	LR	AIC	HQIC	BIC
0	-91.3975		4.01728	4.03217	4.05703*
1	-91.1558	0.48324	4.05025	4.08004	4.12976
2	-88.013	6.2856*	3.95709	4.00176*	4.07635
3	-87.5238	0.97851	3.97929	4.03886	4.13831
4	-87.5238	3.4466	3.94785*	4.02231	4.14661

Note: LL: Log likelihood; LR: Likelihood ratio; AIC: Akaike information criterion; HQIC: Hannan-Quinn Information criterion; BIC: Bayesian information criterion or Schwarz Information criterion.

In Table 5.3, the LR criterion and the HQIC information criterion indicate an optimum number of lags $c = 2$. The other two information criteria, AIC and BIC, indicate an optimum number of lags $c = 4$ and $c = 0$ respectively. As there is a consensus for both LR and HQIC, we have chosen an optimal number of lags $c = 2$ for our Augmented Dickey-Fuller (ADF) test.

Table 5.4 shows a p-value $Z(t) = 0.0001$, which is well below the 1% significance level. Consequently, the null hypothesis that inflation is nonstationary is rejected. In other words, inflation is stationary after a difference. This result shows that our *Inflation rate* series indeed exhibited a stochastic trend.

Table 5.4: ADF test on inflation, Model with constant and trend, 1973 to 2023 period

	Interpolated Dickey-Fuller test			
	Test statistic	1% critical value	5% critical value	10% critical value
$Z(t)$	-5.170	-4.178	-3.512	-3.187

Note: MacKinnon approximate p-value for $Z(t) = 0.0001$.

We then calculate the unconditional autocorrelations from a correlation function on RATS for the first 18 delays of our series, after purging the stochastic trend to check whether there is any time dependency in our series. Figure 5.4 shows the evolution of the calculated unconditional autocorrelations.

Figure 5.4: Evolution of calculated unconditional autocorrelations for inflation

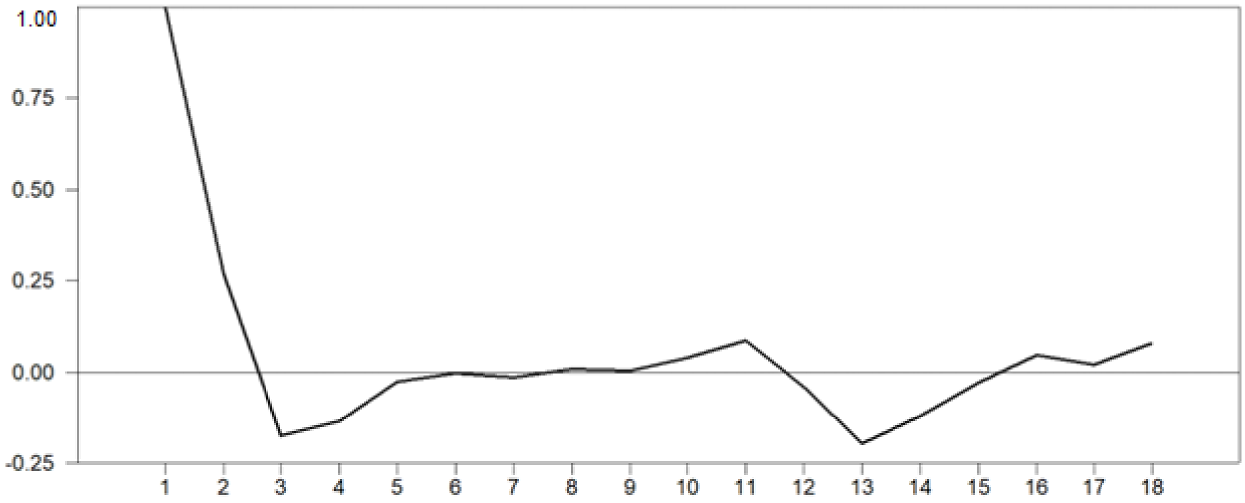


Figure 5.4 shows that autocorrelation tends rapidly toward zero when the number of observations is large. This indicates that our series of inflation has a finite (short) memory. Consequently, following a shock, inflation quickly returns to its pre-shock level. In other words, the shock has a transitory effect.

As mentioned above, the aim of this study is to use an econometric approach to determine the real long-term or short-term impact that inflation could have on the variables *Premiums*, *Total expenses, Combined ratio, Net investment income*, *Operating ratio*, *Pretax operating income*, and *ROA* that influence the profitability of Life and P&C insurers. Figure 5.4 suggests that inflation is likely to have more of a short-term than a long-term impact on these variables, since the result clearly indicates that the inflation shock has a transitory rather than a permanent effect. We will test this prediction by applying the ARDL and ECM models.

5.2 Description of ARDL and ECM models

In this section, we analyze the impact of an inflation shock on different financial variables of insurers. We first want to determine the impact of an inflation shock on the future values of each component of the *Combined ratio*. To do this, we propose to use the Autoregressive Distributive Lagged Model (ARDL) and the Error Correction Model (ECM), as these models allow us to measure the long-term or short-term effect of a shock to an input variable on a given output variable. Again, the data is annual and covers the 1973 to 2023 period.

ARDL model is a time series model that includes the past values of both dependent and independent variables. In this study, we apply a single-equation model with a dependent variable y_t and an independent variable x_t.

The basic ARDL (c,q) model is an econometric specification that explains the dependent variable y_t by its own lagged values up to lag *c* and by the present and lagged values of an independent variable x_t up to lag q. The advantage of this model is that it can be applied to both nonstationary and stationary data.

$$y_t = \beta_0 + \Sigma_{i=1}^{c} \alpha_i y_{t-i} + \Sigma_{j=0}^{q} b_j x_{t-j} + u_t, \quad E(u_t^2) = \sigma^2. \tag{5.1}$$

$E(u_t^2) = \sigma^2$ means that the variance of the error term u_t is a constant and therefore stationary. The residuals are white noise. Under these conditions, the usual tests of coefficient significance (Fisher or Student tests), which are based on the assumption of white noise in the residuals, can be applied.

The ARDL (c,q) model in equation (5.1), although very simple, includes several other models as special cases. The presence of unit roots in the data to be used for estimation influences the form of the model. If the data does not contain a unit root (stationary), then the model must be estimated in levels (equation 5.1), i.e. using untransformed variables. Conversely, if the data contain an unit root (nonstationary), and are not cointegrated, then the model must be estimated in first difference. To do this, we simply replace the variables y_t and x_t by Δy_t and Δx_t in equation (5.1).

$$\Delta y_t = \beta_0 + \Sigma_{i=1}^{c}\alpha_i \Delta y_{t-i+}\Sigma_{j=0}^{q} b_j \Delta x_{t-j} + v_t, \quad E(v_t^2) = \sigma^2. \qquad (5.2)$$

Equation (5.2) describes the short-term dynamics between changes in x_t and in y_t.

When the original variables y_t and x_t are integrated of order 1, I (1), it is better to use their first difference (equation 5.2) rather than estimating equation (5.1). Note that if the dependent variable y_t is I (1), this means that under the null hypothesis, μ_t, the error term, will also be I (1), i.e. nonstationary.

We have to mention that the ARDL (c,q) model in first difference represented by equation (5.2) only takes into account the short-term dynamics between variations in y_t and in x_t and only applies when the variables contain a unit root and are not cointegrated. Consequently, equation (5.2) no longer applies when the variables contain a unit root (nonstationary) and are cointegrated. If stable long-term relationships exist between the variables y_t and x_t, the relationships are cointegrated. The ARDL (c,q) model in levels of equation (5.1) and the ARDL (c,q) first difference model of equation (5.2) cannot account for this. We therefore need a particular class of ARDL (c,q) models, directly related to cointegration theory: the Error Correction Models (ECM).

The starting point for cointegration theory is the fact that many macroeconomic and financial series are stationary. Cointegration theory allows us to study series that are not stationary, but whose linear combination is stationary. It thus lets us specify stable long-term relationships while simultaneously analyzing the short-term dynamics between the variables y_t and x_t. In other words, error correction models (ECM) are dynamic models that incorporate both short-term and long-term changes in the variables. ECMs integrate both short-term fluctuations (represented by first-difference variables) around the long-term equilibrium (given by the cointegration relationship). These models are extremely useful in econometrics, since they can be used when y_t and x_t are stationary or nonstationary variables.

Two nonstationary series y_t and x_t are cointegrated (I (1)) if there is a stationary linear combination of these two series. According to Engle and Granger's (1987) approach, two series y_t and x_t are cointegrated I (1) if the residuals of the long-term relationship between these series are stationary. These authors demonstrated that any set of cointegrated variables can be represented as an error-correction model. The ECM estimation approach used by Engle and Granger (1987) is based on a two-step estimation method. The first step involves estimating the long-run relationship between the variables y_t and x_t. If the variables are cointegrated, i.e. if the residuals of the long-run relationship of these variables are stationary, we proceed to the second step: estimation of the error-correction model. In this study, we have chosen the two-stage estimation method of Engle and Granger (1987) for our estimations that require the use of the ECM model, because of its simplicity of implementation.

- First step: Estimating the long-term relationship

Let the variables y_t and x_t be two I (1) variables. We can estimate the following relationship:

$$y_t = \alpha + bx_t + v_t \tag{5.3}$$

where v_t is the error term. According to this equation, $v_t = y_t - \alpha + bx_t$. That is, the error term v_t is a linear combination of y_t and x_t. In the special case where $b = 0$, v_t is I (1) since it is the sum of a I (1) variable y_t and the constant $-\alpha$. In contrast, if $b \neq 0$, it is possible that v_t is I (0). If we estimate (5.3) by OLS (or another method) and find a high R^2 this indicates the presence of a long-run equilibrium relationship between the variables y_t and x_t. This relationship is known as the cointegration or long-run relationship. If the variables y_t and x_t are cointegrated, i.e. if the residuals of the long-run relationship in equation (5.3) are stationary, we proceed to the second step.

- Second step: Estimation of the ECM model

Let y_t and x_t be two $I\,(1)$ variables. The ECM model is written as follows:

$$\Delta y_t = \gamma \tilde{v}_{t-1} + \Sigma_{i=1}^{c} \alpha_i \Delta y_{t-i} + \Sigma_{j=0}^{q} b_j \Delta y_{t-j} + \varepsilon_t, \quad E(\varepsilon_t^2) = \sigma^2 \tag{5.4}$$

where $0 < \gamma < 1, \varepsilon_t$ is a white noise and $\tilde{v}_{t-1}$ is the residual of the long-term relationship between the one-period lagged variables y_t and $\tilde{v}_{t-1} = y_{t-1} - \tilde{\alpha} - \tilde{b}x_{t-1}$. In the rest of our development, consistent with Kripfganz and Schneider (2020),[5] we will replace the variable x_{t-1} by x_t. Parameters c and q in ARDL are chosen to eliminate serial correlations in ε_t. The model represents the force of recall toward the long-term target, given by the cointegration relationship:

$$\Delta y_t = -\gamma\left(y_{t-1} - \tilde{\alpha} - \tilde{b}x_t\right) + \Sigma_{i=1}^{c} \alpha_i \Delta y_{t-i} + \Sigma_{j=0}^{q} b_j \Delta y_{t-j} + \varepsilon_t \tag{5.5}$$

$$\Delta y_t = \gamma\tilde{\alpha} - \gamma y_{t-1} + \gamma\tilde{b}x_t + \Sigma_{i=1}^{c} \alpha_i \Delta y_{t-i} + \Sigma_{j=0}^{q} b_j \Delta y_{t-j} + \varepsilon_t \tag{5.6}$$

Let $\gamma\tilde{\alpha} = \delta_0$; $\gamma = -\pi_y$, and $\tilde{b} = \pi_x/\gamma$, and let us replace them in equation (5.6) to obtain:

$$\Delta y_t = \delta_0 + \pi_y y_{t-1} + \pi_x x_t + \Sigma_{i=1}^{c} \alpha_i \Delta y_{t-i} + \Sigma_{j=0}^{q} b_j \Delta y_{t-j} + \varepsilon_t \tag{5.7}$$

We must have an adjustment coefficient $\pi_y < 0$; otherwise there is no return to equilibrium. Therefore, if the adjustment coefficient obtained is negative and its value is close to 0, the adjustment

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[5] https://www2.econ.tohoku.ac.jp/~PDesign/dp.html.

is rapid. In contrast, if the adjustment coefficient is negative and its absolute value is close to 1, the adjustment is very slow.

To summarize, the ECM model in equation (5.7) describes an adjustment process. It combines two types of variables: first-difference variables (Δy_{t-i} and Δy_{t-j}), which represent short-term fluctuations (the SR part of the regression results), and level variables (y_t and x_t), which determine the variable v_t to be a linear combination of nonstationary variables. This ensures that the long term is taken into account (ADJ and LR parts of the regression results). The ADJ part determines the coefficient of the dependent variable y_t in level lagged one period (π_y), which measures the speed of adjustment back to equilibrium. The LR part determines the coefficient of the level-independent variable $x_t(\pi_x)$. It measures the long-term relationship between the variables y_t and x_t. The sign of the coefficient of this level-independent variable x_t should normally reflect the sign of the correlation coefficient obtained between these two variables.

The results of the ECM model are generally divided into three parts, represented by column 1 (ADJ), column 2 (LR) and column 3 (SR). Table 5.35 is an example of results of the ECM model. The first part (column 1) shows the adjustment effects of the output variable. The adjustment coefficient measures the speed at which the output variable returns to its equilibrium level after a disequilibrium (speed of convergence to equilibrium). It is preferable for this coefficient to be negative and statistically significant in order to claim that the output variable returns to equilibrium after suffering a shock when this is the case. The second part (column 2) shows the long-term effect, and the third part (column 3) shows the short-term effect.

5.3 Modeling the relationship between *Inflation rate* and the two components of the combined ratio in the P&C sector

We will conduct our analysis in three stages. First, we will test the stationarity of our variables and the cointegrating (long-run) relationship among them. This will enable us to choose the ARDL model best suited to estimating the relationship between inflation and the various insurance variables. As mentioned at the beginning of this section, the presence of unit roots in the data influences the form of the model. If the data does not contain a unit root (are stationary), then the model must be estimated in levels, i.e. using the untransformed variables (equation 5.1: long-run relationship). Conversely, if the data contain a unit root (are nonstationary) and are not cointegrated, then the model must be estimated in first difference (equation 5.2: short-run relationship). If the data are cointegrated (presence of a long-term relationship), the ECM model must be estimated (equation 5.7: long-run relationship and short-run relationship). The second step consists in estimating the relationship between the *Inflation rate* and various insurance variables, using the ARDL model selected. Finally, the third step is to carry out the usual specification tests (Breusch-Godfrey and White) to ensure that the chosen model is well specified and represents the observed reality.

5.3.1 Relationship between *Inflation rate* and P&C *Premiums*

To analyze the relationship between *Inflation rate* and P&C *Premiums*, the first step is to test the stationarity of our two variables. Our ADF test results on the *Inflation rate* variable in the previous section tell us that *Inflation rate* is integrated of order 1. Now we just need to test the stationarity of the P&C *Premiums* variable. To this end, we have estimated various VAR processes for lag orders *c* ranging from 1 to 4 in order to choose the optimal order *c* to retain for the ADF test. For each model, we calculate the Akaike information criterion (AIC), the Bayesian or Schwarz Information criterion (BIC) and the Likelihood ratio (LR). Analysis of these criteria led us to select the lag order $c = 3$ for our ADF test.

Table 5.5: ADF test on P&C *Premiums*, model with constant and trend, 1973 to 2023 period

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
P&C *Premiums*	-2.411	-4.178	-3.512	-3.187	0.3737
P&C D.*Premiums*	-3.201	-4.178	-3.512	-3.187	0.0842

The result of the ADF test on the variable P&C *Premiums* shown in Table 5.5 line (2) indicates a p-value $Z(t)$ = 0.0842, which is below the 10% significance level. Alternatively, the estimated ADF statistic (-3.201) is below the value tabulated by Engle and Yoo (1991) at the 5% level (-3.512). Consequently, the null hypothesis that the P&C D.*Premiums* variable is nonstationary is rejected. In other words, the P&C *Premiums* variable is stationary after a difference. The P&C *Premiums* variable is integrated of order 1, since it must be differentiated once to make it stationary. Since the inflation variable is integrated of order 1 and the P&C *Premiums* variable is also integrated of order 1, it is therefore worth studying the cointegration between the two variables. Table 5.6 presents the cointegration test according to Kripfganz and Schneider (2020). This table indicates that the null hypothesis that there is no long-term relationship between inflation and the P&C *Premiums* variables is not rejected at all levels.

Table 5.6: Kripfganz and Schneider (2020) critical values and approximate *p*-values, 1973 to 2023 period

H0: no level relationship $F = 3.075$, $t = -2.140$

	10%		5%		1%		*p*-value	
	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$
F	4.133	4.939	5.124	6.026	7.437	8.531	0.207	0.309
t	-2.575	-2.936	-2.899	-3.277	-3.547	-3.949	0.220	0.345
Decision	.a		.a		.a			

Note: Decision: no rejection (.a), inconclusive (.), or rejection (.r) at indicated levels.

To summarize, the *Inflation rate* and P&C *Premiums* variables are integrated of the same order but are not cointegrated. Since there is no long-term relationship between these two variables, the ARDL (c,q) first-difference model, which describes the short-term relationship, seems a more appropriate choice. It corresponds to equation (5.2).

Before proceeding with model estimation, we will choose the optimal number of delays for each of the parameters *c* and *q* of the ARDL (c,q) model, which will provide an error term that follows a white noise process. This will enable us to ensure that the chosen model is well specified and represents reality. To this end, we estimate various ARDL model from combinations ranging from 1 to 3 (the highest optimal number of delays of all our variables) for parameter *c* and from 0 to 3 for parameter *q*. In other words, we estimate the following 12 models: ARDL (1.0), ARDL (1.1), ARDL (1.2), ARDL (1.3), ARDL (2.0), ARDL (2.1), ARDL (2.2), ARDL (2.3), ARDL (3.0), ARDL (3.1), ARDL (3.2) and ARDL (3.3). To select the most appropriate model for our estimation, we apply a 4-step approach.

The first step is to calculate the Breusch-Godfrey test for autocorrelation of residuals and the White test for homoscedasticity for each of the 12 models estimated. In the second step, we calculate the Akaike information criterion (AIC) and the Bayesian or Schwarz Information criterion (BIC). In our third step, we select the model that is best suited to our estimation in order to apply the selection method based on the BIC and AIC criteria to only retain the models that allow us to not reject both the absence of autocorrelation (BG (*p*-value) greater than 5%) and of homoscedasticity. Finally, in the fourth stage, when there is a consensus for both the AIC and BIC around a model retained based on the absence of autocorrelation and the presence of homoscedasticity, then this model is retained for our estimation. In the event of a conflict between these two-selection criteria, we will use the maximum likelihood method to decide between the two choices. This method involves calculating the log-likelihood ratio statistic between the two models from the log-likelihood (LL) values of each model, in order to decide which model to choose.

In Table 5.7, the AIC information criterion selects the ARDL model (3,0), while the BIC information criterion selects the ARDL model (2,0). There is therefore no consensus between the two selection criteria. The log-likelihood ratio (LR) statistic also confirms the ARDL (2,0) model. We have therefore chosen the ARDL (2,0) model to estimate the short-term impact of *Inflation rate* on P&C *Premiums.* Table 5.7 also shows that the *p*-value of the Breusch-Godfrey first-order autocorrelation test is 0.2129 for the ARDL (2,0) model. This value is above the 5% significance level. The null hypothesis H0 that there is no serial autocorrelation in the residuals is therefore not rejected. Also, the *p*-value of the White test for heteroscedasticity is 0.2458 for the ARDL Model (2,0). This value is above the 5% significance level. The null hypothesis H0 that the residuals are homoscedastic is therefore not rejected. In other words, there is no heteroscedasticity. Since the ARDL (2,0) model passes both the test for absence of autocorrelation and the test for absence of heteroscedasticity in the residuals, we can argue that the short-term impact of *Inflation rate* on P&C *Premiums* is well captured by the ARDL (2,0) model.

Table 5.7: Model selection by Akaike information criterion (AIC),
Bayesian information criterion (BIC), and Log likelihood ratio (LR), 1973 to 2023 period

	BG (*p*-value)	White (*p*-value)	AIC	BIC	LR
ARDL (1,0)	0.1669	0.0981	381.6713	387.2849	
ARDL (1,1)	0.1539	0.1901	383.6661	391.1509	
ARDL (1,2)	0.1310	0.1746	385.4914	394.8474	0.0050
ARDL (1,3)	0.1330	0.0837	380.0634	391.1642	0.1748
ARDL (2,0)	0.2129	0.2458	382.0385	374.6379*	7.4280*
ARDL (2,1)	0.0658	0.3858	376.622	385.8727	1.4256
ARDL (2,2)	0.0405	0.3121	378.3071	389.408	0.0158
ARDL (2,3)	0.0974	0.1364	379.697	392.6481	0.3150
ARDL (3,0)	0.4255	0.3930	366.4009*	375.5441	0.6100
ARDL (3,1)	0.3823	0.7071	368.33	379.3018	9.2962
ARDL (3,2)	0.3232	0.2077	370.2727	383.0732	0.0708
ARDL (3,3)	0.5614	0.1608	371.0302	385.6593	0.0574

Note: BG: Breusch-Godfrey test; White: White test (1980); AIC: Akaike information criterion; Bayesian information criterion; LR: Log likelihood ratio.

The results shown in Table 5.8 indicate that a shock to the *Inflation rate* variable has a significant short-term influence on the P&C *Premiums* variable. There is no long-term relationship between *Inflation rate* and P&C *Premiums*.

Table 5.8: ARDL (2,0) model estimation results, 1973 to 2023 period

Variable	Coefficient
P&C L.D.*Premiums*	0.743*** (0.148)
P&C L2.D.*Premiums*	-0.236 (0.165)
D.*Inflation rate*	1.992* (1.079)
Constant	8.091*** (2.795)
Observations	45
R-squared	0.517

5.3.2 Relationship between *Inflation rate* and P&C total operating expenses (LAE)

To analyze the relationship between *Inflation rate* and P&C *Total expenses* (for short), the first step is to test the stationarity of our two variables. As we have already shown that the *Inflation rate* variable is integrated of order 1, we now just need to test the stationarity of the P&C *Total expenses* variable.

Table 5.9: ADF test P&C *Total expenses*, model with constant and trend,
1973 to 2023 period

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
P&C Loss & LAE	-2.811	-4.159	-3.504	-3.182	0.1929
P&C D.Loss & LAE	-3.891	-4.168	-3.508	-3.185	0.0125

The results in Table 5.9 row (2) indicate that the variable P&C *Total expenses* is integrated of order 1. Since both the P&C *Total expenses* variable and the *Inflation rate* variable are integrated of order 1, it is worth studying the cointegration between the two variables.

Table 5.10: Kripfganz and Schneider (2020) critical values and approximate p-values,
1973 to 2023 period

H0: no levels relationship $F = 11.239$, $t = -2.118$

	10%		5%		1%		p-value	
	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$
F	4.162	4.935	5.146	6.006	7.430	8.451	0.001	0.002
t	-2.590	-2.952	-2.910	-3.288	-3.544	-3.944	0.236	0.367
Decision	.a		.a		.a			

Note: Decision: no rejection (.a), inconclusive (.), or rejection (.r) at indicated levels.

Table 5.10 shows that the null hypothesis that there is no long-term relationship between *Inflation rate* and the variable P&C *Total expenses* is not rejected at all levels. In other words, there is a short-run relationship between *Inflation rate* and the variable P&C *Total expenses*. The *Inflation rate* variable and the *Total expenses* variable are thus cointegrated at all levels.

Table 5.11: Model selection by Akaike information criterion (AIC) and Bayesian information criterion (BIC), 1973 to 2023 period

	BG (*p*-value)	White (*p*-value)	AIC	BIC
ARDL (1,0)	0.3554	0.0629	411.9735	417.5871
ARDL (1,1)	0.1811	0.0840	413.9724	421.4572
ARDL (1,2)	0.1823	0.1691	415.8866	425.2426
ARDL (1,3)	0.1691	0.4719	410.2168	421.3177
ARDL (2,0)	0.1992	0.0803	403.7824	411.183
ARDL (2,1)	0.0260	0.2077	405.6539	414.9046
ARDL (2,2)	0.0228	0.3261	407.605	418.7059
ARDL (2,3)	0.0331	0.6306	409.5246	422.4756
ARDL (3,0)	0.5516	0.4004	392.5793*	401.7225*
ARDL (3,1)	0.6298	0.6322	394.4156	405.3875
ARDL (3,2)	0.6191	0.7448	396.367	409.1675
ARDL (3,3)	0.5166	0.8590	397.9942	412.6233

Note: BG: Breusch-Godfrey test; White: White test (1980); AIC: Akaike information criterion; BIC: Bayesian information criterion.

Table 5.11 shows that there is a consensus for the two-selection criteria, AIC and BIC, around the ARDL (3,0) model. This leads us to retain the ARDL (3,0) model to estimate the short-term impact of the *Inflation rate* variable on the P&C *Total expenses* variable. Table 5.11 also shows that the ARDL (3,0) model passes the test for absence of autocorrelation and the test for absence of heteroscedasticity in the residuals. This suggests that the ARDL (3,0) model captures the impact of the *Inflation rate* variable on the variable P&C *Total expenses*.

To summarize, the *Inflation rate* and P&C *Total expenses* are integrated of the same order, but are not cointegrated. Since there is no long-term relationship between these two variables, the ARDL (c,q) first-difference model is the most appropriate. It corresponds to equation (5.2). Our approach to choosing the optimal number of delays for each of the parameters *c* and *q* also led us to select an ARDL (3,0) process. Table 5.12 shows the results obtained.

The results in Table 5.12 indicate that a shock to the *Inflation rate* variable has a significant short-term influence on the P&C *Total expenses* variable. To summarize, we find that there is no long-term relationship between *Inflation rate* and the *Total expenses* variable. However, our analysis of short-term dynamics indicates that a shock to the inflation variable has a positive and statistically significant short-term impact on the variable P&C *Total expenses*. We also noted that an inflation shock has a positive short-term impact on P&C *Premiums*.

Table 5.12: ARDL (3,0) model estimation results, 1973 to 2023 period

Variable	Coefficient
P&C L.D.*Total expenses*	0.376** (0.144)
P&C L2.D.*Total expenses*	-0.273* (0.153)
P&C L3.D.*Total expenses*	0.364** (0.162)
D.*Inflation rate*	4.807*** (1.506)
Constant	9.045** (4.303)
Observations	46
R-squared	0.402

5.4 Modeling the relationship between *Inflation rate* and the two components of the *Combined ratio* in the Life sector

5.4.1 Relationship between *Inflation rate* and Life *Premiums*

Table 5.13: Life *Premiums* ADF test, model with constant and trend,
1973 to 2023 period

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
Life *Premiums*	-0.967	-4.159	-3.504	-3.182	0.9484
Life D.*Premiums*	-8.391	-4.159	-3.504	-3.182	0.0000

The results in Table 5.13 row (2) indicate that the variable Life D.*Premiums* is integrated of order 1. Since both our variables Life *Premiums* and *Inflation rate* are integrated of order 1, it is legitimate to be interested in the study of cointegration between the two variables.

Table 5.14: Kripfganz and Schneider (2020) critical values and approximate p-values,
1973 to 2023 period

H0: no level relationship, $F = 7.313$, $t = -2.536$

	10%		5%		1%		p-value	
	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$
F	4.162	4.935	5.146	6.006	7.430	8.451	0.011	0.021
t	-2.590	-2.952	-2.910	-3.288	-3.544	-3.944	0.111	0.207
Decision	.a		.a		.a			

Note: Decision: no rejection (.a), inconclusive (.), or rejection (.r) at indicated levels.

Table 5.14 shows that there is no long-term relationship between *Inflation rate* and the variable Life *Premiums* is not rejected at all levels. Consequently, they are not cointegrated.

Table 5.15 shows that there is a consensus for both selection criteria AIC and BIC around the ARDL (1,0) model. We have therefore chosen the ARDL (1,0) model to estimate the short-term impact of the *Inflation rate* variable on the Life *Premiums* variable. Table 5.15 also shows that the ARDL (1,0) model passes the test for the absence of autocorrelation and the test for the absence of heteroscedasticity in the residuals. Accordingly, the ARDL (1,0) model captures the impact of the *Inflation rate* variable on the Life *Premiums* variable presented in Table 5.16.

Table 5.15: Model selection by Akaike information criterion (AIC)
and Bayesian information criterion (BIC), 1973 to 2023 period

	BG (*p*-value)	White (*p*-value)	AIC	BIC
ARDL (1,0)	0.9318	0.2815	-150.4986*	-144.8850*
ARDL (1,1)	0.5858	0.4000	-148.9448	-141.4600
ARDL (1,2)	0.4442	0.1046	-147.5118	-138.1558
ARDL (1,3)	0.2338	0.1595	-143.4654	-132.3645
ARDL (2,0)	0.9435	0.4282	-145.2380	-137.8374
ARDL (2,1)	0.0162	0.5599	-144.3550	-135.1042
ARDL (2,2)	0.0081	0.4238	-143.3692	-132.2683
ARDL (2,3)	0.0119	0.2907	-141.6751	-128.7240
ARDL (3,0)	0.8044	0.9404	-146.4361	-137.2929
ARDL (3,1)	0.4440	0.9427	-145.2456	-134.2738
ARDL (3,2)	0.2189	0.8127	-145.2562	-132.4557
ARDL (3,3)	0.3901	0.7288	-146.0145	-131.3854

Note: BG: Breusch-Godfrey test; White: White test (1980); AIC: Akaike information criterion; BIC: Bayesian information criterion.

To summarize, the *Inflation rate* and Life *Premiums* variables are integrated of the same order, but are not cointegrated. It is therefore possible to estimate the ARDL model in first difference. Consequently, we estimate equation (5.2). Our approach to choosing the optimal number of delays for each of the parameters *c* and *q* also led us to select an ARDL (1,0) process. The results of this estimation are shown in Table 5.16.

Table 5.16: ARDL (1,0) model estimation results, 1973 to 2023 period

Variable	Coefficient
Life L.D.*Premiums*	-0.217 (0.145)
D.*Inflation rate*	5.365* (2.883)
Constant	16.76*** (5.173)
Observations	48
R-squared	0.140

Table 5.16 shows that a short-term shock to the *Inflation rate* variable has a statistically significant short-term effect on the Life *Premiums* variable.

5.4.2 Relationship between *Inflation rate* and Life *Total expenses*

Table 5.17: Test of long-term relationship between *Inflation rate* and Life *Total expenses* (LAE), 1973 to 2023 period

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
Life *Total expenses*	-1.274	-4.159	-3.504	-3.182	0.8941
Life D.*Total expenses*	-6.116	-4.159	-3.504	-3.182	0.0000

The results in Table 5.17 row (2) indicate that the variable Life *Total expenses* is integrated of order 1. Since both our variables Life *Total expenses* and *Inflation rate* are integrated of order 1, it is worth examining the cointegration between the two variables.

Table 5.18: Kripfganz and Schneider (2020) critical values and approximate *p*-values,
1973 to 2023 period

	10%		5%		1%		*p*-value	
	I (0)	*I* (1)	*I* (0)	*I* (1)	*I* (0)	*I* (1)	*I* (0)	*I* (1)
F	4.162	4.935	5.146	6.006	7.430	0.464	0.341	0.464
t	-2.590	-2.952	-2.910	-3.288	-3.544	-3.944	0.478	0.606
Decision	.a		.a		.a			

Note: Decision: no rejection (.a), inconclusive (.), or rejection (.r) at indicated levels.

Table 5.18 shows that the null hypothesis that there is no long-term relationship between *Inflation rate* and the variable Life *Total expenses* is not rejected. The *Inflation rate* variable and the Life *Total expenses* variable are not cointegrated.

Table 5.19: Model selection by Akaike information criterion (AIC)
and Bayesian information criterion (BIC), 1973 to 2023 period

	BG (*p*-value)	White (*p*-value)	AIC	BIC
ARDL (1,0)	0.9359	0.9890	-90.7399*	-85.1263*
ARDL (1,1)	0.7978	0.9998	-88.8939	-81.4091
ARDL (1,2)	0.8517	1.0000	-87.2098	-77.8538
ARDL (1,3)	0.6366	0.9991	-82.5491	-71.4482
ARDL (2,0)	0.8749	0.9996	-85.8342	-78.4336
ARDL (2,1)	0.2413	1.0000	-84.1570	-74.9063
ARDL (2,2)	0.4286	1.0000	-82.5537	-71.4528
ARDL (2,3)	0.3381	0.9946	-80.5582	-67.6072
ARDL (3,0)	0.8239	1.0000	-81.5104	-81.5104
ARDL (3,1)	0.6331	1.0000	-79.7254	-68.7535
ARDL (3,2)	0.9604	0.9995	-78.5740	-65.7735
ARDL (3,3)	0.8636	0.9871	-76.6140	-61.9849

Note: BG: Breusch-Godfrey test; White: White test (1980); AIC: Akaike information criterion; BIC: Bayesian information criterion.

Table 5.19 shows that there is a consensus for both selection criteria AIC and BIC around the ARDL (1,0) model. We have therefore chosen the ARDL (1.0) model to estimate the short-term impact of the *Inflation rate* variable on the Life *Total expenses* variable. Table 5.19 also shows that model ARDL (1,0) passes the test for absence of autocorrelation and the test for absence of heteroscedasticity in the residuals. From this standpoint, the ARDL (1,0) model captures well the impact of the *Inflation rate* variable on the Life *Total expenses* variable.

To summarize, the variables *Inflation rate* and Life *Total expenses* are integrated of the same order, but are not cointegrated. It is therefore possible to estimate the ARDL model in first difference. Consequently, we estimate equation (3.2). Our approach to choosing the optimal number of lags for each of the parameters *c* and *q* also led us to adopt an ARDL (1,0) process to estimate the impact of the *Inflation rate* variable on the Life *Total expenses* variable. The results of this estimation are shown in Table 5.20.

Table 5.20: ARDL (1,0) model estimation results, 1973 to 2023 period

Variable	Coefficient
Life L.D.*Total expenses*	0.162 (0.146)
D.*Inflation rate*	3.917 (2.722)
Constant	14.87*** (5.407)
Observations	48
R-squared	0.071

The results shown in Table 5.20 indicate that a shock to the *Inflation rate* variable has no significant short-term influence on the Life *Total expenses* variable. Thus, a shock to inflation has no short-term or long-term impact on *Total expenses* in the Life sector.

Overall, our analysis of the impact of inflation on the two components of the *Combined ratio* shows that in the Life sector, a shock to inflation has a positive and statistically significant short-term effect on the Life *Premiums* variable. A shock to inflation also has a positive effect on the Life *Total expenses* variable, although the effect is not statistically significant.

5.5 Impact of the *Inflation rate* on the *Combined ratio*

5.5.1 P&C sector

The results obtained from the analysis of the impact of the two components (*Premiums* and *Total expenses)* show that both the *Total expenses* component and the *Premiums* component are directly influenced by an inflation shock in P&C. Consequently, we can expect inflation to have an ambiguous short-term effect on the P&C *Combined ratio.* We will now test this hypothesis.

Table 5.21: Test of long-term relationship between *Inflation rate* and P&C *Combined ratio*, 1973 to 2023 period

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
P&C *Combined ratio*	-3.617	-4.159	-3.504	-3.182	0.0284

The results of the test in Table 5.21 indicate a p-value $Z(t)$ = 0.0284, which is below the 5% significance level. Thus, the null hypothesis that the P&C *Combined ratio* variable is nonstationary is rejected. In other words, the P&C *Combined ratio* variable is stationary in level. Consequently, the P&C *Combined ratio* variable is integrated of order 0, while the *Inflation rate* variable is integrated of order 1. It is therefore possible to estimate the simple ARDL model with equation (5.1).

Table 5.22: Model selection by Akaike information criterion (AIC)
and Bayesian information criterion (BIC), 1973 to 2023 period

	BG (*p*-value)	White (*p*-value)	AIC	BIC
ARDL (1,0)	0.2317	0.4580	285.6062	291.3422
ARDL (1,1)	0.2090	0.5334	287.1247	294.7728
ARDL (1,2)	0.2519	0.5942	284.3593	293.8184
ARDL (1,3)	0.3954	0.8014	278.3593	289.5865
ARDL (2,0)	0.4357	0.7805	281.7414	289.3087
ARDL (2,1)	0.4958	0.7934	283.0623	292.5214
ARDL (2,2)	0.9264	0.6499	284.8196	296.1705
ARDL (2,3)	0.5670	0.8472	278.8049	291.9033
ARDL (3,0)	0.1303	0.8777	278.4936*	287.8496*
ARDL (3,1)	0.1249	0.8923	279.998	291.2252
ARDL (3,2)	0.8119	0.7937	281.4201	294.5185
ARDL (3,3)	0.4822	0.9002	280.7572	295.7268

Note: BG: Breusch-Godfrey test; White: White test (1980); AIC: Akaike information criterion; BIC: Bayesian information criterion.

Table 5.22 shows that there is a consensus for both selection criteria, AIC and BIC, around the ARDL (3.0) model. We have therefore chosen the ARDL (3.0) model to estimate the impact of the *Inflation rate* variable on the P&C *Combined ratio* variable. Table 5.22 also shows that the ARDL (3.0) model passes the test for absence of autocorrelation and the test for absence of heteroscedasticity in the residuals. Therefore, we can say that the ARDL (3.0) model captures well the impact of the *Inflation rate* variable on the P&C *Combined ratio* variable. The results of this estimation are shown in Table 5.23.

Table 5.23: ARDL (3,0) model estimation results, 1973 to 2023

Variable	Coefficient
P&C L.*Combined ratio*	0.798*** (0.150)
P&C L2.*Combined ratio*	-0.213 (0.189)
P&C L3.*Combined ratio*	0.108 (0.147)

Variable	Coefficient
Inflation rate	0.246 (0.231)
Constant	30.75** (14.26)
Observations	48
R-squared	0.485

The *Inflation rate* variable has no significant impact on the P&C *Combined ratio* variable, as indicated in Table 5.23.

5.5.2 Life sector

The results obtained from the analysis of the impact of the two components (*Premiums* and *Total expenses)* show that only the premium component of the *Combined ratio* is influenced by an inflation shock in the Life sector. Consequently, inflation can be expected to have an effect on the Life *Combined ratio*. We will now test this hypothesis.

Table 5.24: Test of long-term relationship between the *Inflation rate* and Life *Combined ratio*, 1973 to 2023 period

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
Life *Combined ratio*	-2.141	-4.159	-3.504	-3.182	0.5233
Life D.*Combined ratio*	-5.232	-4.168	-3.508	-3.185	0.0001

The results of the test in Table 5.24 line 2 indicate a p-value $Z(t)$ = 0.0001, which is below the 1% significance level. This means that the null hypothesis is rejected according to the Life D.*Combined ratio* variable. Life D.*Combined ratio* is stationary after differentiation. Consequently, the Life *Combined ratio* variable is integrated of order 1, as is the *Inflation rate* variable.

Table 5.25: Kripfganz and Schneider (2020) critical values and approximate *p*-values, 1973 to 2023 period

H0: no level relationship. $F = 0.814$ $t = -0.921$

	10%		5%		1%		*p*-value	
	I (0)	*I* (1)	*I* (0)	*I* (1)	*I* (0)	*I* (1)	*I* (0)	*I* (1)
F	4.162	4.935	5.146	6.006	7.430	8.451	0.774	0.855
t	-2.590	-2.952	-2.910	-3.288	-3.544	-3.944	0.770	0.837
Decision	.a		.a		.a			

Note: Decision: no rejection (.a), inconclusive (.), or rejection (.r) at indicated levels.

Table 5.25 shows that the null hypothesis that there is no long-term relationship between *Inflation rate* and the Life *Combined ratio* variable is not rejected at all levels. In other words, there is no long-term relationship between *Inflation rate* and the Life *Combined ratio* variable. Thus, the *Inflation rate* variable and the Life *Combined ratio* variable are not cointegrated.

Table 5.26: Model selection by Akaike information criterion (AIC) and Bayesian information criterion (BIC), 1973 to 2023 period

	BG (*p*-value)	White (*p*-value)	AIC	BIC
ARDL (1,0)	0.7572	0.7665	347.9267	353.5403
ARDL (1,1)	0.5943	0.9700	349.8804	357.3652
ARDL (1,2)	0.8988	0.9848	351.2936	360.6496
ARDL (1,3)	0.8037	0.4792	347.1111	358.212
ARDL (2,0)	0.9845	0.9530	343.3916	350.7922
ARDL (2,1)	0.9577	0.9875	345.3884	354.6391
ARDL (2,2)	0.8530	0.9899	346.7807	357.8816
ARDL (2,3)	0.7674	0.7528	348.7807	361.7318
ARDL (3,0)	0.8043	0.9947	338.9973*	348.1405*
ARDL (3,1)	0.7789	0.9979	340.9952	351.967
ARDL (3,2)	0.9099	0.9977	342.498	355.2985
ARDL (3,3)	0.6435	0.5902	344.4954	359.1245

Note: BG: Breusch-Godfrey test; White: White test (1980); AIC: Akaike information criterion; BIC: Bayesian information criterion.

Table 5.26 shows that there is a consensus for the two-selection criteria AIC and BIC around the ARDL (3,0) model. This leads us to retain the ARDL (3,0) model to estimate the short-term impact of the *Inflation rate* variable on the Life *Combined ratio* variable. The results of this estimation are presented in Table 5.27. Table 5.26 also shows that the ARDL (3,0) model passes the test for absence of autocorrelation and the test for absence of heteroscedasticity in the residuals. Thus, the ARDL (3.0) model captures the impact of the *Inflation rate* variable on the Life *Combined ratio* variable.

To summarize, the *Inflation rate* and Life *Combined ratio* variables are integrated of the same order, but are not cointegrated. It is therefore possible to estimate the ARDL model in first difference. Consequently, we need to estimate equation (5.2). Our approach to choosing the optimal number of lags for each of the parameters *c* and *q* led us to select an ARDL (3,0) process. The results of this estimation are shown in Table 5.27.

Table 5.27: ARDL (3,0) model estimation results, 1973 to 2023 period

Variable	Coefficient
Life L.D.*Combined ratio*	-0.0444 (0.166)
Life L2.D.*Combined ratio*	-0.0767 (0.164)
Life L3.D.*Combined ratio*	0.0438 (0.169)
D.*Inflation rate*	-0.358 (0.852)
Constant	0.920 (1.377)
Observations	46
R-squared	0.015

Table 5.27 shows that a short-term shock to the *Inflation rate* variable has no statistically significant effect on the Life *Combined Ratio* variable. To summarize, a shock to inflation has no short-term or long-term impact on the *Combined ratio* variable in the Life sector.

5.6 Modeling the relationship between *Inflation rate* and *Net investment income*

5.6.1 P&C sector

Table 5.28: Test of long-term relationship between *Inflation rate* and P&C *Net investment income*,
1973 to 2023 period

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
P&C *Net investment income*	-3.008	-4.159	-3.504	-3.182	0.1299
P&C D.*Net investment income*	-3.854	-4.168	-3.508	-3.185	0.0140

The results in Table 5.28 line (2) show that the p-value = 0.0140, which is below the usual significance level of 5%. In other words, the variable P&C *Net investment income* is stationary after differentiation and is therefore integrated of order 1.

Table 5.29: Kripfganz and Schneider (2020) critical values and approximate p-values,
1973 to 2023 period

H0: no level relationship, F = 24.929, t = -1.616

	10%		5%		1%		p-value	
	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
F	4.162	4.935	5.146	6.006	7.430	8.451	0.000	0.000
t	-2.590	-2.952	-2.910	-3.288	-3.544	-3.944	0.462	0.593
Decision	.a		.a		.a			

Note: Decision: no rejection (.a), inconclusive (.), or rejection (.r) at indicated levels.

Table 5.29 shows that the null hypothesis there is no long-term relationship between *Inflation rate* and the variable P&C *Net investment income* is not rejected at all levels. In other words, there is no long-run relationship between *Inflation rate* and the variable P&C *Net investment income.* Consequently, the *Inflation rate* variable and the P&C *Net investment income* variable are not cointegrated.

Table 5.30: Model selection by Akaike information criterion (AIC) and Bayesian information criterion (BIC), 1973 to 2023 period

	BG (*p*-value)	White (*p*-value)	AIC	BIC
ARDL (1,0)	0.2201	0.4279	-111.2812*	-105.6676*
ARDL (1,1)	0.2085	0.7458	-109.3395	-101.8547
ARDL (1,2)	0.2182	0.7878	-107.4905	-98.13445
ARDL (1,3)	0.2802	0.9580	-102.2418	-91.14093
ARDL (2,0)	0.4413	0.3083	-107.267	-99.86641
ARDL (2,1)	0.6502	0.6293	-105.5059	-96.25513
ARDL (2,2)	0.6940	0.3354	-103.5607	-92.45977
ARDL (2,3)	0.6216	0.6108	-101.6565	-88.70546
ARDL (3,0)	0.0240	0.7281	-105.9153	-96.77211
ARDL (3,1)	0.0237	0.9238	-104.7536	-93.7818
ARDL (3,2)	0.0124	0.7411	-102.9885	-90.18803
ARDL (3,3)	0.0120	0.8801	-100.9898	-86.36063

Note: BG: Breusch-Godfrey test; White: White test (1980); AIC: Akaike information criterion; BIC: Bayesian information criterion.

Table 5.30 shows that there is a consensus for the two-selection criteria AIC and BIC around the ARDL (1,0) model. We have therefore chosen the ARDL (1,0) model to estimate the short-term impact of the *Inflation rate* on the P&C *Net investment income* variable. Table 5.30 also indicates that the ARDL (1,0) model passes the test for absence of autocorrelation and the test for absence of heteroscedasticity in the residuals. Accordingly, we can say that the ARDL (1,0) model is appropriate for analyzing the impact of the *Inflation rate* variable on the P&C *Net investment income* variable.

To summarize, the variables *Inflation rate* and P& *Net investment income* are integrated of the same order, but are not cointegrated. It is therefore possible to estimate the ARDL model in first difference. Consequently, we need to estimate equation (5.2). Our approach to choosing the optimal number of delays for each of the parameters c and q also led us to select an ARDL (1,0) process. The results of this estimation are shown in Table 5.31.

Table 5.31: ARDL (1,0) model estimation results, 1973 to 2023 period

Variable	Coefficient
P&C L.D.*Net investment income*	0.178 (0.179)
D.*Inflation rate*	0.709** (0.274)
Constant	1.289** (0.513)
Observations	48
R-squared	0.139

Table 5.31 shows that a shock to the *Inflation rate* variable has a positive and statistically significant short-term effect on the variation in P&C *Net investment income*.

5.6.2 Life sector

Table 5.32: Test of long-term relationship between *Inflation rate* and Life *Net investment income*, 1973 to 2023 period

$Z(t)$	Test statistic	1% Critical Value	5% critical value	10% critical value	p-value
Life *Net investment income*	-2.278	-4.178	-3.512	-3.187	0.4462
Life D.*Net investment income*	-5.929	-4.168	-3.508	-3.185	0.0000

Table 5.32, line (2), shows that the *p*-value = 0.0000, which is below the usual significance level of 1%. In other words, the Life *Net investment income* variable is stationary after differentiation and is therefore integrated of order 1.

Table 5.33: Kripfganz and Schneider (2020) critical values and approximate *p*-values, 1973 to 2023 period

H0: no level relationship $F = 9.671$, $t = -3.642$.

	10%		5%		1%		*p*-value	
	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$
F	4.116	4.935	5.106	6.028	7.425	8.552	0.002	0.005
t	-2.566	-2.928	-2.893	-3.271	-3.545	-3.948	0.008	0.021
Decision	.r		.r		.			

Decision: no rejection (.a), inconclusive (.), or rejection (.r) at indicated levels.

Table 5.33 shows that the null hypothesis that there is no long-term relationship between the *Inflation rate* variable and the Life *Net investment income* variable is rejected at 5% and 10% levels. In other words, there is a long-run relationship between *Inflation rate* and Life *Net investment income* variable. Consequently, the *Inflation rate* variable and the Life *Net investment income* variable are cointegrated.

Table 5.34: Model selection by Akaike information criterion (AIC) and Bayesian information criterion (BIC), 1973 to 2023 period

	BG (*p*-value)	White (*p*-value)	AIC	BIC
ARDL (1,0)	0.0849	0.1210	-114.1173	-108.3812
ARDL (1,1)	0.0368	0.1422	-116.4883	-108.8402
ARDL (1,2)	0.0320	0.7409	-116.0691	-106.61
ARDL (1,3)	0.0284	0.8848	-111.2729	-100.0457
ARDL (2,0)	0.0198	0.1156	-111.9355	-104.3682
ARDL (2,1)	0.0848	0.2241	-120.6327	-111.1736
ARDL (2,2)	0.0943	0.2793	-119.6723	-108.3213
ARDL (2,3)	0.0176	0.6221	-114.3166	-101.2182
ARDL (3,0)	0.5149	0.2542	-114.8441	-105.4881

	BG (p-value)	White (p-value)	AIC	BIC
ARDL (3,1)	0.3955	0.3526	-119.6903*	-108.4631*
ARDL (3,2)	0.6809	0.6245	-119.3651	-106.2667
ARDL (3,3)	0.7005	0.6718	-118.1822	-103.2126

Note: BG: Breusch-Godfrey test; White: White test (1980); AIC: Akaike information criterion; BIC: Bayesian information criterion.

Table 5.34 shows that there is a consensus for the two-selection criteria AIC and BIC around the ARDL (3,1) model. We have therefore chosen the ARDL (3,1) model to estimate the long-term impact of the *Inflation rate* variable on the Life *Net investment income* variable. Table 5.34 also indicates that the ARDL (3,1) model passes the test for absence of autocorrelation and the test for absence of heteroscedasticity in the residuals. Therefore, we can say that the ARDL (3,1) model is suitable for analyzing the impact of the *Inflation rate* variable on the Life *Net investment income* variable.

To summarize, the variables *Inflation rate* and Life *Net investment income* are integrated of the same order and are cointegrated. It is therefore possible to estimate the ECM model. Consequently, we need to estimate equation (5.7). Our approach to choosing the optimal number of delays for each of the parameters *c* and *q* also led us to select an ARDL (3,1) process. The results of this estimation are shown in Table 5.35.

Table 5.35: ARDL (3,1) model estimation results, 1973 to 2023 period. ECM version

Variable	(1) ADJ	(2) LR	(3) SR
Life L.D.*Net investment income*			0.268*
			(0.140)
Life L2.D.*Net investment income*			-0.375**
			(0.145)
D.*Inflation rate*			3.819***
			(1.378)

Variable	(1) ADJ	(2) LR	(3) SR
Life L.*Net investment income*	-0.0363 (0.0304)		
Inflation rate		-27.63 (23.47)	
Constant			0.368*** (0.100)
Observations	48	48	48
R-squared	0.359	0.359	0.359

The results in Table 5.35 indicate that the adjustment coefficient captured by the variable Life L.*Net investment income* (column 1) is negative but not statistically significant. This means that the long run disequilibrium has not to be corrected; the two series Life *Net investment income* and *Inflation rate* have similar evolutions in the long run. Column 2 shows that the long-term effect of *Inflation rate* on the Life *Net investment income* variable is not statistically significant. We also note that, in the short term (column 3), the inflation shock has a positive and statistically significant impact on the Life *Net investment income* variable. Finally, the significance of the D.*Inflation rate* coefficient (SR) compared with the non-significant coefficient of the *Inflation rate* variable (LR) indicates that the short-term relationship outweighs the long-term one. To summarize, a shock to inflation has a positive short-term impact on Life *Net investment income.*

Overall, our analysis of the impact of inflation on *Net investment income* shows that an inflation shock has a positive short-term effect on the *Net investment income* variable in both the P&C and Life sectors.

5.7 Modeling the relationship between *Inflation rate* and *Operating ratio*

5.7.1 P&C sector

The results of the test in Table 5.36 indicate a p-value $Z(t)$= 0.0171, which is below the 5% significance level. Consequently, the null hypothesis that the P&C *Operating ratio* variable is nonstationary is rejected. Thus, the P&C *Operating ratio* variable is integrated of order 0, while the *Inflation rate* variable is integrated of order 1. It is therefore possible to estimate the simple ARDL model with equation (3.1).

Table 5.36: Test of long-term relationship between *Inflation rate* and P&C *Operating ratio*, 1973 to 2023 period

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
P&C *Operating ratio*	3.789	-4.168	-3.508	-3.185	0.0171

Table 5.37 shows that there is a consensus for both selection criteria, AIC and BIC, around the ARDL (3,0) model. We have therefore chosen the ARDL (3,0) model to estimate the impact of the *Inflation rate* variable on the P&C *Operating ratio* variable. Table 5.37 also shows that the ARDL (3,0) model passes the test for absence of autocorrelation and the test for absence of heteroscedasticity in the residuals. Accordingly, we can say that the ARDL (3,0) model captures the impact of the *Inflation rate* variable on the P&C *Operating ratio.*

Table 5.37: Model selection by Akaike information criterion (AIC) and Bayesian information criterion (BIC), 1973 to 2023 period

	BG (p-value)	White (p-value)	AIC	BIC
ARDL (1,0)	0.0480	0.8986	279.9838	285.7199
ARDL (1,1)	0.0455	0.7734	281.722	289.3701
ARDL (1,2)	0.0964	0.9513	278.5094	287.9685
ARDL (1,3)	0.2505	0.9829	271.9343	283.1615

	BG (*p*-value)	White (*p*-value)	AIC	BIC
ARDL (2,0)	0.5942	0.9599	273.339	280.9063
ARDL (2,1)	0.5192	0.8462	274.9669	284.426
ARDL (2,2)	0.3076	0.9453	276.8467	288.1976
ARDL (2,3)	0.1724	0.9857	270.3389	283.4373
ARDL (3,0)	0.8326	0.9639	269.9825*	279.3385*
ARDL (3,1)	0.9561	0.8319	271.2878	282.515
ARDL (3,2)	0.3989	0.9754	272.8993	285.9977
ARDL (3,3)	0.0643	0.8645	271.659	286.6286

Note: BG: Breusch-Godfrey test; White: White test (1980); AIC: Akaike information criterion; BIC: Bayesian information criterion.

Our approach to choosing the optimal number of delays for each of the parameters *c* and *q* also led us to select an ARDL (3,0) process for the estimation effect of inflation on P&C *Operating ratio*.

Table 5.38: ARDL (3,0) model estimation results, 1973 to 2023 period

Variable	Coefficient
P&C L.*Operating ratio*	0.642*** (0.150)
P&C L2.*Operating ratio*	-0.205 (0.176)
P&C L3.*Operating ratio*	-0.0399 (0.148)
Inflation rate	0.0854 (0.208)
Constant	54.74*** (15.05)
Observations	48
R-squared	0.329

Table 5.38 shows that the *Inflation rate* variable has no statistically significant effect on the P&C *Operating ratio* variable.

5.7.2 Life sector

Table 5.39: Test of long-term relationship between *Inflation rate* and Life *Operating ratio*, 1973 to 2023 period

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
Life *Operating ratio*	-2.076	-4.159	-3.504	-3.182	0.5597
Life D.*Operating ratio*	-7.022	-4.159	-3.504	-3.182	0.0000

Table 5.39, line (2), shows that the p-value = 0.00, which is below the usual significance level of 1%. In other words, the Life *Operating ratio* variable is stationary after differentiation, and is therefore integrated of order 1.

Table 5.40: Kripfganz and Schneider (2020) critical values and approximate p-values, 1973 to 2023 period

H0: no level relationship F = 1.389, t = -0.953

	10%		5%		1%		p-value	
	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
F	4.162	4.935	5.146	6.006	7.430	8.451	0.592	0.710
t	-2.590	-2.952	-2.910	-3.288	-3.544	-3.944	0.759	0.829
Decision	.a		.a		.a			

Note: Decision: no rejection (.a), inconclusive (.), or rejection (.r) at indicated levels.

Table 5.40 shows that the null hypothesis that there is no long-term relationship between the *Inflation rate* and the Life *Operating ratio* variable is not rejected at all levels. Consequently, the *Inflation rate* variable and the Life *Operating ratio* variable are not cointegrated.

Table 5.41 shows that there is a consensus for both selection criteria AIC and BIC around the ARDL (3,0) model. We have therefore chosen the ARDL (3,0) model to estimate the short-term impact of the *Inflation rate* variable on the Life *Operating ratio* variable. Table 5.41 also shows that the

ARDL (3,0) model passes the test for the absence of autocorrelation and the test for the absence of heteroscedasticity in the residuals. Accordingly, we can say that the ARDL (3,0) model captures the impact of the *Inflation rate* variable on the Life *Operating ratio* variable.

Table 5.41: Model selection by Akaike information criterion (AIC) and Bayesian information criterion (BIC), 1973 to 2023 period

	BG (*p*-value)	White (*p*-value)	AIC	BIC
ARDL (1,0)	0.9394	0.9940	337.9028	343.5164
ARDL (1,1)	0.9481	0.9999	339.8674	347.3522
ARDL (1,2)	0.8843	1.0000	340.9947	350.3507
ARDL (1,3)	0.8095	0.9998	337.0335	348.1344
ARDL (2,0)	0.9044	0.9995	333.7964	341.197
ARDL (2,1)	0.7881	1.0000	335.7962	345.0469
ARDL (2,2)	0.9700	1.0000	336.9462	348.0471
ARDL (2,3)	0.8169	1.0000	338.9444	351.8954
ARDL (3,0)	0.7031	1.0000	329.5101*	338.6533*
ARDL (3,1)	0.5181	0.5181	331.5091	342.481
ARDL (3,2)	0.7558	1.0000	332.8439	345.6443
ARDL (3,3)	0.4267	0.9999	334.8435	349.4727

Note: BG: Breusch-Godfrey test; White: White test (1980); AIC: Akaike information criterion; BIC: Bayesian information criterion.

To summarize, the *Inflation rate* and Life *Operating ratio* variables are integrated of different orders, but are not cointegrated. It is therefore possible to estimate the ARDL model in first difference. Consequently, we need to estimate equation (5.2). Our approach to choosing the optimal number of delays for each of the parameters *c* and *q* also led us to select an ARDL (3,0) process.

Table 5.42 shows that a short-term shock to the *Inflation rate* variable has no statistically significant effect on the Life *Operating ratio* variable. To summarize, a shock to inflation has no short-term or long-term impact on the *Operating ratio* variable in the Life sector.

Table 5.42: ARDL (3,0) model estimation results, 1973 to 2023 period

Variable	Coefficient
Life L.D.*Operating ratio*	0.0601 (0.164)
Life L2.D.*Operating ratio*	-0.0342 (0.161)
Life L3.D.*Operating ratio*	0.0436 (0.166)
D.*Inflation rate*	-0.663 (0.758)
Constant	0.380 (1.227)
Observations	46
R-squared	0.024

5.8 Modeling the relationship between *Inflation rate* and the profitability of the insurance business as measured by the *Pretax operating income*

5.8.1 P&C sector

Table 5.43: Test of long-term relationship between *Inflation rate* and P&C *Pretax operating income*

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
P&C *Pretax operating income*	-2.140	-4.159	-3.504	-3.182	0.5236
P&C D.*Pretax operating income*	-7.291	-4.159	-3.504	-3.182	0.0000

The results in Table 5.43 line (2) indicate that the p-value = 0.00, which is below the usual significance level of 1%. In other words, the P&C *Pretax operating income* variable is stationary after differentiation and is therefore integrated of order I (1).

Table 5.44: Kripfganz and Schneider (2020) critical values and approximate *p*-value, 1973 to 2023 period

H0: no level relationship $F = 1.898$, $t = -1.947$

	10%		5%		1%		*p*-value	
	I (0)	*I* (1)	*I* (0)	*I* (1)	*I* (0)	*I* (1)	*I* (0)	*I* (1)
F	4.162	4.935	5.146	6.006	7.430	8.451	0.446	0.574
t	-2.590	-3.288	-2.910	-3.288	-3.544	-3.944	0.306	0.443
Decision	.a		.a		.a			

Note: Decision: no rejection (.a), inconclusive (.), or rejection (.r) at indicated levels

Table 5.44 shows that the null hypothesis that there is no long-term relationship between the inflation and the P&C *Pretax operating income* variable is not rejected at all levels. Consequently, the *Inflation rate* variable and the P&C *Pretax operating income* variable are not cointegrated.

Table 5.45: Model selection using Akaike information criterion (AIC) and Bayesian information criterion (BIC), 1973 to 2023 period

	BG (*p*-value)	White (*p*-value)	AIC	BIC
ARDL (1,0)	0.8346	0.8963	364.8392	370.4528
ARDL (1,1)	0.9546	0.9775	366.7965	374.2813
ARDL (1,2)	0.7893	0.9965	368.6805	378.0365
ARDL (1,3)	0.4062	0.9747	364.0348	375.1357
ARDL (2,0)	0.9027	0.9740	360.3363	367.7369
ARDL (2,1)	0.4144	0.9967	362.2555	371.5063
ARDL (2,2)	0.8080	0.9993	364.1183	375.2192
ARDL (2,3)	0.1525	0.9936	366.0288	378.9798
ARDL (3,0)	0.7896	0.9969	355.3899*	364.5331*
ARDL (3,1)	0.9895	0.9997	357.3429	368.3148
ARDL (3,2)	0.6868	0.9943	358.9929	371.7934
ARDL (3,3)	0.9694	0.9707	360.9551	375.5843

Note: BG: Breusch-Godfrey test; White: White test (1980); AIC: Akaike information criterion; BIC: Bayesian information criterion.

Table 5.45 shows that there is a consensus for both selection criteria AIC and BIC around the ARDL (3,0) model. We have therefore chosen the ARDL (3,0) model to estimate the short-term impact of the inflation variable on the P&C *Pretax operating income* variable. Table 5.45 also indicates that the ARDL (3,0) model passes the test for absence of autocorrelation and the test for absence of heteroscedasticity in the residuals. Accordingly, the ARDL (3,0) model captures the impact of the inflation variable on the P&C *Pretax operating income* variable.

To summarize, the variables *Inflation rate* and P&C *Pretax operating income* are integrated of the same order but are not cointegrated. It is therefore possible to estimate the ARDL model in first difference. Consequently, we need to estimate equation (5.2). Our approach for choosing the optimal number of lags for each of the parameters *p* and *q* also led us to select an ARDL (3,0) process. The results of this estimation are shown in Table 5.46.

Table 5.46: ARDL (3,0) model estimation results, 1973 to 2023 period

Variable	Coefficient
P&C L.D.*Pretax operating income*	-0.066 (0.155)
P&C L2.D.*Pretax operating income*	0.008 (0.156)
P&C L3.D.*Pretax operating income*	0.056 (0.156)
D.*Inflation rate*	-0.590 (0.966)
Constant	-0.125 (1.615)
Observations	46
R-squared	0.017

Table 5.46 shows that a short-term shock to the inflation variable has no statistically significant effect on the P&C *Pretax operating income* variable. Thus, a shock to inflation has no short-term or long-term impact on the variable *Pretax operating income of* P&C *Premiums*.

5.8.2 Life sector

Table 5.47: Test of long-term relationship between *Inflation rate* and *Pretax operating income*

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
Life *Pretax operating income*	-4.178	-4.159	-3.504	-3.182	0.0048

The results of the test in Table 5.47 indicate a p-value $Z(t)$ = 0.0048, which is below the 5% significance level. Thus, the null hypothesis that the Life *Pretax operating income* variable is nonstationary is rejected. In other words, the Life *Pretax operating income* variable is stationary in level. Consequently, the Life *Pretax operating income* variable is integrated of order 0, and the inflation variable is integrated of order 1. We can then estimate equation (5.1) for ARDL.

Table 5.48 shows that there is a consensus for the two-selection criteria AIC and BIC around the ARDL (2,3) model. We have therefore chosen the ARDL (2,3) model to estimate the impact of the inflation variable on the Life *Pretax operating income* variable. Table 5.48 also indicates that the ARDL (2,3) model passes the test for absence of autocorrelation and the test for absence of heteroscedasticity in the residuals. Thus, the ARDL (2,3) model captures the impact of the inflation variable on the Life *Pretax operating income* variable.

Table 5.48: Model selection by Akaike information criterion (AIC) and Bayesian information criterion (BIC), 1973 to 2023 period

	BG (*p*-value)	White (*p*-value)	AIC	BIC
ARDL (1,0)	0.0777	0.9091	278.5229	284.259
ARDL (1,1)	0.0721	0.8001	280.3097	287.9578
ARDL (1,2)	0.1395	0.9432	277.1851	286.6442
ARDL (1,3)	0.3042	0.9735	270.3119	281.5391
ARDL (2,0)	0.7407	0.9448	272.5989	280.1662
ARDL (2,1)	0.6590	0.7818	274.3383	283.7974
ARDL (2,2)	0.2850	0.9308	276.0333	287.3843
ARDL (2,3)	0.1863	0.9725	269.1727*	282.2711
ARDL (3,0)	0.5725	0.9426	269.403	278.759*
ARDL (3,1)	0.6233	0.7777	270.919	282.1462
ARDL (3,2)	0.4226	0.9448	272.172	285.2704
ARDL (3,3)	0.0832	0.8072	270.7801	285.7497

Note: BG: Breusch-Godfrey test; White: White test (1980); AIC: Akaike information criterion; BIC: Bayesian information criterion.

Our approach for choosing the optimal number of lags for each of the parameters *c* and *q* also led us to select an ARDL (2,3) process. The results of this estimation are shown in Table 5.49.

Table 5.49: ARDL (2,3) model estimation results, 1973 to 2023 period

Variable	Coefficient
Life L.*Pretax operating income*	0.633*** (0.155)
Life L2.*Pretax operating income*	0.0911 (0.157)
Inflation rate	-1.779 (3.916)
L.*Inflation rate*	2.868 (5.648)
L2.*Inflation rate*	0.424 (5.668)

Variable	Coefficient
L3.*Inflation rate*	-1.073 (3.832)
Constant	4.806 (11.64)
Observations	48
R-squared	0.493

Table 5.49 shows that the inflation variable has no significant effect on the Life *Pretax operating income* variable. Therefore, a shock to inflation has no short-term or long-term impact on the Life *Pretax operating income* variable.

Overall, our analysis of the impact of inflation on profitability as measured by the *Pretax operating income* indicator shows that an inflation shock has no short-term or long-term effect on the variable in the P&C and Life insurance sectors.

5.9 Modeling the relationship between ***Inflation rate*** and firm value as measured by the ***ROA*** ratio

5.9.1 P&C sector

Table 5.50: Test of long-term relationship between *Inflation rate* and P&C *ROA*

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
P&C *ROA*	-3.859	-4.168	-3.508	-3.185	0.0138

The results of the test in Table 5.50 indicate a p-value $Z(t)$ = 0.0138, which is below the significance level of 5 %, so the null hypothesis according to which the P&C *ROA* variable is nonstationary is rejected. In other words, the P&C *ROA* variable is stationary in level. Consequently, the P&C *ROA* variable is integrated of order 0, while the *Inflation rate* variable is integrated of order 1.

Table 5.51: Model selection by Akaike information criterion (AIC), Bayesian information criterion (BIC), and BG and White statistics, 1973 to 2023 period

	BG (*p*-value)	White (*p*-value)	AIC	BIC
ARDL (1,0)	0.0042	0.3949	-282.3378	-276.6017
ARDL (1,1)	0.0037	0.3274	-280.5191	-272.871
ARDL (1,2)	0.0240	0.1556	-274.2045	-264.7454
ARDL (1,3)	0.0457	0.3679	-270.0587	-258.8315
ARDL (2,0)	0.2634	0.8459	-283.1614*	-275.5942*
ARDL (2,1)	0.2187	0.7860	-281.6796	-272.2205
ARDL (2,2)	0.2456	0.7393	-279.6925	-268.3415
ARDL (2,3)	0.1504	0.8976	-275.4921	-262.3937
ARDL (3,0)	0.8090	0.9182	-276.0318	-266.6758
ARDL (3,1)	0.8541	0.8590	-275.2307	-264.0035
ARDL (3,2)	0.9358	0.8986	-273.2429	-260.1445
ARDL (3,3)	0.0878	0.6550	-274.7383	-259.7686

Note: BG: Breusch-Godfrey test; White: White test (1980); AIC: Akaike information criterion; BIC: Bayesian information criterion.

Table 5.51 shows that there is a consensus for both selection criteria, AIC and BIC, around the ARDL (2,0) model. We have therefore chosen the ARDL (2,0) model to estimate the impact of the inflation variable on the P&C *ROA* variable. Table 3.51 also indicates that the ARDL (2,0) model passes the test for absence of autocorrelation and the test for absence of heteroscedasticity in the residuals. Thus, the ARDL (2,0) model captures the impact of the inflation variable on the P&C *ROA* variable.

To summarize, the inflation and P&C *ROA* variables are integrated of different orders. Consequently, we need to estimate the simple ARDL model (equation 3.1).

Table 5.52: ARDL (2,0) model estimation results, 1973 to 2023 period

Variable	Coefficient
L.P&C *ROA*	0.773*** (0.136)
L2.P&C *ROA*	-0.374*** (0.137)
Inflation rate	0.000411 (0.0007)
Constant	0.0128*** (0.0038)
Observations	49
R-squared	0.436

Table 5.52 shows that the *Inflation rate* variable has no significant effect on the P&C *ROA* variable. In short, a shock to *Inflation rate* has no short-term or long-term impact on the *ROA* variable in the P&C sector.

5.9.2 Life sector

Table 5.53: Test of long-term relationship between *Inflation rate* and Life *ROA*

$Z(t)$	Test statistic	1% critical value	5% critical value	10% critical value	p-value
ROA Life	-2.031	-4.159	-3.504	-3.182	0.5843
Life D.ROA	-7.105	-4.159	-3.504	-3.182	0.0000

The results in Table 5.53 line (2) shows that the p-value = 0.00, which is below the usual significance level of 1%. In other words, the Life *ROA* variable is stationary after differentiation, and is therefore integrated of order I.

Table 5.54: Kripfganz and Schneider (2020) critical values and approximate *p*-values, 1973 to 2023 period

H0: no level relationship $F = 1.564$, $t = -1.769$

	10%		5%		1%		*p*-value	
	I (0)	*I* (1)	*I* (0)	*I* (1)	*I* (0)	*I* (1)	*I* (0)	*I* (1)
F	4.162	4.935	5.146	6.006	7.430	8.451	0.539	0.663
t	-2.590	-2.952	-2.910	-3.288	-3.544	-3.944	0.387	0.525
Decision	.a		.a		.a			

Note: Decision: no rejection (.a), inconclusive (.), or rejection (.r) at indicated levels.

Table 5.54 shows that the null hypothesis that there is no long-term relationship between the inflation and the Life *ROA variable* is not rejected at all levels. In other words, there is no long-term relationship between inflation and the Life *ROA* variable. Consequently, the inflation variable and the Life *ROA* variable are not cointegrated.

Table 5.55: Model selection by Akaike information criterion (AIC) and Bayesian information criterion (BIC), 1973 to 2023 period

	BG (*p*-value)	White (*p*-value)	AIC	BIC
ARDL (1,0)	0.8214	0.9552	-248.8347*	-243.2211*
ARDL (1,1)	0.8455	0.9937	-246.841	-239.3562
ARDL (1,2)	0.4736	0.9996	-244.9511	-235.5951
ARDL (1,3)	0.2089	0.9798	-237.099	-225.9981
ARDL (2,0)	0.7029	0.9878	-240.6117	-233.2111
ARDL (2,1)	0.2731	0.9991	-238.6273	-229.3766
ARDL (2,2)	0.8072	0.9999	-236.7677	-225.6668
ARDL (2,3)	0.0957	0.9982	-235.1942	-222.2431
ARDL (3,0)	0.9383	0.9977	-233.2705	-224.1273
ARDL (3,1)	0.9774	0.9999	-231.2734	-220.3016
ARDL (3,2)	0.6545	1.0000	-229.6157	-216.8152
ARDL (3,3)	0.7422	0.9065	-227.8748	-213.2457

Note: BG: Breusch-Godfrey test; White: White test (1980); AIC: Akaike information criterion; BIC: Bayesian information criterion.

Table 5.55 shows that there is a consensus for both selection criteria AIC and BIC around the ARDL (1,0) model. We have therefore chosen the ARDL (1,0) model to estimate the short-term impact of the inflation variable on the *ROA* Life variable. Table 5.55 also indicates that the ARDL (1,0) model passes the test for absence of autocorrelation and the test for absence of heteroscedasticity in the residuals. Thus, the ARDL (1,0) model captures the impact of the inflation variable on the Life *ROA* variable.

To summarize, the inflation and Life *ROA* variables are integrated of the same order (1) but are not cointegrated. It is therefore possible to estimate the ARDL model in first difference. Consequently, we need to estimate equation (5.2). Our approach for choosing the optimal number of lags for each of the parameters *c* and *q* also led us to select an ARDL process (1,0). The results of this estimation are shown in Table 5.56.

Table 5.56: ARDL (1,0) model estimation results, 1973 to 2023 period

Variable	Coefficient
Life L.D.*ROA*	-0.0387 (0.149)
D.*Inflation rate*	-0.000686 (0.00147)
Constant	-0.000437 (0.00254)
Observations	48
R-squared	0.007

Table 5.56 shows that a short-term shock to the inflation variable has no statistically significant effect on the Life *ROA* variable. In short, a shock to inflation has no short-term or long-term impact on the *ROA* variable in the Life sector.

Overall, our analysis of the impact of inflation on *ROA* shows that an inflation shock has no short-term or long-term impact on the *ROA* variable in the P&C sector and in the Life sector.

Table 5.57: Summary of results with ARDL models of inflation

		P&C Sector		LIFE Sector	
Financial variable	Model	Short run	Long run	Short run	Long run
Premiums	First difference ARDL model	+*			
	First difference ARDL model			+*	
Total expenses	First difference ARDL model	+***			
	First difference ARDL model			+	
Net investment income	First difference ARDL model	+**			
	ECM version ARDL model			+***	–
Combined ratio	Simple ARDL model		+		
	First difference ARDL model			–	
Operating ratio	Simple ARDL model		+		
	First difference ARDL model			–	
Pretax operating income	First difference ARDL model	–			
	Simple ARDL model				–
ROA	Simple ARDL model		+		
	First difference ARDL model			–	

Note: * significant at 10%; *** significant at 1%.; +, –, not significant at 10%.

5.10 Summary of results

In this section of the report, we have modeled the links between inflation and the variables *Premiums, Total expenses, Combined ratio, Net investment income*, *Operating ratio, Pretax operating income* and *ROA* in each of the two insurance sectors, using the ARDL (c,q) model. The advantage of this model is that it can be applied to both nonstationary and stationary data. However, we worked with stationary variables exclusively. We differentiated our variables that turned out to be nonstationary to make them stationary. This approach enables us to use usual tests of coefficient significance (Fisher or Student tests), which are based on the assumption of white noise in stationary residuals. As the series are stationary, they can be modeled using a VAR process, as we will see in the next section.

Table 5.57 indicates that *Premiums*, *Total expenses*, and *Net investment income* variables are positively affected by inflation, which is a quite natural result. These effects seem to compensate each others since profitability variables such as *Combined ratio*, *Operating ratio*, *Pretax operating income*, and *ROA* are not affected by inflation according to the ARDL models. In addition, since almost all the results lead us to accept the null hypothesis of the absence of a long-term relationship (cointegration), it makes sense to proceed with the estimation of a VAR model in difference, in a next step.

Appendix A5: Variables definitions

Table A5.1: Variables descriptions, data sources and descriptions (LIFE)

Variable	Description	Data source
Total expenses ($ billion)	Life insurance company expenditures include benefit payments and other contract payments, operating expenses, taxes and investment expenses.	American Council of Life Insurers (ACLI) database
Premiums ($ billion)	Premium receipts – derived from sales of Life insurance, Health insurance, and annuities.	American Council of Life Insurers (ACLI) database
Combined ratio (%)	*Combined ratio* is *Total expenses* (ACLI database) to *Premiums* (ACLI database)	Our calculations
Net investment income ($ billion)	The *Net investment income* is total gross investment income less investment expenses, taxes, and deductions. The total gross investment income is sum of bonds, preferred stock, common stock, mortgage loans, real estate, contract loans, cash/short-term investments, other invested assets, derivative instruments and other write-ins.	American Council of Life Insurers (ACLI) database
Operating ratio (%)	Operating Ratio is *Combined ratio* less net investment income to *Premiums*	Our calculations
Pretax operating income ($ billion) before dividends to policyholders and federal income taxes	*Pretax operating income* is total income (ACLI database) less total expenses (ACLI database), before policyholder dividends federal income taxes and realized capital gains/losses. Total income is sum of *Premiums* and *Net investment income*.	Our calculations
Total assets	Total assets is the sum of cash, invested assets (bonds, stocks, mortgage loans, real estate, contract loans, derivatives and other invested assets), investment income due and accrued, uncollected and deferred *Premiums* and considerations, amounts receivable under reinsurance contracts, current and deferred net tax assets, guaranty funds receivable or on deposit, furnitures and equipments, receivables from parent, subsidiaries and affiliates, aggregate write-ins for other-than-invested assets, separate accounts, segregated accounts and protected cell accounts.	American Council of Life Insurers (ACLI) database
Net investment income (ratio)	*Net investment income to Total assets* is *Net investment income* (ACLI database) divided by *Total assets* (ACLI database)	Our calculations
ROA (ratio)	*ROA* is *Pretax operating income* (our calculations) divided by *Total assets* (ACLI database).	Our calculations

Table A5.2: Variables descriptions, data sources and descriptions (P&C)

Variable	Description	Data source
Total expenses ($ billion)	P&C insurance company expenditures include benefit payments and other contract payments, operating expenses, taxes and investment expenses.	AMBest database
Premiums written ($ billion)	*Premiums* written is the sum of direct *Premiums* written, minus the *Premiums* ceded to reinsurance companies (to affiliates and non- affiliates), plus any reinsurance assumed (from affiliates and non-affiliates)	AMBest database
Combined ratio (%)	*Combined ratio* before dividend to policyholders: It is the sum of the loss and loss adjustment expenses ratio and the total underwriting expense to *Premiums*. It measures the insurance company's overall underwriting profitability.	AMBest database
Net investment income ($ billion)	The *Net investment income* is total gross investment income less investment expenses, taxes, and deductions The total gross investment income is sum of bonds, preferred stock, common stock, mortgage loans, real estate, contract loans, cash/short-term investments, other invested assets, derivative instruments and other write-ins.	AMBest database
Operating ratio (%)	*Operating ratio* is *Combined ratio* less *Net investment income* to *Premiums*	Our calculations
Pretax operating income ($ billion)	*Pretax operating income* before dividends to policyholders and federal income taxes is the sum of net underwriting income, other income/expense, and net investment income, minus change in contingency reserve. It measures the internal capital generation from operating earnings by the insurance company.	AMBest database
Total assets	Total assets is the sum of cash, invested assets (bonds, stocks, mortgage loans, real estate, contract loans, derivatives and other invested assets), investment income due and accrued, uncollected and deferred *Premiums* and considerations, amounts receivable under reinsurance contracts, current and deferred net tax assets, guaranty funds receivable or on deposit, furnitures and equipments, receivables from parent, subsidiaries and affiliates, aggregate write-ins for other-than-invested assets, separate accounts, segregated accounts and protected cell accounts.	AMBest database
Net investment income (ratio)	*Net investment income to Total assets* is *Net investment income* (AMBest database) divided by *Total assets* (AMBest database)	Our calculations
ROA (ratio)	*ROA* is *Pretax operating income* (AMBest database) divided by *Total assets* (AMBest database).	Our calculations

6 VAR process and impulse response analysis of inflation on insurers' financial variables

We have just shown that an inflation shock has a significant short-term impact on the following six variables: P&C *Premiums,* P&C *Total expenses*, P&C *Net investment income,* Life *Premiums,* Life *Total expenses*, and Life *Net investment income.* In other words, our analysis enabled us to document an effect of inflation on each of these variables. Given that the insurance industry is a key component of the economy in terms of direct *Premiums* earned and investments made, it would be worth examining the potential impact of each of these six variables on inflation. To answer this question, we turned to VAR (p) (*Vector Autoregressive*) processes, which were introduced by Sims (1980) as alternatives to Keynesian macroeconometric models. In empirical applications, one of the main uses of VAR processes is impulse response analysis. This analysis represents the effect of a schock from an innovation on current and future endogenous variables.

6.1 P&C *Total expenses*

The structure of the VAR model estimated in level or difference when the variables are nonstationary can influence the results of the impulse response analysis. It is preferable to estimate only stationary variables to avoid numerical discrepancies in the estimated values.

We have shown above that the *Inflation rate* variable becomes stationary after a difference. The same applies to the P&C *Total expenses* variable. In other words, the *Inflation rate* variable and the P&C *Total expenses* variable are integrated of order 1.

With the P&C *Total expenses* variable made stationary after one difference (D.Log P&C *Total expenses*), as well as the inflation variable, we now estimate the VAR (p). The first step is to determine which order p to choose. To this end, we have estimated various VAR processes on the stationary variables D.Log P&C *Total expenses* and D.*Inflation rate* for lag orders p ranging from 1 to 4. We therefore used a difference VAR model. For each model, we calculated the Akaike information criterion (AIC), the Schwarz Information criterion (BIC) and the log-likelihood ratio (LR) to test the order p of the VAR model. The technique consists in estimating a constrained VAR (p) model and an unconstrained VAR (p+1) model and performing the log-likelihood ratio (LR) test. In other words, we can test the order p of the VAR model by considering the following equations:

$$H_0: \Phi_{p+1} = 0\text{: VAR process } (p) \tag{6.1}$$

$$H_1: \Phi_{p+1} \neq 0\text{: VAR process } (p+1). \tag{6.2}$$

Under the null hypothesis, the LR statistic follows a chi-square distribution with q degrees of freedom. The q value is obtained by taking the difference between the p of the unconstrained VAR (H_1) and the constrained VAR (H_0) multiplied by the number of equations (N) squared.

$$q = (p_{H_1} - p_{H_0})N^2. \tag{6.3}$$

Table 6.1: VAR model selection statistics, 1972 to 2022

VAR (p)	AIC	BIC	LL	LR
p = 1	-34.56687	-23.21595*	23.28344	–
p = 2*	-40.64646	-21.93445	30.32323	14.07958*
p = 3	-42.6167 *	-16.71463	35.30835	9.97024*
p = 4	-38.51976	-5.604214	37.25988	3.90306

Note: AIC: Akaike information criterion; BIC: Bayesian information criterion; LL: Log likelihood; LR: Likelihood ratio statistics.

Table 6.1 shows the different statistics of interest for the choice of p. The AIC chooses VAR (3) and the BIC chooses VAR (1). The log-likelihood ratio statistic selects VAR (2) and VAR (3). The LR statistic is 14.08 for VAR (2) and 9.97 for VAR (3), and each of these values is above the critical value of the LR statistic, which comes from the $\chi^2(4)$ distribution since we have 2 equations $(N^2 = 4)$ and the difference between the p of the unconstrained VAR (H_1) and the constrained VAR (H_0) is 1. The critical value at 5% is 9.49. We can see that the LR tests select the VAR model (2) as well as the VAR model (3). In other words, the log-likelihood ratio statistic selects VAR model (2) and VAR model (3). Since VAR (3) is not rejected from LR and AIC, we retain VAR (3).

Table 6.2: Estimation of VAR process (3)

Variable	Log Loss & LAE, commissions & other P&C expenses	D.*Inflation rate*
L.D.Log Loss and LAE, commissions and other P&C expenses	0.336** (0.134)	-17.12 (10.69)
L2.D.Log Loss and LAE, commissions and other P&C expenses	-0.0761 (0.149)	7.565 (11.89)
L3.D.Log Loss and LAE, commissions and other P&C expenses	0.413*** (0.137)	10.54 (10.89)
L.D.*Inflation rate*	-0.00213 (0.00188)	0.249* (0.150)
L2.D.*Inflation rate*	-0.00170 (0.00171)	-0.333** (0.136)
L3.D.*Inflation rate*	-0.00326* (0.00178)	-0.179 (0.142)
Constant	0.00704 (0.00473)	-0.0704 (0.377)
Observations	47	47

The results in Table 6.2 indicate that the variable P&C *Total expenses* is negatively dependent on inflation lagged by 3 periods. This suggests that an inflation shock has a significant impact on the future value of the variable Total P&C *Total expenses.* This variable also depends positively on its lagged value of one and three periods. By comparison, the *Inflation rate* depends on its lagged past values of one period (positively) and two periods (negatively). In other words, the results suggest that a shock to inflation has an impact on P&C *Total expenses,* while a shock to P&C *Total expenses* has no contemporaneous impact on the *Inflation rate*.

Figure 6.3 traces the impulse response of the variable P&C *Total expenses* to the inflation shock. The gray area represents the confidence interval at 95%. We are interested in the effects of the shock over 10 periods.

Figure 6.3: Impulse response function of P&C *Total expenses* to inflation shocks

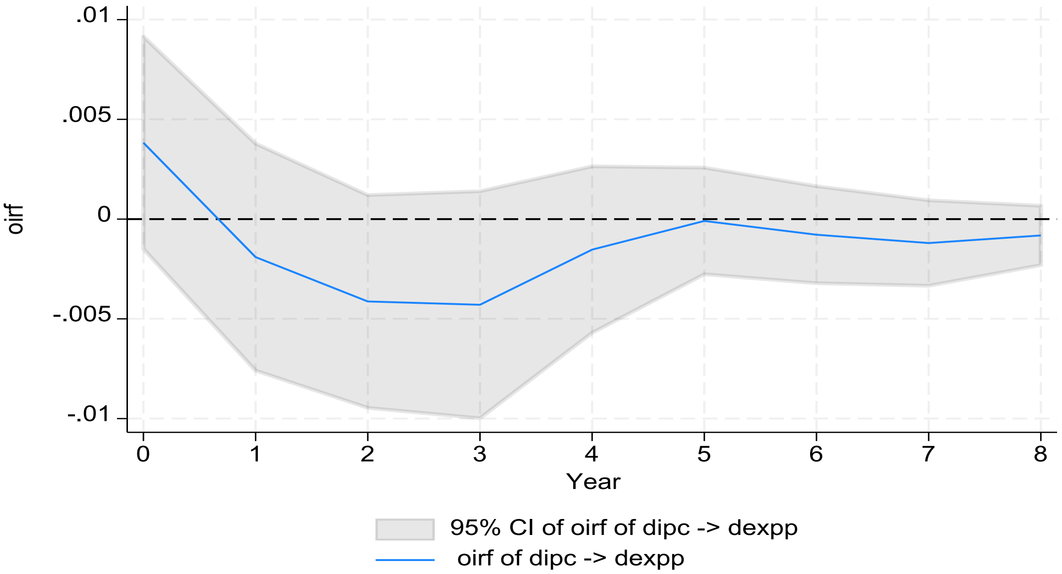


Figure 6.3 shows that an inflation shock causes the P&C *Total expenses* variable to rise sharply by around 0.04% in the year of the shock (year 0). It falls below its normal level after one year. It then falls by a maximum of around -0.04% after 3 years, then slowly returns to its normal level after 5 years. The results allow us to draw the following conclusion: the inflation shock positively affects the current value of P&C *Total expenses* (i.e. in the year of the shock, year 0) and negatively affects the future value of P&C *Total expenses*, with a significant effect after 3 years (see Table 6.2). The positive effect of the inflation shock on the current value of P&C *Total expenses* in the year of the

shock (year 0) suggests that an inflation shock has an instantaneous impact on the variable P&C *Total expenses,* which explains why the curve for the P&C *Total expenses* variable does not depart from the origin in the year of the shock. The result obtained from the ARDL (1,1) model presented in Table 5.12 had predicted this immediate impact of the inflation shock on the P&C *Total expenses* variable. Note that the consequences of this shock disappear after 5 years.

6.2 P&C *Combined ratio*

We have shown above that the P&C *Combined ratio* variable is stationary in level, i.e. integrated of order 0. The *Inflation rate* variable series is made stationary after a difference, i.e. integrated of order 1. We will now estimate the VAR (p). The first step is to determine the order *p* to retain. To this end, we estimated various VAR processes on the stationary variables P&C *Combined Ratio* and D.*Inflation rate* for lag orders *p* ranging from 1 to 4. For each model, we calculated the Akaike information criterion (AIC), the Bayesian or Schwarz Information criterion (BIC) and the LR statistic. Analysis of these criteria led us to select a VAR (2) process.

Table 6.4: VAR model selection statistics, 1972 to 2022

VAR (p)	AIC	BIC	LL	LR
$p = 1$	479.1704	490.5213	-233.5852	–
$p = 2$*	458.659	477.371*	-219.3295	14.2557*
$p = 3$	454.5101	480.4122	-213.2551	6.0744
$p = 4$	447.0951*	480.0106	-205.5475	7.7076

Note: AIC: Akaike information criterion; BIC: Bayesian information criterion; LL: Log likelihood; LR: Likelihood ratio statistics.

Table 6.4 shows the different statistics of interest for the choice of *p*. The AIC chooses VAR (4) and BIC chooses VAR (2). The log-likelihood ratio statistic chooses VAR (2), as does BIC. As there is a consensus around VAR (2) for the LR and BIC statistics, we have chosen VAR (2).

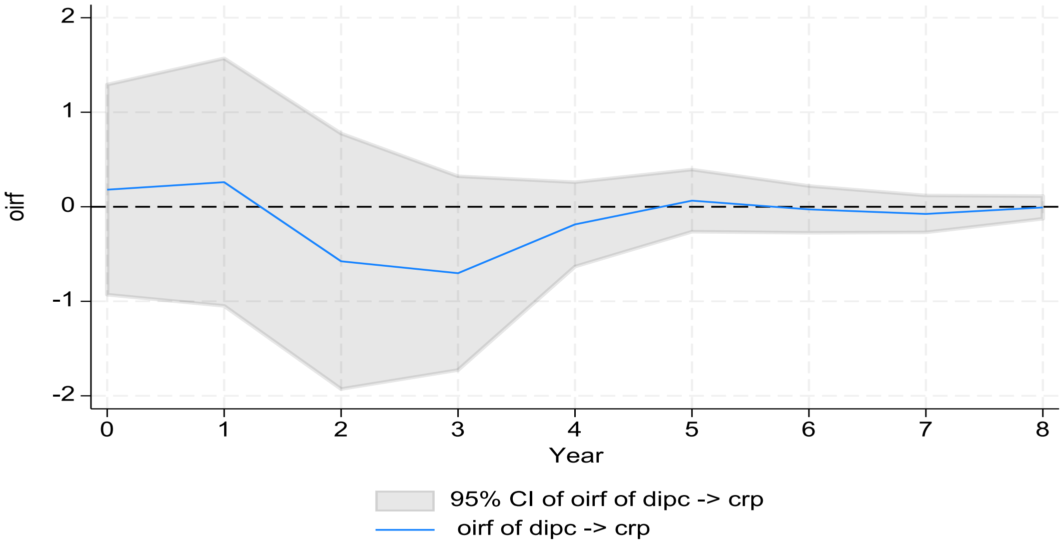
Table 6.5: Estimation of VAR process (2), 1972 to 2022

Variable	P&C *Combined ratio*	D.*Inflation rate*
L.P&C *Combined ratio*	0.805*** (0.138)	-0.149*** (0.0507)
L2.P&C *Combined ratio*	-0.203 (0.146)	0.0725 (0.0536)
L.D.*Inflation rate*	0.0797 (0.340)	0.207* (0.125)
L2.D.*Inflation rate*	-0.536* (0.324)	-0.371*** (0.119)
Constant	41.11*** (12.09)	7.787* (4.425)
Observations	48	48

The results in Table 6.5 show that the P&C *Combined Ratio* depends negatively on inflation lagged 2 periods. It also depends positively on its past value. The *Inflation rate* depends on its lagged past values of one period (positively) and two periods (negatively). The *Inflation rate* also depends negatively on the one-period lagged *Combined ratio*. In other words, the results show that an inflation shock has an impact on the P&C *Combined ratio.* Further, a shock to the P&C *Combined ratio* has an impact on inflation. Figure 6.6 traces the impulse function of the response of the P&C *Combined ratio* variable to the inflation shock. The gray area represents the confidence interval at 95%.

Figure 6.6 shows that an inflation shock has a dampening effect on the P&C *Combined ratio.* The impact disappears after 5 years. The fact that the P&C *Combined ratio* curve starts from the origin suggests that the inflation shock does not have an instantaneous influence on the P&C *Combined ratio* variable.

Figure 6.6: Impulse response function of P&C *Combined ratio* to inflation shocks



To summarize, comparing the results obtained in Table 6.2 and Table 6.5, on the one hand, and the results obtained in Figures 6.3 and 6.6, on the other hand, confirms our finding that inflation influences the combined P&C (the profitability of the P&C sector) through the *Total expenses* variable.

6.3 P&C *Net investment income*

We have shown above that the *Inflation rate* series is made stationary after one difference, as is the variable P&C *Net investment income.* We will now estimate the VAR (p). The first step is to determine the order *p* to be retained. To this end, we have estimated various VAR processes on the stationary variables D.P&C *Net investment income* and D.*Inflation rate* for lag orders *p* ranging from 1 to 4. For each model, we calculated the Akaike information criterion (AIC), the Bayesian or Schwarz Information criterion (BIC) and the LR statistic. Analysis of these criteria led us to select a VAR (2) process.

Table 6.7: VAR model selection statistics, 1972 to 2022

VAR (p)	AIC	BIC	LL	LR
$p = 1$	6.565748	17.91667	2.717126	−
$p = 2$*	-1.021414*	17.6906*	10.51071	15.587168*
$p = 3$	6.109367	32.01143	10.94532	0.86922
$p = 4$	1.198879	34.11442	17.40056	12.91048

Note: AIC: Akaike information criterion; BIC: Bayesian information criterion; LL: Log likelihood; LR: Likelihood ratio statistics.

Table 6.7 shows the different statistics of interest for the choice of p. The AIC chooses VAR (2) and the BIC chooses VAR (2). The log-likelihood ratio statistic selects the VAR (2) model. All three criteria led us to choose the VAR (2) model because a consensus emerges around it.

Table 6.8: Estimation of VAR process (2), 1972 to 2022

Variable	D.Log P&C *Net investment income*	D.*Inflation rate*
L.D.Log P&C *Net investment income*	0.473***	2.728
	(0.160)	(7.636)
L2.D.Log P&C *Net investment income*	0.117	-9.228
	(0.159)	(7.604)
L.D.*Inflation rate*	0.00206	0.176
	(0.00270)	(0.129)
L2.D.*Inflation rate*	-0.00184	-0.344***
	(0.00274)	(0.131)
Constant	0.0116*	0.107
	(0.00609)	(0.291)
Observations	48	48

The results in Table 6.8 indicate that the variable P&C *Net investment income* depends positively on its past value. The results support the view that an inflation shock has no impact on the P&C *Net investment income* variable.

Figure 6.9: Impulse response function of P&C *Net investment income* to inflation shocks

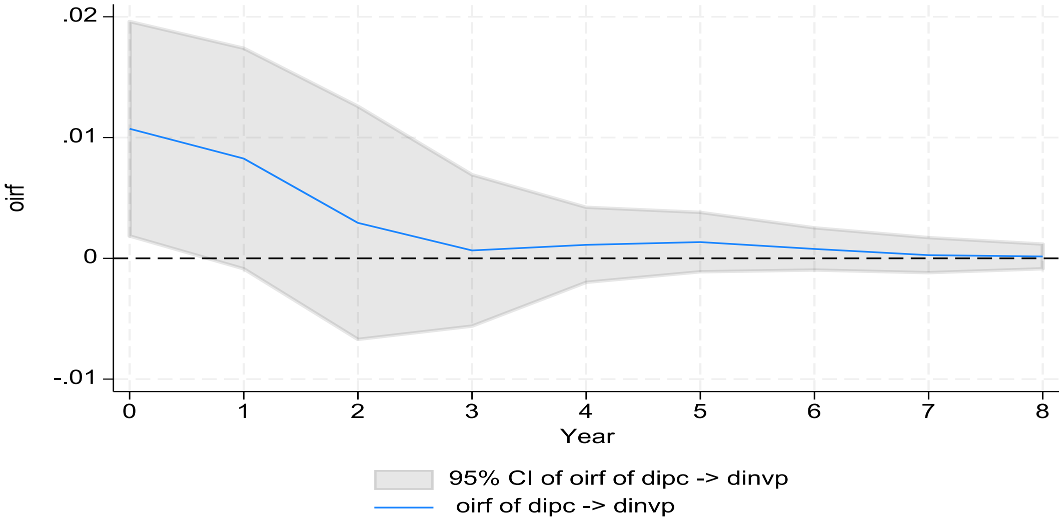


Figure 6.9 shows that an inflation shock had no significant impact on the variable P&C *Net investment income,* since this variable did not really move away from its pre-shock value. Of course, Figure 6.9 shows that an inflation shock had a dampening effect on P&C *Net investment income*, disappearing after 4 years, but the effect was not significant. The non-significant coefficients L.D.*Inflation rate* and L2.D.*Inflation rate* in Table 6.8 support this idea.

6.4 Life *Net investment income*

We have shown above that the inflation series is made stationary after one difference, as is the variable P&C *Net investment income.* We will now estimate the VAR (p). The first step is to determine the order *p* to choose. To this end, we have estimated various VAR processes on the stationary variables Life D.*Net investment income* and D.*Inflation rate* for lag orders *p* ranging from 1 to 4. For each model, we calculated the Akaike information criterion (AIC), the Bayesian or Schwarz Information criterion (BIC) and the LR statistic. Analysis of these criteria led us to select a VAR (2) process.

Table 6.10: VAR model selection statistics, 1972 to 2022

VAR (p)	AIC	BIC	LL	LR
$p = 1$	6.232559	17.58348	2.88372	
$p = 2$*	-1.867575*	16.84444*	10.93379	16.10014*
$p = 3$	2.198384	28.10045	12.90081	3.93404
$p = 4$	6.608709	39.52425	14.69565	3.58968

Note: AIC: Akaike information criterion; BIC: Bayesian information criterion; LL: Log likelihood; LR: Likelihood ratio statistics.

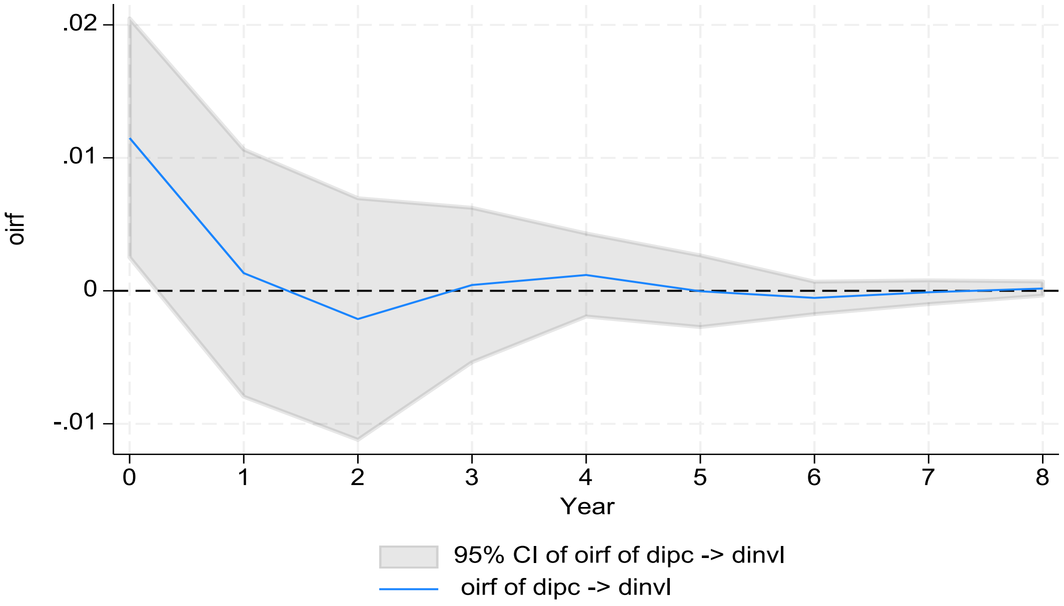
Table 6.10 shows the different statistics of interest for the choice of p. The AIC chose the VAR (2) and the BIC chose the VAR (2). The log-likelihood ratio statistic also chose the VAR (2). In other words, all three criteria led us to choose the VAR (2) model.

Table 6.11: Estimation of VAR process (2), 1972 to 2022

Variable	D.log Life *Net Investment income*	D.*Inflation rate*
L.D.log Life *Net investment income*	0.532*** (0.153)	-7.710 (7.066)
L2.D.log Life *Net Investment income*	-0.203 (0.156)	-5.305 (7.240)
L.D.*Inflation rate*	-0.00315 (0.00291)	0.210 (0.135)
L2.D.*Inflation rate*	0.000144 (0.00281)	-0.362*** (0.130)
Constant	0.0186*** (0.00647)	0.298 (0.300)
Observations	48	48

The results in Table 6.11 show that the Life *Net investment income* variable depends positively on its past value. The results support the view that inflation shock has no significant impact on the Life *Net investment income* variable.

Figure 6.12: Impulse response function of Life *Net investment income* to inflation shocks



6.5 Life *ROA*

We now estimate the VAR (p) model for the link between inflation and Life *ROA*. We apply the previous steps of analysis.

Table 6.13: VAR model statistics, 1972 to 2022

VAR (p)	AIC	BIC	LL	LR
$p = 1$	-176.5126*	-167.1805*	94.2563	–
$p = 2$	-172.0483	-156.7847	96.02416	3.53572*
$p = 3$	-164.7496	-143.7985	96.37482	0.70132
$p = 4$	-150.6432	-124.2599	93.32159	-6.10646

Note: AIC: Akaike information criterion; BIC: Bayesian information criterion; LL: Log likelihood; LR: Likelihood ratio statistics.

We observe from Table 6.13 that AIC and BIC select VAR (1). We then retain the VAR (1) model.

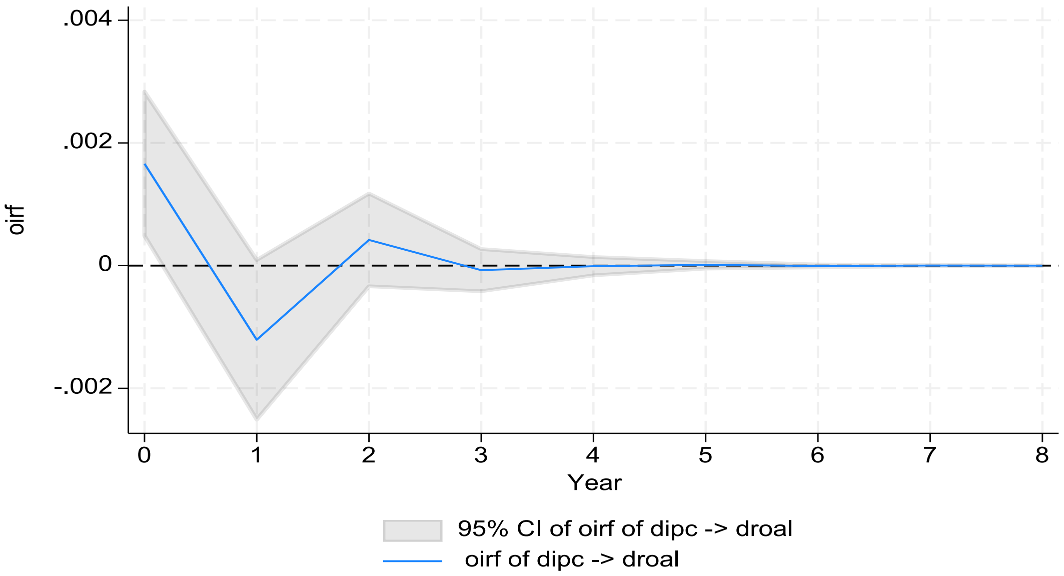
Table 6.14: Estimation of VAR (1) process, 1972 to 2022

Variable	D.Life *ROA*	D.*Inflation rate*
L.D.Life *ROA*	-0.0569	91.61
	(0.185)	(58.79)
L.D.*Inflation rate*	-0.000941	-0.442**
	(0.000627)	(0.199)
Constant	-0.00103	0.130
	(0.000647)	(0.205)
Observations	35	35

Table 6.14 shows that an inflation shock has no significant effect on the future value of Life *ROA*.

Figure 6.15 shows how an inflation shock increases the Life *ROA* variable of 0.018% during the schock year (0). We observe a return to equilibrium after four years. This instantaneous effect was measured in Table 3.65. The effect of the shock disappears after 4 years.

Figure 6.15: Impulse response function of the Life *ROA* to inflation shocks



7 Robustness checks of VAR model

7.1 Literature review

In the previous section, we used a VAR specification, which is a linear global approximation of Data Generating Process (DGP), to represent the dynamics between dependent variables and to derive impulse responses of insurance variables to inflation shocks. This standard procedure to recover impulse responses consist in two-step procedure. The first step involves a linear estimation of the VAR coefficients via ordinary least square (OLS). The second step consists in inverting the VAR estimates to find the impulse responses using the Wold decomposition theorem. The Wold transformation states that any covariance-stationary time series can be rewritten as an infinite order vector moving average (VMA (∞)) and allows to recover the VMA coefficients recursively as a nonlinear function of the autoregressive parameters.

This estimation procedure is theoretically justified when the model coincides with the underlined DGP. This linear approximation of the DGP enables the VAR to produce optimal and robust one-period ahead forecasting even when the model is misspecified. However, impulse responses are function of forecasts at ever-increasing horizons for which a VAR may provide a poor approximation due to recursiveness. In fact, IRF (Impulse Response Function) suffers from well-known small-sample bias in the VMA coefficients due the bias in the estimation of the autoregressive parameters. More importantly, this bias increases as the forecasting horizon increases.

Jorda (2005) has introduced a novel model-free methodology to estimate the impulse response function, namely the Local Projection (LP) estimator. Interestingly, the LP estimator does not need the invertibility assumption as for the VAR estimation. Moreover, the LP allows the estimation of the IRF without reference to the unknown DGP even when its Wold decomposition does not exist. Jorda (2005) pointed out that linear models, such as VARs, have four restrictive properties on their implied impulse responses: (1) *symmetry*, where responses to positive and negative shocks are mirror images of each other; (2) *shape invariance*, where responses to shocks of different magnitudes are scaled versions of one another; (3) *history independence*, where the shape of the responses is independent of the local conditional history; and (4) *multidimensionality*, where responses are high-dimensional nonlinear functions of parameter estimates which complicates the calculation of standard errors and quickly compound misspecification errors.

The local projections have numerous advantages: (1) they can be estimated by simple OLS regression; (2) they are more robust to misspecification of the true DGP; (3) joint or point-wise analytic inference is simple; and (4) they can be easily adapted to a nonlinear specification by including nonlinear regressors. However, local projection procedure has a major drawback. It consumes data along both the lag and the lead dimensions which reduces the sample available for the estimation itself, while VAR estimation consumes data only along the lag dimension.

This novel, flexible and model-free methodology gained in popularity in the econometric and applied macroeconomic literatures. Researchers used the LP and the standard VAR estimations as competitive approaches. Haug and Smith (2011) use local projections to investigate the effects of monetary policy on GDP, interest rates, inflation and exchange rates for a small open economy, New Zealand, and they compare them to those from standard VAR estimations. Haug and Smith (2011) find some important differences between the impulse responses by both approaches, in particular the magnitude and volatility of the responses. Overall, the authors argue that impulse responses by LP method are more robust than the ones from the standard VAR which are more sensitive to identification schemes and model specification. Hamilton (2011) uses impulse responses by LP methods to review some of the literature on the macroeconomic effects of oil price shocks with a particular focus on possible nonlinearities in the relation between oil price and economic growth. Hamilton (2011) asserts that we cannot rely on impulse responses from off-the-shelf linear methods for an answer about the effects of oil price shocks.

Kilian and Kim (2011) open the debate on the reliability of the LP estimator. They compare the finite-sample performance of impulse response confidence intervals based on LP and VAR models in linear stationary settings using simulations. Kilian and Kim (2011) find that in small samples, the asymptotic LP interval often is less accurate than the bias-adjusted bootstrap VAR (c) interval. Brugnolini (2018) revisits the critics addressed by Kilian and Kim (2011) to the LPs method. In a Monte Carlo experiment, he demonstrates that the results by Kilian and Kim (2011) are driven by the authors' choice about lag-length inducing a comparison between a well-specified VAR and a misspecified local projection model. Indeed, Brugnolini (2018) proves that the LP estimator is a competitive alternative when the sample size is small, and the VAR model lag-length is misspecified.

Tenreyro and Thwaites (2016), Ambrogio Cesa-Bianchi (2020), Miranda-Agrippino and Ricco (2021), and Swanson (2021) investigate the effect of monetary policy shocks on real and financial variables (output, inflation, exchange rates, expenditures, investment) using the LP estimator.

Recently, Plagborg-Møller and Wolf (2021) argue that neither LPs nor VARs dominate the other in terms of mean squared error in finite samples, and asymptotically the two methods estimate the same impulse responses given that the lag length used for estimation tends to infinity. This finding is valid, nevertheless of identification scheme and regardless of the underlying data generating process. In finite samples and with finite lag lengths, Plagborg-Møller and Wolf (2021) conjecture that both methods should estimate equivalent impulse response functions for short forecasting horizons. However, divergencies appear for intermediate and long horizons when the number of forecasting periods exceeds the lag-length used for the estimation. Hence, there is a bias-variance trade-off between the direct estimation by LP and the iterative estimation by VAR of the impulse responses at longer horizons. Montiel Olea and Plagborg-Møller (2021) prove that lag-augmented local projections with normal critical values are asymptotically valid over (i) both stationary and nonstationary data, and over (ii) a wide range of response horizons. The authors show that lag augmentation avoids the need to correct standard errors for serial correlation in residuals. Therefore, Montiel Olea and Plagborg-Møller (2021) argue that local projection inference is both simpler than previously thought and more robust than standard autoregressive inference.

Plagborg-Møller et al., (2024) undertake comprehensive simulation study of LP and VAR estimators of structural impulse responses across thousands of data generating processes, designed to mimic the properties of many quarterly US macroeconomic time series spanning a wide variety of variable categories. They also consider various identification schemes and several variants of LP and VAR estimators, employing bias correction, shrinkage, or model averaging. The objective of the analysis is to identify which estimators perform well across these DGPs and hence may serve as practical default procedures. Plagborg-Møller et al., (2024) find that a clear and unavoidable bias-variance trade-off emerges. In fact, for intermediate and long forecasting horizons: small bias and large variance for LP estimator, and large bias and small variance for VAR estimator. For short horizons, both methods yield similar estimations.

7.2 Statistical results with the local projective (LP) estimator

In this section, we revisit the impulse responses derived from the VAR estimations to investigate whether our conclusions about insurance variables' responses to inflation shocks are robust to an alternative econometric methodology, namely the LP estimation. Empirically, we estimate the same VAR specifications discussed previously in Section 6 and we draw the impulse response functions generated by the local projection estimations alongside the VAR estimations. For both methods, we apply a small-sample degrees-of-freedom adjustment when estimating covariance matrix of residuals. We opt also for a heteroskedasticity- and autocorrelation-consistent Huber/White/sandwich estimator for the standard errors.

Figure 7.1: Impulse response function of the P&C *Total expenses* to inflation shocks

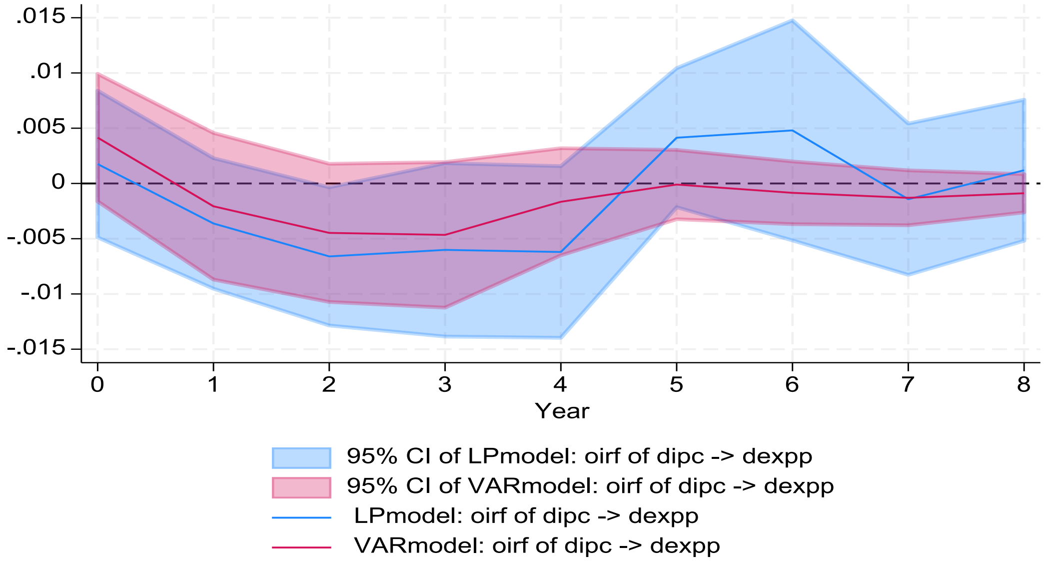
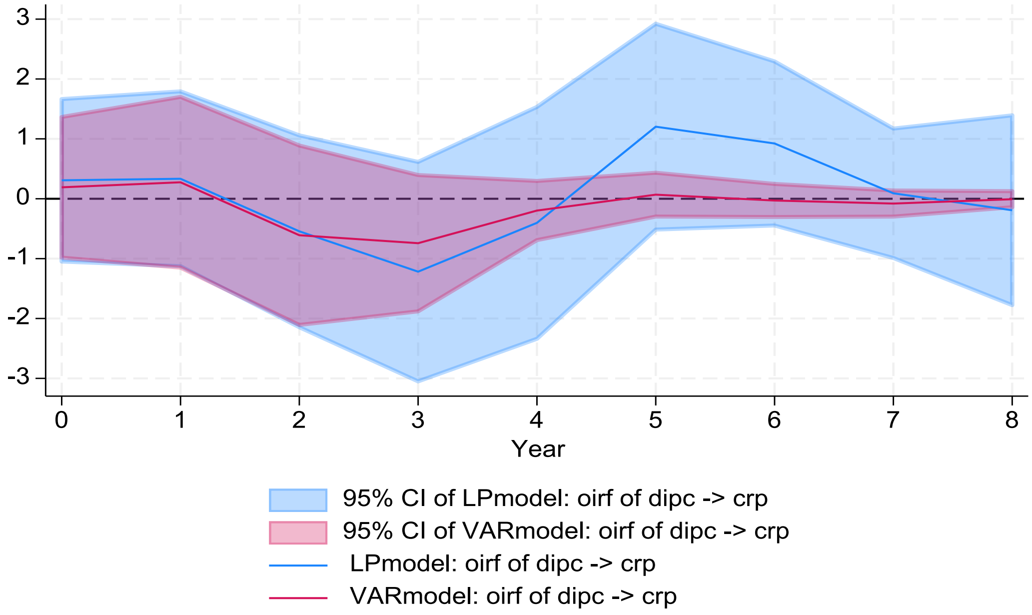


Figure 7.1 depicts the orthogonalized impulse response function of P&C *Total expenses* to inflation shocks produced by the local projection and VAR estimations alongside their respective 95% confidence intervals. Figure 7.1 reveals that, for near horizons, both methodologies give relatively

similar estimations for the impact of a shock in inflation on the P&C *Total expenses*. However, for longer forward times, the discrepancy between both procedures becomes bigger. More importantly, Figure 7.1 shows that the responses by the VAR are smoother and less volatile than the responses by the local projections. Overall, these findings corroborate conclusions by Montiel Olea and Plagborg-Møller (2021), Plagborg-Møller and Wolf (2021) and Plagborg-Møller et al., (2024).

Figure 7.2: Impulse response function of P&C *Combined ratio* to inflation shocks



Interestingly, Figure 7.2 shows that the orthogonalized impulse response functions of P&C *Combined ratio* operating to inflation shocks generated by both methodologies are approximately identical for a forecasting horizon of two years (notice that the lag-length is also two) as predicted by simulation-based literature discussed previously. Afterward, the discrepancy is larger. The local projection produces negative responses that are larger for three and four years ahead than the VAR estimations. For 5 years ahead and after, Figure 7.2 shows a recovery in the *Combined ratio* which appears to be more pronounced with the local projection estimation that with the VAR. Figure 7.2 shows that the LP estimations are more volatile than the VAR estimation as predicted by the theory.

Figure 7.3: Impulse response function of the P&C *Net Investment income* to inflation shocks

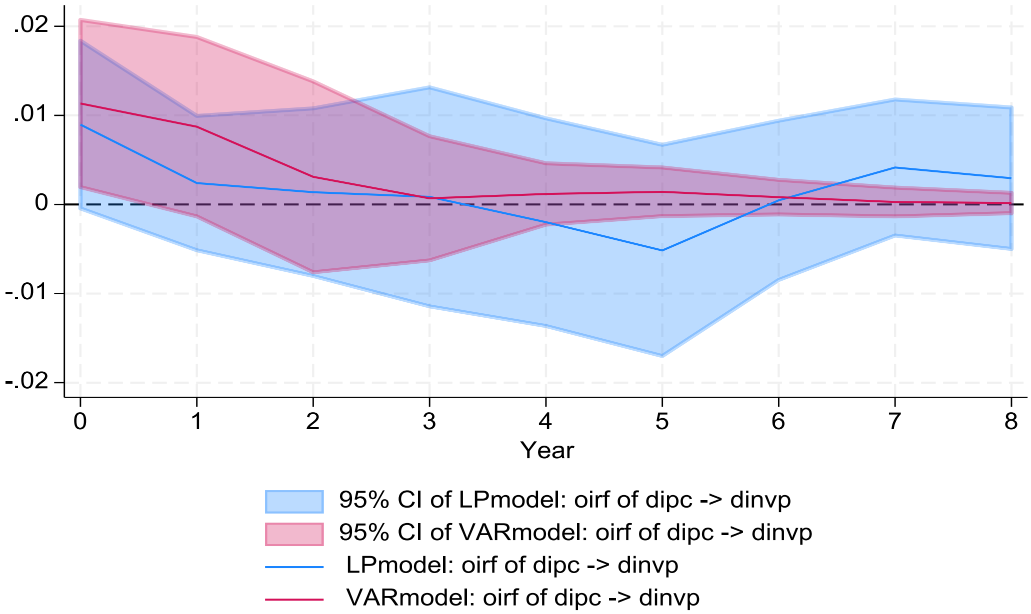


Figure 7.3 shows that the orthogonalized impulse response functions of the P&C *Net investment income* to inflation shocks produced by both procedures pursue different patterns for the different forecasting horizons. For short term horizon, this finding contradicts the theory and results by simulation-based studies of LPs and VARs, namely, both methods yield identical responses for short horizons. Figure 7.3 indicates that the impacts of shocks in inflation on investment revenues, estimated by the local projection method, are noticeably lower and more volatile for the different horizons than these generated by the VAR estimation.

Figure 7.4: Impulse response function of the Life *Net Investment income* to inflation shocks

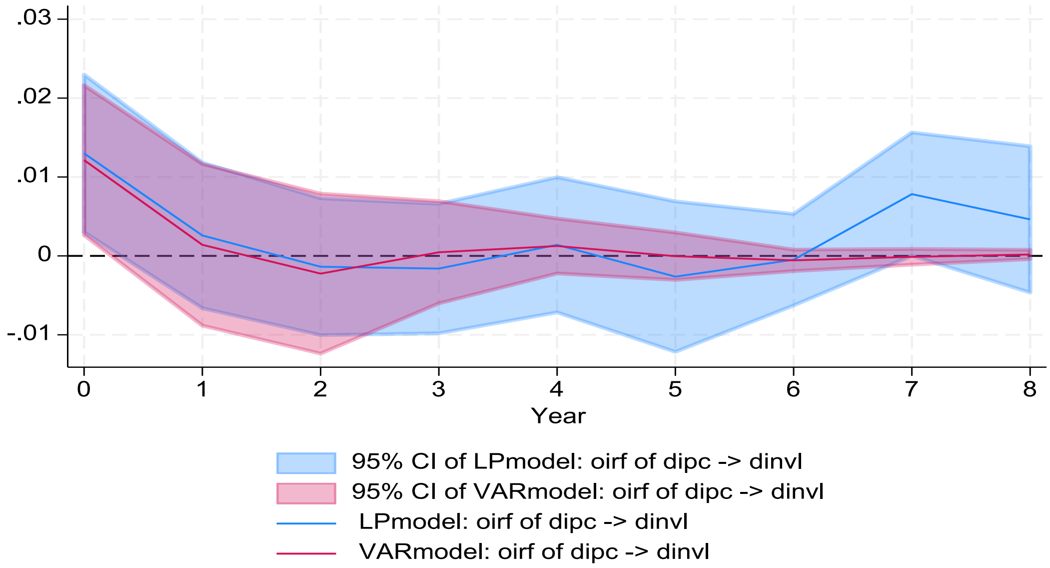


Figure 7.4 depicts the orthogonalized impulse response functions of the Life *Net investment income* to inflation shocks produced and shows, as predicted, that both methodologies produce similar response functions for near forecasting horizon, up to 2 years ahead. Afterward, the estimation by the local projection deviates from the one by the VAR method and is more volatile.

Overall, we can say that both methodologies give similar impulse responses function for near forecasting horizons as predicated by the theory and as conjectured by simulation-based literature comparing LP and VAR estimations. However, for more distant forecasting, discrepancies between the two approaches become more apparent. Particularly, the VAR estimation depicts smoother response pattern than the ones estimated by local projection (LP) as argued by Plagborg-Møller et al. (2024).

8 Nonlinear stochastic processes of inflation during the 1973-2023 period

In this section, we present nonlinear stochastic processes in variance, followed by nonlinear stochastic processes in the mean.

8.1 Nonlinear stochastic process in variance: ARCH, GARCH and EGARCH models

8.1.1 ARCH model

The ARCH model was introduced by Engle (1982). The null hypothesis tested is that of homoscedasticity $\alpha_0 = \cdots = \alpha_q = 0$ versus the alternative hypothesis of conditional heteroscedasticity where at least one coefficient $\alpha_i (i = 1, \dots, q)$ is non-zero. If the null hypothesis is not rejected, the conditional variance is constant. Conversely, if the null hypothesis is rejected, the residuals follow an ARCH (q) process.

Let us assume that the mean equation is described by an ARMA process. Consider the series Y_t generated by the following system of equations:

$$\Phi(L)Y_t = \theta(L)\tilde{e}_t \tag{8.1}$$

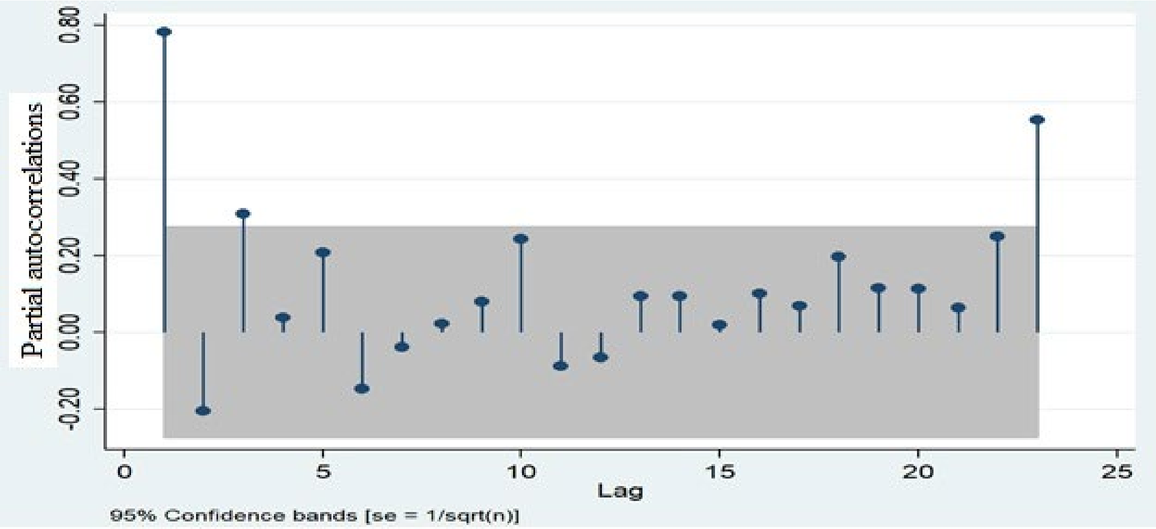
$$\alpha_t^2 = \alpha_0 + \Sigma_{i=1}^{q} \alpha_i \tilde{e}_t^2 \tag{8.2}$$

Y_t represents the *Inflation rate* series and $\tilde{e}_t$ represents the residuals from estimating the mean equation. The parameter $\Phi(L)$ represents the lag polynomial of the *Inflation rate* series (Y_t). Parameter $\theta(L)$ represents the lag polynomial of the residuals from the estimation of the mean equation $(\tilde{e}_t)$.

The ARCH test is implemented in three stages from the model presented in (8.1) and (8.2). The first step is to estimate the mean equation. We then recover the estimated residuals $\tilde{e}_t$ and calculate the series $\tilde{e}_t^2$. Second, we regress $\tilde{e}_t^2$ on a constant and its q past values (only significant lags are retained). Third, we calculate the TR^2 statistic, where T is the number of observations and R^2 is the coefficient of determination associated with the regression in step 2. Under the null hypothesis of homoscedasticity, the TR^2 statistic follows a chi-square distribution with q degrees of freedom. The decision rule is as follows: If $TR^2 \leq \chi^2(q)$, the null hypothesis is not rejected. In other words, there is no ARCH effect. Conversely, if $TR^2 > \chi^2(q)$, the null hypothesis is rejected in favor of the alternative hypothesis of conditional heteroscedasticity.

To select the ARMA (c,q) model for our estimation, we apply the method of Box and Jenkins (1970) and Box, Jenkins et al. (2015). The Box and Jenkins method consists, first, in selecting the number of lags *c* and *q* using visual inspection of sampled autocorrelations and partial autocorrelations. As mentioned earlier, ARMA (c,q) processes are a natural extension of AR (1) and MA (q) processes. For an AR (l) process, the partial autocorrelations cancel out from rank *c*+1. This property is used to identify the order *c* of AR processes. For an MA (q) process, the autocorrelations cancel out from rank q+1. This second property is used to identify the order *q* of MA processes.

Figure 8.1: Partial *Inflation rate* autocorrelations, 1973-2023 period

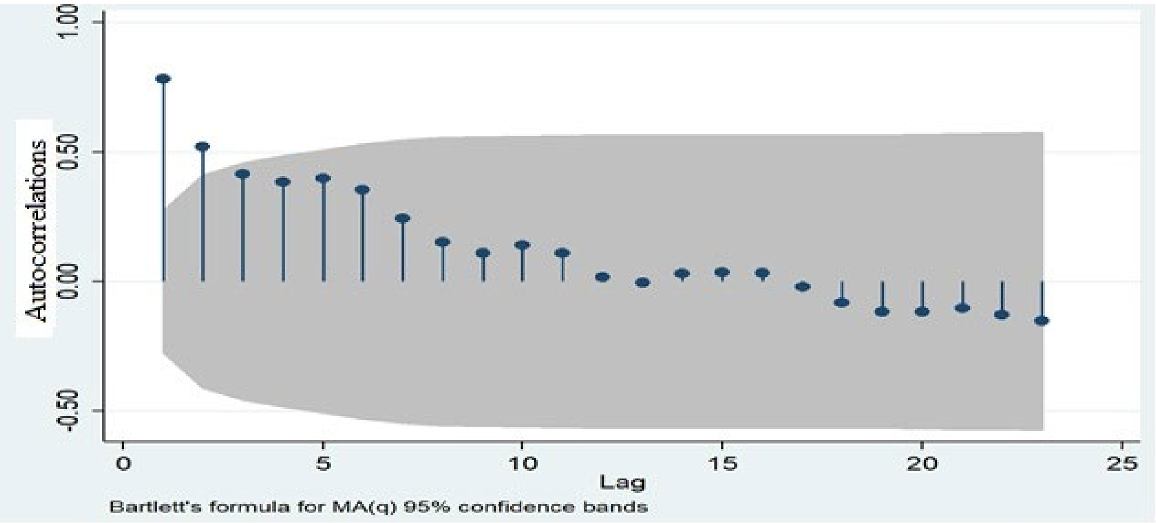


Source: World Bank and our calculations.

The fact that the first partial autocorrelation in Figure 8.1 is highly statistically significant while the others are not could indicate an AR (1) process, i.e., $c = 1$. Moreover, Figure 8.2 implies that we could choose MA (2) because the autocorrelations are not statistically significant starting from order 3.

To summarize, visual inspection of the sampled autocorrelations and partial autocorrelations enabled us to select the AR (1) and MA (2) models. The AR (2), MA (1), ARMA (1,1), ARMA (1,2), ARMA (2,1) and ARMA (2,2) models, derived from the combination of c and q with a maximum number of lags equal to 2, may also be logical candidates.

Figure 8.2: *Inflation rate* autocorrelations, 1973-2023 period



Source: World Bank and our calculations.

Table 8.1: Information criteria for estimated models, 1973-2023 period

	AIC	BIC
AR (1)	211.3436	217.1391
AR (2)	211.0094	218.7367
MA (1)	218.4029	224.1984
MA (2)	210.4831	218.2104
ARMA (1,1)	207.1818*	214.9091*
ARMA (1,2)	207.6114	217.2706
ARMA (2,1)	215.2440	224.9031
ARMA (2,2)	209.0835	220.6745

Note: The asterisk indicates the model to be retained according to the selected criterion.

A comparison of the selection criteria between the different models estimated is shown in Table 8.1. This leads us to select the ARMA (1,1) process for the *Inflation rate*. The estimation of this process is shown in Table 8.2.

Table 8.2: Estimation of the mean equation: ARMA (1, 1) process, 1973-2023 period

Variable	*Inflation rate*
L.ar	0.556*** (0.151)
L.ma	0.596*** (0.183)
Constant	3.913*** (0.927)
Sigma	1.683*** (0.132)
Adjusted R-squared	0.133
Observations	51

Note: L.ar and L.ma represent respectively the AR (1) and MA (1) components of the ARMA (1,1) model. Robust standard errors in parentheses. *** p<0.01.

The second stage of our ARCH test consists in recovering the residuals $\tilde{e}_t$ from the estimation of the ARMA (1,1) mean equation and regressing $\tilde{e}_t^2$ on a constant and its q past values. To estimate the second-stage regression, we first need to determine the number of q lags to be considered. To do this, we selected the number of q lags from the graph of partial autocorrelations shown in Figure 8.3.

Figure 8.3: Partial autocorrelations of squared residuals ($\tilde{e}_t^2$), 1973-2023 period

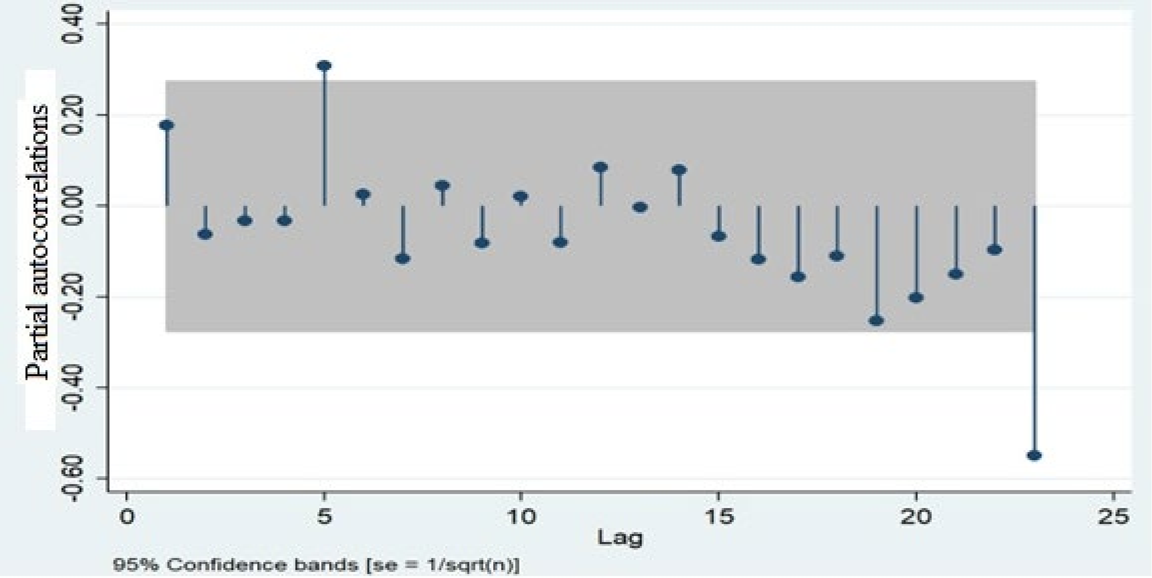


Figure 8.3 shows that only the fifth partial autocorrelation is significantly different from zero. We therefore use a number of q lags equal to 5 to perform the ARCH test. The results are shown in Table 8.3.

Table 8.3: ARCH test results, 1973-2023 period

Variable	RES_t^2
L.1.RES_t^2	0.293*** (0.048)
L.2.RES_t^2	-0.039 (0.101)
L.3.RES_t^2	-0.050 (0.054)
L.4.RES_t^2	-0.085 (0.059)
L.5.RES_t^2	0.308 (0.215)
Constant	1.360 (0.989)
Observations	46
R-squared	0.230
Adjusted R-squared	0.133

Note: RES_t^2 represents the squared residuals from estimating the mean equation. Robust standard errors in parentheses. *** $p<0.01$.

The results in Table 8.3 allow us to calculate a TR^2 statistic of 10.58 and a $\chi^2(5)$, which gives us a value of 9.236 at the 10% threshold. Given that $TR^2 \geq \chi^2(5)$, we reject the null hypothesis in favor of the alternative hypothesis of conditional heteroscedasticity. We find that the autoregressive coefficient associated with one-period lagged squared residuals is significantly different from zero. In other words, there is an ARCH effect in our inflation series.

ARCH (q) applications are often used in finance to account for ARCH effect. However, certain criticisms have been leveled at ARCH models. According to Nelson (1991), ARCH models may prove inadequate for two main reasons. The first is that the choice of a quadratic form for the conditional variance has important consequences for the time path of the series. Choosing a symmetrical quadratic form for the conditional variance does not allow us to model the phenomenon of asymmetry. The second reason is that ARCH models remain strongly constrained to a positive conditional variance. This implies that a shock, whatever its sign, always has a positive effect on current volatility: the impact increases with the size of the shock.

These criticisms led to the development of the EGARCH (Exponential GARCH) model. The EGARCH model (Nelson, 1991) takes into account the possibility that variance responds asymmetrically to positive and negative shocks.

8.1.2 EGARCH (c,q) model

An EGARCH process is given by:

$$y_t = \mu_t + \sigma_t \varepsilon_t \quad \varepsilon_t \sim N(0,1) \tag{8.3}$$

Where u_t and σ_t^2, respectively, denote the conditional mean and variance of y_t (the inflation series) for a set of information consisting of the variables observed up to time[6] $t-1(\Omega_{t-1})$. ε_t represents the innovation (shock) of an ARMA-type process fitted to the series under study y_t. Nelson (1991) proposed the following model:

$$\ln\sigma_t^2 = \alpha_0 + \Sigma_{j=1}^{c}\beta_j \ln\sigma_{t-j}^2 + \Sigma_{i=1}^{q}\alpha_i g(z_{t-i}), \quad z_{t-i} = \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \sim iid(0,1) \tag{8.4}$$

where z_{t-i} represents normalized innovations and $g(\cdot)$ is a function of normalized innovations (z_{t-i}). β_j is the coefficient associated with the EGARCHI part and α_i is the coefficient associated with the ARCH (q) part of the EGARCH (c,q) model.

Unlike GARCH models, whose specialization concerns the quadratic nature of the conditional variance, the specification of the EGARCH model concerns the logarithm of the conditional variance and thus avoids positivity constraints on the coefficients α_i and β_j of equation (8.4).

8.1.3 Estimation with the maximum likelihood method

We apply the maximum likelihood method. Table 8.4 shows the estimation of the ARMA (1,1)-EGARCH (1,1) model. The table suggests that the negative and statistically significant coefficient of the variable $\beta_j < 0$ implies that a shock with a negative effect on inflation will have a greater impact on volatility than would a shock with an equivalent positive effect. In other words, inflation reacts more strongly to a negative shock than to a positive one, reflecting the asymmetry effect. Table 8.4 shows that all the coefficients of the variables in the variance equation are significantly different from zero. Furthermore, the coefficients of the variance equation β_j and α_i are

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[6] $\Omega_{t-1} = [y_1, y_2 \ldots\ldots\ldots, y_{t-1}]$.

statistically different from zero, indicating the presence of asymmetry. The significance of these two coefficients indicates that the EGARCH (1,1) model indeed takes into account the asymmetry observed in the inflation series.

Table 8.4: ARMA (1,1)-EGARCH (1,1) model estimates
1973-2023 period

Dependent variable	*Inflation rate*
L1.ar	0.462** (0.204)
L1.ma	0.434* (0.259)
Constant	2.820*** (0.394)
Variance equation (σ_t^2)	
L1.egarch $\left(\beta_j\right)$	-0.696*** (0.131)
L1.arch (α_i)	0.180*** (0.057)
Constant	0.940*** (0.364)
Observations	51

Note: L1.ar and L1.ma represent respectively the AR (1) and MA (1) components of the ARMA (1,1) model. L1.egarch and L1.arch respectively represent the EGARCH (1) and ARCH (1) components of the EGARCH (1,1) model. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

8.2 Stochastic nonlinear processes in the mean: Markov regime-switching model

For the application of nonlinear processes in the mean, we have chosen the Markov regime-switching model because the Markov model seems to fit our inflation data if we refer to the graphical analysis in Figure 2.2. This figure clearly shows that the US *Inflation rate* series observed over the 1973-2023 period is characterized by a regime-switching process, possibly split into two different subsamples or even three.

8.2.1 Regime detection

To detect the presence of regimes, we used the Markov model approach (Hamilton, 1994). This procedure identifies regimes in the levels (constant) and volatility (lnsigma) of the inflation series. These two moments are estimated simultaneously. In the remainder of our analysis, we will focus on level regimes (controlling for volatility) because the Markov regime-switching model we propose to use for inflation analysis seems more appropriate. The process under study is a nonlinear stochastic process in the mean of the insurance variables of interest.

Graphically, it can be argued that the two-regime Markov model is best suited to our inflation series. Indeed, Figure 2.2 shows that the US inflation series underwent a structural change due to a monetary policy led by Paul Volcker at the Fed in 1979. It has also undergone two major changes linked to Oil shocks of the 1970s and the *COVID-19* shock of 2020-2023. These nonlinearities suggest that *Inflation rate* dynamics in the United States differ from one subsample (regime) to the next. Figure 2.2 indicates that the period from 1983 to 2020 was marked by a lower level of *Inflation rate*, while the rest of the sample (periods of 1973 to 1982 and 2021 to 2023) displays a higher level of the *Inflation rate*. This suggests that a two-state model seems reasonable. A three-regime model may also be a potential candidate, as there may be a very low or even negative level of the *Inflation rate*, as in 2009. To properly test our two-regime hypothesis, we ask the following question: Would the three-regime Markov model be better than the two-regime Markov model suggested by our graphical analysis?

8.2.2 Two-regime model vs. three-regime model

We propose here a Markov model of regimes with a constant. The existence of two states of the world $s_t \in (1,2)$ is assumed to be the two-regime model and $s_t \in (1,2,3)$ is assumed for the three-regime model. It is also supposed that, in each regime, the dynamics are potentially different.

- Two-regime model

We assume the existence of two states of the world $s_t \in (1,2)$ for the two-regime model; μ_1 is the mean in the low-inflation state and μ_2 is the mean in a high-inflation state.

$$y_{s_t} = \mu_{s_t} + \sigma_{s_t} z_t, \quad z_t \sim N(0,1) \tag{8.5}$$

where y_{s_t} is the *Inflation rate*, the index s_t designates the regime and μ_{s_t} is the average for each regime.

The hypothesis tested is that the dynamics of the inflation data in our two subsamples (regimes) are potentially different. The null hypothesis H_0 $(\mu_1 = \mu_2)$ means no change in regime levels. In other words, our approach is to test the null hypothesis (H_0) that the average *Inflation rate* estimated in State 1 and the average *Inflation rate* estimated in State 2 are statistically the same, where State 2 is the high-inflation regime. The data used is observed annual data over the 1973-2023 period (51 periods).

The results in Table 8.5 show that the low-inflation regime (State 1) has an estimated average *Inflation rate* of 2.87%, while the high-inflation regime (State 2) has an average *Inflation rate* of 8.82%. The results clearly show that the estimated average *Inflation rate* in State 1 and the estimated average *Inflation rate* in State 2 are not statistically the same.

Table 8.5: Two-regime model with constant inflation, 1973-2023 period

Variable	*Inflation rate*
Constant (State 1)	2.870*** (0.278)
Constant (State 2)	8.820*** (0.102)
lnsigma	1.726 (0.176)
p11	0.980** (0.022)
p21	0.044** (0.065)
Observations	51

Note: Insigma is a volatility parameter. *** p<0.01, ** p<0.05.

The parameter p11 is the estimated probability of remaining in State 1. The value 0.98 implies that State 1 is highly persistent. This means that a year of low inflation is followed 98% of the time by a year of low inflation. Parameter p21, which is the probability of moving from State 1 to State 2 (transition), is 0.04. The probability of remaining in State 2 (p22) is therefore 1 – 0.04 = 0.96, which implies that State 2 is also persistent. This result indicates that a year of high inflation is followed 96% of the time by a year of high inflation. Table 8.5 also shows that the estimated inflation volatility (Insigma) is not statistically significant. The results obtained indicate that the data segmentation determined by the Markov regime-switching model is largely influenced by the behavior of the *Inflation rate* series. In other words, the two-regime Markov model takes into account the presence of the stochastic (or random) trend and nonlinearity detected in the *Inflation rate* series, since we have already documented the presence of the stochastic trend and nonlinearity that give rise to the asymmetry phenomenon observed in the inflation series.

- Three-regime model

We assume the existence of three states $s_t \in (1,2,3)$ for the three-regime model; μ_1 is the mean in the low-inflation state, μ_2 is the mean in the moderate inflation state and μ_3 is the mean in the high-inflation state.

The hypothesis tested is that the dynamics of the inflation data in our three subsamples (regimes) are potentially different. The three potential subsamples analyzed in the three-regime model can be identified by reading Figure 2.2. Indeed, Figure 2.2 indicates that the periods from 1973 to 1982 and from 2021 to 2023 display a high-*Inflation rate* (State 3), the 1983 to 1991 period displays a moderate *Inflation rate* (State 2) while the rest of the sample, i.e. the 1992 to 2020 period, is marked by a low-*Inflation rate* (State 1). Table 8.6 shows the estimation results for the three-regime model.

Table 8.6: Three-regime model with constant inflation,
1973-2023 period

Variable	*Inflation rate*
Constant (State 1)	2.593*** (0.281)
Constant (State 2)	6.038*** (0.786)
Constant (State 3)	11.070*** (0.786)
lnsigma	11.069** (0.551)
p11	0.930** (0.051)
p12	0.007** (0.051)
p21	0.213** (0.170)
p22	0.550** (0.232)

Variable	*Inflation rate*
p31	8.32e-31 (.)
p32	0.422 (.)
Observations	51

Note: Insigma is a volatility parameter. *** $p<0.01$, ** $p<0.05$.

The transition probabilities in the three-regime model indicate a parameter p11, i.e. the estimated probability of remaining in State 1, of 0.93 (State 1 is highly persistent); and a parameter p22, i.e. the estimated probability of remaining in State 2, of 0.55 (State 2 is moderately persistent). The probability of remaining in State 3 (p33) is therefore $1 - 8.3e - 31 - 0.422 = 0.58$, implying that State 3 is also moderately persistent. These results indicate that a year of low inflation is followed 93% of the time by a year of low inflation, a year of moderate inflation is followed 55% of the time by a year of moderate inflation, and a year of high inflation is followed 58% of the time by a year of high inflation. The results in Table 8.6 indicate that the three-regime model also appears to be a potential candidate for modeling the nonlinearity of the US *Inflation rate*. However, the strong persistence of the two states (State 1 and State 2) of the two-regime model seems to better capture the nonlinearity of the US *Inflation rate* than does the three-regime model. We use the AIC, SBIC (Singular BIC) and LL information criteria to separate the two-regime model from the three-regime model.

Table 8.7: Comparison criteria for estimated models,
1973-2023 period

	AIC	SBIC	LL
2 States	4.1436	4.3709*	-99.6630*
3 States	4.0940*	4.4728	-94.3981

Note: The asterisk indicates the model to be retained according to the selected criterion.

Table 8.7 shows the different statistics of interest for regime selection. The AIC selects the three-regime Markov model and the SBIC selects the two-regime Markov model. The log-likelihood ratio statistic confirms the result of the SBIC test. Calculating the LR statistic gives us 10.52. This value is higher than the critical value derived from the distribution $\chi^2(1)$ since we have only one constraint (k=1). The critical value at 5% is 5.99. In this case, H_0 is not rejected. Thus, according to the LR test, we choose the two-regime Markov model over the 3-regime Markov model.

Figure 8.4: Evolution of probabilities of being in the high-inflation regime detected from January 1972 to December 2023

Figure 8.4 shows three periods of high-inflation states and two periods of low-inflation states. The high-inflation regime is detected during 1970s oil shocks (1973 to 1982) and during the *COVID-19* period. Note that 1970s oil shocks period was a longer period of high and sustained inflation rates, compared with the *COVID-19* period. In contrast, the low-inflation regime was detected over the rest of the sample.

8.3 Comparison of nonlinear stochastic processes in variance (EGARCH) and nonlinear stochastic processes in the mean (Markov)

The results show that the two forms of nonlinear stochastic process, namely the nonlinear stochastic process in variance (EGARCH (1,1) model) and the nonlinear stochastic process in the mean (two-regime Markov model), are well suited to capture the asymmetry observed in the US inflation series. To select the process best suited to our data, we use the selection criteria shown in Table 8.8 to distinguish between the two forms of nonlinear stochastic process.

Table 8.8: Comparison criteria for estimated models, 1973-2023 period

	EGARCH	Markov
LL	-93.8176	-87.4665*
AIC	199.6351	188.9331*
BIC	211.2261	202.3172*

Note: LL is the log-likelihood value at the optimum, AIC and BIC are the information criteria of Akaike (1969) and Schwarz (1978) respectively. The asterisk indicates the model to be retained according to the selected criterion.

A comparison of the selection criteria shows, first, that the results obtained differ very little, suggesting that the EGARCH model of the GARCH class (nonlinear stochastic process in variance) and the Markov (nonlinear stochastic process in the mean) are relevant for modeling the inflation series. However, the comparison shows a slight advantage for the Markov regime-switching model over the EGARCH model. All three information criteria (LL, AIC and BIC) lead us to select the Markov regime-switching model.

Despite their many empirical successes, EGARCH models share two major weaknesses. First, they fail to produce unconditional distributions of inflation with tails as thick as those observed in reality, even when replacing $z_t \sim N(0,1)$ by a distribution with thicker tails than $N(0,1)$, such as the *t*-distribution. Second, in EGARCH models, the conditional variance of the inflation (σ_t^2) is nonrandom, as shown in equation (8.3). This is a problem because financial theoretical models assume that volatility is a random process. The class of models known as random volatility models, such as the case of the Markov SV model where the conditional variance of the inflation (σ_{st}^2) is random because it depends on the state of the regime $s_t \in (1,2)$, solves both of these problems.

9 Effect of inflation on US insurance markets: A Markov-switching model analysis

Abstract

We analyze the characteristics of the US *Inflation rate* series observed over the 1973 to 2023 period in order to estimate the effect of inflation on the insurance industry. Two important conclusions emerge from the data: The US *Inflation rate* series is characterized by a random trend and nonlinear dynamics. These results led us to select the two-regime Markov-switching model to study the impact of inflation on various fundamental indicators of insurance industry performance. We show that performance indicators are differently affected by inflation in the Life and P&C insurance sectors according to the inflation regime considered.

9.1 Introduction

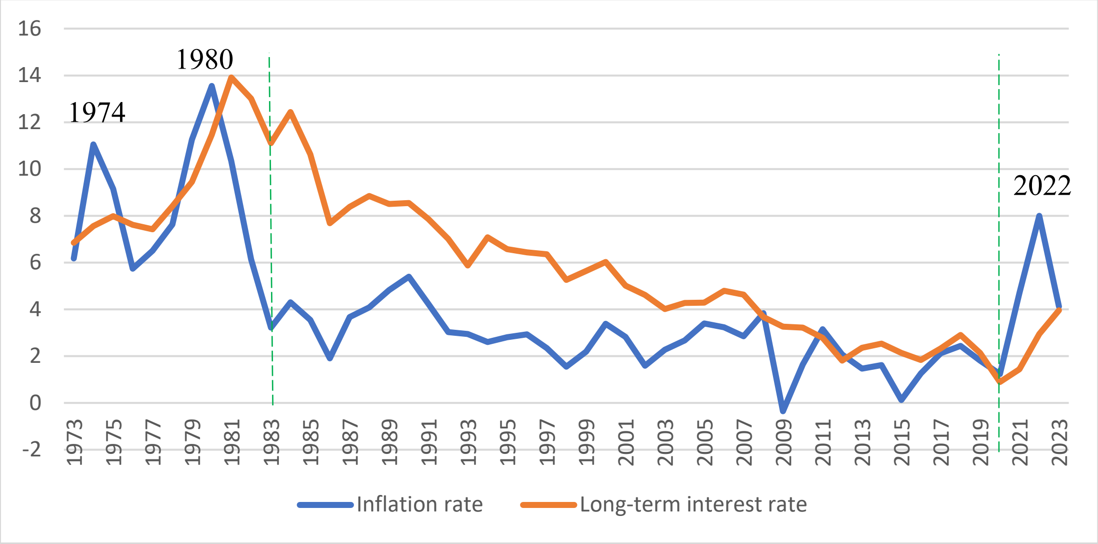
We analyze the characteristics of the US *Inflation rate* series observed over the 1973 to 2023 period in order to estimate the effect of inflation on the insurance industry. Two important conclusions emerge from this analysis: The US *Inflation rate* series is characterized by a random trend and nonlinear dynamics. To take these two characteristics into account, we have drawn on two approaches most commonly used in econometrics to address the issue of the presence of a random trend and the presence of nonlinear dynamics in macro-econometric and financial series. The first approach is based on the use of processes with stochastic nonlinearity in variance (GARCH models) and the second is based on the use of processes with stochastic nonlinearity in the mean such as the regime-switching model. For the application of processes with stochastic nonlinearity in variance, we did not reject the MS-GARCH model. For the application of processes with nonlinearity in the mean, we did not reject the Markovian regime model. We then carried out statistical tests to choose which of the two models was best suited to the US *Inflation rate* data. The results obtained led us to select the two-regime Markov-switching model.

We used this model to analyze the impact of inflation on the various fundamental determinants of insurance industry performance. What is important under a regime switching environment is the relationship within each regime, not across all regimes to take into account short-run effects that matter for inflation management. We show that performance indicators are differently affected by inflation in the Life and P&C insurance sectors and according to the inflation regime considered.

The rest of the section is organized as follows. Subsection 9.2 presents the main characteristics of the US inflation during the 1973–2023 period and discusses the motivation of our study. Subsection 9.3 analyses the nonlinear stochastics processes of inflation and Subsection 9.4 measures the effects of inflation on the insurance industry using the Markov model. Subsection 9.5 concludes the section.

9.2 US *Inflation rate* trend and research motivation

Figure 9.1: Trends in *Inflation rate*
and the nominal rate of LT (10-year) government bonds, 1973 to 2023 period



Note: The *Inflation rate* is the percentage change of the Consumer Price Index (*CPI*).
Source: World Bank.

Figure 9.1 shows that the United States has experienced three inflationary thresholds since 1973. The first threshold was observed in 1974. It is linked to a first shock to the oil price, starting in 1973. The second threshold, the most important of this period, was observed in 1980. It is linked to a second shock to the oil price, starting in 1979. The third threshold, seen in 2022, is associated with the *COVID-19* pandemic of 2020-2023.

In addition, Figure 9.1 shows that the US *Inflation rate* series from 1973 to 2023 is characterized by nonlinear dynamics. We can see that the US *Inflation rate* series is separated into two distinctive subsamples. The period from 1983 to 2020 is marked by a lower average level of the *Inflation rate*, while the rest of the sample shows a higher average level of the *Inflation rate*. The fact that the inflation series differs from one subsample to another illustrates the potential presence of a regime-switching process in the US *Inflation rate* series. Finally, Figure 9.1 shows how LT interest rate is correlated with *Inflation rate*.

Two major changes are believed to have caused the separation of the US *Inflation rate* series into these subsamples. The first is linked to Paul Volcker's arrival at the Fed in 1979 and the resulting monetary policy reform. The US *Inflation rate* fell from 13.9% in 1980 to 3.2% in 1983. The year 1983 marked the break with the higher inflation subperiod and the transition to a lower inflation subperiod observed over the 1983-2019 period. Ahlgrim and D'Arcy (2012) mentioned that 1983 marks the start of the period of moderate levels of inflation for the insurance industry.

The second change is linked to the *COVID-19* pandemic shock. Appearing in early 2020, this shock marks the break with the lower inflation regime and the shift to a new higher inflation regime from 2021 to 2023.

9.3 Properties of the US *Inflation rate* series

In this subsection, we look at some empirical regularities in the US *Inflation rate* series as measured by the annual percentage change of the unbiased BLS Consumer Price Index (*CPI*). We also present nonlinear stochastic processes in the mean, followed by nonlinear stochastic processes in the variance. See Appendix B9 for more details on the properties of inflation during the period of analysis.

9.3.1 Stochastic nonlinear processes in the data

One can examine the relationship between inflation and different variables such as underwriting profit margins, investment income, combined ratio, and *ROA*, over an entire time period. What is important under a regime switching environment is the relationship within each regime, not across all regimes. Thus, we must verify if the historical data is broken into different regimes, if any.

Table 9.1: Descriptive statistics for inflation, 1973 to 2023 period

Mean	Median	Std. Dev.	Skewness	Kurtosis
4.0107	3.1568	2.9388	1.4437	4.7359

Table 9.1 presents the main statistics of the *Inflation rate* over the 1973 to 2023 period. We note from Table 9.1 that the skewness parameter is positive. This illustrates the presence of asymmetry. The positive skewness coefficient indicates that inflation reacts more to a positive shock than to a negative shock. Moreover, the kurtosis coefficient is greater than 3. This excess kurtosis value indicates a high probability of extreme points occurring. In other words, the distribution of the US *Inflation rate* series has thicker tails than for a normal distribution. We performed a normality test and rejected the null hypothesis that the *Inflation rate* series follows a normal distribution at the 5% threshold. In Appendix D9, we present a detailed analysis of nonlinear stochastic processes in the data. The results suggest the presence of different regimes. We then estimated a Markov-Switching (MS) model and a Markov-Switching GARCH (MS-GARCH) model.

9.3.2 Markov-switching (MS) model

For the application of nonlinear processes in the mean, we have chosen the Markov-switching model because this model seems to fit our inflation data if we refer to the graphical analysis in Figure 9.1. This figure shows that the US *Inflation rate* series observed over the 1973 to 2023 period may be characterized by a regime-switching process, possibly split into two different subsamples or even three.

We propose a Markov-Switching model with a constant. We assume the existence of two states of the world $s_t \in (1,2)$ for the two-regime model or three states of the world $s_t \in (1,2,3)$ for the three-regime model. We also assume that the dynamics of inflation are potentially different in each regime, as in equation (9.1):

$$y_t = \mu_{s_t} + z_t \qquad z_t \sim N(0,\sigma^2) \tag{9.1}$$

where y_t is the *Inflation rate*, s_t is the index of the regime, *t* is for time, μ_{s_t} is the mean in each regime, σ^2 is the variance of z_t, and z_t is a random variable.

The null hypothesis H_0 ($\mu_1 = \mu_2$) means that there is no change in the mean of each regime. We first test the null hypothesis that the average *Inflation rate* estimated in the two states are statistically the same.

Table 9.2: Two-regime Markov model with inflation constant in each regime, 1973 to 2023 period

Variable	Coefficient	SE
Constant (State 1)	2.870***	(0.278)
Constant (State 2)	8.820***	(0.102)
lnsigma	1.726**	(0.176)
Transition Probabilities		
p11	0.98**	(0.02)
p22	0.96**	(0.07)
Observations	51	
Log likelihood	-105.143	
AIC	220.286	
BIC	229.945	
Wald χ^2 (1)	87.91	
Prob > χ^2	0.000	

Note: Insigma is the volatility parameter. *** p<0.01, ** p<0.05.

The results in Table 9.2 indicate that the low-inflation regime (State 1) has an estimated average *Inflation rate* of 2.87%, while the high-inflation regime (State 2) has an estimated average *Inflation rate* of 8.82%. The parameter p11 is the estimated probability of remaining in State 1. The value of 0.98 implies that State 1 is highly persistent. The probability of remaining in State 2 (p22) is also highly persistent at 96%. The Wald test p-value is 0.00. This indicates that the null hypothesis that there is no switch in mean regime ($\mu_1 = \mu_2$) is rejected at the 5% significance level.

We then test the hypothesis that the dynamics of the *Inflation rate* data is in three subsamples. The null hypothesis H_0 becomes $\mu_1 = \mu_2 = \mu_3$, meaning that there is no regime switch in the mean. The estimation results are presented in Table 9.3.

Table 9.3: Three-regime model with inflation constant in each regime, period 1973 to 2023

Variable	Coefficient	SE
Constant (State 1)	2.593***	(0.281)
Constant (State 2)	6.038***	(0.786)
Constant (State 3)	11.07***	(0.786)
lnsigma	11.069**	(0.551)
Transition probabilities		
p11	0.93**	(0.051)
p22	0.55**	(0.232)
p33	0.58**	(.)
Observations	51	
Log likelihood	-97.377	
AIC	212.753	
BIC	230.140	
Wald χ^2 (2)	233.97	
Prob > χ^2	0.00	

Note: Insigma is the volatility parameter. *** p<0.01, ** p<0.05.

The transition probabilities in the three-regime model indicate that the estimated probabilities of remaining in State 2 and in State 3 are moderately persistent. The Wald test confirms the null hypothesis that there is no change in mean regime ($\mu_1 = \mu_2 = \mu_3$) is rejected at the 5% threshold. In other words, the average inflation rates are significantly different in the three regimes. The three-regime model also appears to be a potential candidate for modeling the nonlinearity of the US *Inflation rate*.

The LR test based on log likelihood (LL) values in a regime-switching context can lead to false detection according to Hamilton (1994) because the LR test assumption is not satisfied to obtain an asymptotic distribution of χ^2. For these reasons, we retained the BIC criterion. This criterion is convergent and leads to an asymptotically correct model selection, which is not the case with the AIC criterion. Furthermore, the BIC criterion penalizes the estimation more severely than the AIC criterion does in terms of introducing too many variables into the model (Box et al., 2015).

Table 9.4: Criteria for comparing estimated regime models, period from 1973 to 2023

Markov model	LL	AIC	BIC	Log (ML)	Prob > χ^2 (Wald)
2 states	-105.1429	220.2857	229.9449*	-141.99461*	0.0000
3 states	-97.37672	212.7534	230.1399	-142.02618	0.0000

Note: Marginal likelihood (ML) is computed using Laplace-Metropolis approximation.

The BIC value is roughly equivalent for both models. Table 9.4 shows a value of 229.95 for the two-regime Markov model and a value of 230.14 for the three-regime model. We favor the two-regime model over the three-regime model because it has the lowest BIC. The marginal likelihood test confirms this result, with a higher log-Bayes factor (Log (ML)) value for the two-regime model.

Figure 9.2 shows the regimes detected by the two-regime Markov model. It indicates three periods of high inflation and two periods of low inflation. The high-inflation regime is detected during the period of the shocks to the oil price of the 1970s (1973 to 1982) and during the *COVID-19* period. The low-inflation regime was detected in the rest of the sample.

Figure 9.2: Evolution of the probabilities of being in the high-inflation regime detected from January 1973 to December 2023 using the two-regime Markovian model

9.3.3 Markov-switching GARCH (MS-GARCH) model

Following the suggestion of a reader, we estimate a Markov-switching GARCH (MS-GARCH) model that accounts for the dependence of conditional variance on shocks. The MS-GARCH model can be defined by the following equations (Bauwens et al, 2010):

$$y_t = \mu_{s_t} + \sigma_t \varepsilon_t \qquad \varepsilon_t \sim N(0, 1) \tag{9.2}$$

$$\sigma_t^2 = \omega_{s_t} + \alpha_{s_t} \eta_{t-1}^2 + \beta_{s_t} \sigma_{t-1}^2 \tag{9.3}$$

where $\eta_{t-1} = y_{t-1} - \mu_{s_{t-1}}$, y_t is the *Inflation rate*, the index s_t is the regime, and μ_{s_t} and σ_t^2 denote respectively the conditional mean and conditional variance of y_t to an information set consisting of the variables observed up to time *t*–l (Ω_{t-1}). By assumption $\omega_{s_t} > 0$ and $\alpha_{s_t}^2$ and β_{s_t} are almost strictly positive. Equation (9.2) represents the equation of the mean estimated by a two-regime Markov process. The process η_{t-1} is not observable; it corresponds to the Markovian innovation (shock) with two regimes adjusted to the series studied. Equation (9.3) represents the equation of the conditional variance of the process η_t. The specification of the conditional variance is of the EGARCH (Exponential GARCH type, Nelson, 1991).

We chose the EGARCH model to model the conditional variance of the η_t process in order to take into account the possibility that the variance responds asymmetrically to positive and negative shocks. Thus, the β_{s_t} parameter of the variance equation indicates the coefficient associated with the EGARCH part specific to each regime, and the α_{s_t} parameter indicates the coefficient associated with the ARCH model specific to each regime. A necessary and sufficient condition for the stationarity of the EGARCH (1,1) process is that $\alpha_{s_t} + \beta_{s_t} < 1$. The estimation of the model is presented in Table 9.5.

Table 9.5: MS-GARCH results (2 states)

Variable	Coefficient	SE
Low-inflation regime		
Constant (μ_1)	2.550***	(0.217)
Alpha (α_1)	0.0387	(0.041)
Beta (β_1)	0.0211**	(0.009)
Lnsigma (ω_1)	1.1705**	(0.135)
High-inflation regime		
Constant (μ_2)	8.529***	(1.084)
Alpha (α_2)	0.071	(0.082)

Beta (β_2)	-0.023	(0.029)
Lnsigma (ω_2)	2.385**	(0.681)
Transition probabilities		
p11	0.96**	(0.032)
p22	0.87**	(0.121)
Observations	51	
Log likelihood	-95.0566	
AIC	210.1132	
BIC	229.2334	
Wald χ^2 (2)	5.64	
Prob > χ^2	0.0597	

Note: Insigma is the volatility parameter. *** p<0.01, ** p<0.05.

When we examine the conditional mean of the MS-GARCH model, we find that the mean parameters μ_1 and μ_2 appear to differ from one regime to another and are highly significant (at the 1% threshold). This is not the case for all volatility parameters; that do not appear to be different from one regime to another. We find that apart from the parameters β_1, ω_1, and ω_2, which are statistically significant at 5%, all other volatility parameters are not statistically significant. We find however that the EGARCH (1,1) process is stationary because α_{s_t} +β_{s_t} < 1, indicating a good specification of the conditional variance of the US *Inflation rate* series.

9.3.4 Model selection

To summarize, the results indicate that the regime change observed in the *Inflation rate* series is a regime change in the mean (level) and not necessarily a regime change in variance. In other words, the variation in the conditional mean of y_t in each regime is not necessarily accompanied by a variation in the conditional variance.

Table 9.6: Comparison criteria for estimated models,
1973 to 2023 period

	LL	AIC	BIC	Wald Prob > χ^2
Markov 2 states	-105.1429	220.2857	229.9449	0.0000*
MS-GARCH 2 states	-95.0566	210.1132	229.2334	0.0597

Table 9.6 shows the various statistics of interest for model selection. The BIC value is roughly equivalent for both models. In this case, Box and Jenkins' principle of parsimony leads us prefer the two-regime Markovian model. Since both models are nested, the log-likelihood ratio statistic and the Wald test p-value obtained for both models can confirm this preference. The LR statistic calculation gives us 10.52. This value is lower than the critical value from the χ^2 (5) distribution of 11.07. There is no rejection of H_0 (constrained model not rejected). So according to the LR test, we choose the two-regime Markovian model over the two-regime MS-GARCH model. The comparison of the Wald test p-value chooses the two-regime Markovian model over the two-regime MS-GARCH model. For robustness, we also show that the Markovian model dominates the EGARCH model in Appendix D9.

9.4 Estimating the effect of inflation on insurance industry

In this section, we analyze the impact of inflation on different fundamental indicators of insurance company performance in the United States. The Markov regime-switching model is estimated (Kim et al., 2008; Zucchini and Macdonald, 2009). The maximum likelihood method is applied to estimate the parameters.

To do this, we measured the performance of insurance companies with eight performance measures. The first is the *Loss ratio*. It indicates the proportion of *Premiums* to *Claims*. We also considered the *Expense ratio* and the *Combined ratio*. The *Expense ratio* is the ratio to underwriting expenses to *Premiums*. The *Combined ratio* measures the underwriting management efficiency of the insurance business. The next determinant is the *Net investment income to Total assets* ratio, which isolates the performance of the investment business. The sum of the *Combined ratio* and the *Net investment income* is the *Operating ratio*, which indicates insurers' overall performance (for the insurance underwriting and investment business combined). The last indicator is Return on Assets (*ROA*), which describes insurers' financial accounting profitability. Finally, we considered variations in *Premiums* and *Claims*.

9.4.1 Regression model

The main independent variable is the *Inflation rate*. This independent variable of interest varies according to time and the state of the regime (s_t). We expanded the model with other macroeconomic variables (Z_t) that are likely to influence the profitability of insurance companies' activities. These variables represent our macroeconomic control variables. They also depend on the state of the regime (s_t); the GDP variable is one example. Finally, we supplement the econometric model with a series of sectoral control variables (X_t) that are likely to influence the profitability of insurance companies over the entire period. Unlike macroeconomic control variables, we assume that sectoral control variables do not vary according to the state of the regime. They represent long-term relationships inside the two sectors. Appendix C9 describes the main performance indicators.

Empirically, we postulate the following Markov-switching regression model where s_t represents the state of the regime and the index t represents the time. We assume that the dynamics are potentially different between regimes.

$$y_t = \mu_{s_t} + IR_t\delta_{s_t} + Z_t\beta_{s_t} + X_t\alpha + \varepsilon_t, \tag{9.4}$$

where:

y_t: dependent variable representing an insurer performance measure;

μ_{s_t}: state-dependent intercept;

IR_t: *Inflation rate* variable with state-dependent coefficients δ_{s_t};

Z_t: vector of macroeconomic variables with state-dependent coefficients β_{s_t};

X_t: vector of sectoral variables with state-invariant coefficients α;

$\varepsilon_t \sim N(0,\sigma^2)$.

9.4.2 Data on insurance company performance measurement variables

The database used to analyze the performance of the insurance industry corresponds to sector-aggregated data observed in the two main sectors of American insurance industry (P&C and Life insurance) over a 51-year period. These are time series composed of annual data, for the 1973 to 2023 period, on nominal variables such as *Premiums* collected, *Claims* costs, and profitability (*ROA*). Data for fundamental indicators of insurance company performance in the P&C insurance sector are all sourced from AM Best. Data on the fundamental indicators of performance for insurance companies in the Life insurance sector are all taken from the American Council of Life Insurers (ACLI) database, with the exception of *ROA* (own estimation). Sources and definitions of variables are documented in Appendix A9. Descriptive statistics for the main variables are presented in Appendix E9.

9.4.3 Estimated impact of inflation on insurers

- Estimated effect of inflation on *Claims* and *Premiums*

The results in Table 9.7 indicate a negative and statistically significant effect of inflation on *Premiums* collected and a non-significant effect on claims paid in the P&C sector during periods of high inflation (State 2). Neither effect is significant during periods of low inflation. Table 9.8 shows that inflation has a negative effect on *Premiums* collected and claims paid in the Life sector in both inflation states. The degree of significance is lower in State 2.

Table 9.7: Estimated impact of inflation on P&C *Claims* (in log)
and P&C *Premiums* (in log), 1973 to 2023 period

	P&C *Claims*			P&C *Premiums*		
	Variable	Coefficient	SE	Variable	Coefficient	SE
State 1	*Inflation rate*	0.002	(0.01)	*Inflation rate*	-0.01	(0.01)
	S&P 500 return	0.65***	(0.16)	*S&P 500 return*	0.06	(0.13)
	GDP per capita growth	0.02	(0.01)	*GDP per capita growth*	-0.03	(0.02)
	Real interest rate	0.08***	(0.01)	*Real interest rate*	0.06***	(0.01)
	Constant	3.36***	(0.16)	Constant	2.95***	(0.14)
State 2	*Inflation rate*	0.01	(0.01)	*Inflation rate*	-0.03***	(0.01)
	S&P 500 return	-0.11	(0.09)	*S&P 500 return*	-0.02	(0.19)
	GDP per capita growth	0.01	(0.02)	*GDP per capita growth*	-0.06***	(0.02)
	Real interest rate	-0.002	(0.01)	*Real interest rate*	0.05***	(0.01)
	Constant	4.53***	(0.15)	Constant	3.49***	(0.14)
Sector	*Household consumption*	-0.002	(0.02)	*Household consumption*	0.04**	(0.02)
	Real Dhutry House	0.00***	(1.25e-05)	*Real Dhutry House*	0.00***	(1.10e-05)
	Sigma	0.09**	(0.01)	Sigma	0.09**	(0.06)
	p11	0.97**	(0.04)	p11	0.87**	(0.06)
	p21	0.02**	(0.02)	p21	0.20**	(0.09)
	Observations	51		Observations	51	
	AIC criterion	61.17		AIC criterion	29.18	
	BIC criterion	37.19		BIC criterion	20.70	
	Log likelihood	-48.09		Log likelihood	-29.59	

Note: *** $p<0.01$, ** $p<0.05$.

In Table 9.7, we also observe that of our three macroeconomic control variables, only the *S&P 500 return* and *Real interest rate* variables are significant in State 1 and each has the predicted sign for the *Claims* variable (see Appendix E9 for predicted signs of control variables). Regarding the dependent variable P&C *Premiums*, only the control variable *Real interest rate* is significant and has the predicted sign in State 1. In State 2, the control variables *GDP per capita growth* and *Real interest rate* are significant, and each has the predicted sign for the dependent variable P&C *Premiums*. Our two selected P&C sectoral control variables, *Household consumption* and *Real Dhutry House*, proved to be significant and have the predicted sign for the dependent variable P&C *Premiums*. Only *Real Dhutry House* is significant for P&C *Claims*.

Table 9.8: Estimated impact of inflation on Life *Claims* (in log) and Life *Premiums* (in log), 1973 to 2023 period

	Life *Claims*			Life *Premiums*		
	Variable	Coefficient	SE	Variable	Coefficient	SE
State 1	*Inflation rate*	-0.09***	(0.02)	*Inflation rate*	-0.14***	(0.02)
	S&P 500 return	0.54*	(0.29)	*S&P 500 return*	0.59**	(0.24)
	GDP per capita growth	0.01	(0.03)	*GDP per capita growth*	0.02	(0.03)
	Real interest rate	0.06***	(0.02)	*Real interest rate*	0.04**	(0.02)
	Constant	1.58	(1.52)	Constant	-1.07	(1.35)
State 2	*Inflation rate*	-0.07*	(0.04)	*Inflation rate*	-0.08**	(0.04)
	S&P 500 return	0.01	(0.25)	*S&P 500 return*	0.03	(0.26)
	GDP per capita growth	0.07	(0.05)	*GDP per capita growth*	0.13***	(0.05)
	Real interest rate	-0.10***	(0.02)	*Real interest rate*	-0.08***	(0.02)
	Constant	3.45**	(1.42)	Constant	-0.11	(1.25)
Sector	*Household consumption*	-0.08*	(0.04)	*Household consumption*	-0.14***	(0.04)
	Death rate crude	0.06	(0.07)	*Death rate crude*	0.09	(0.07)
	Employment to pop ratio	0.05**	(0.02)	*Employment to pop ratio*	0.10***	(0.02)
	Sigma	0.19**	(0.02)	Sigma	0.18**	(0.02)
	p11	0.98**	(0.03)	p11	0.98**	(0.02)
	p21	0.02**	(0.02)	p21	0.02**	(0.02)
	Observations	51		Observations	51	
	AIC criterion	20.76		AIC criterion	9.09	
	BIC criterion	51.66		BIC criterion	40.00	
	Log likelihood	-5.62		Log likelihood	-11.45	

Note: *** p<0.01, ** p<0.05, * p<0.1.

In Table 9.8, of our three macroeconomic control variables, only the variables *S&P 500 return* and *Real interest rate* are significant in State 1. They each have the predicted positive sign for the dependent variable Life *Premiums* and on the dependent variable Life *Claims*, in line with the theory. In State 2, the *Real interest rate* variable is significant for each of the Life *Premiums* and Life *Claims* dependent variables and has the predicted sign. The *GDP per capita growth* variable is also statistically significant on the *Premiums* dependent variable and has the predicted positive sign. Further, all of our selected Life sectoral control variables are significant except for the *Death rate* variable.

- Estimated impact of inflation on *Loss ratio*

The *Loss ratio* is equal to the ratio between *Claims* paid and *Premiums* collected during a year. It indicates the proportion of *Premiums* collected used to pay *Claims*. An increase in this ratio indicates a decline in the insurer's underwriting performance. Inflation can cause the *Loss ratio* to rise or fall as it affects both components of the ratio.

Table 9.9: Estimated impact of inflation on *Loss ratio* (P&C and Life)
measured by the *Claims* to *Premiums* ratio, 1973 to 2023 period

	P&C *Loss ratio*			Life *Loss ratio*		
	Variable	Coefficient	SE	Variable	Coefficient	SE
State 1	*Inflation rate*	0.079	(0.39)	*Inflation rate*	2.84***	(1.07)
	S&P 500 return	3.00	(5.32)	*S&P 500 return*	6.52	(13.25)
	GDP per capita growth	-1.49***	(0.52)	*GDP per capita growth*	3.47**	(1.52)
	Real interest rate	0.27	(0.33)	*Real interest rate*	-3.16**	(1.42)
	Constant	76.74***	(5.11)	Constant	-62.68	(50.50)
State 2	*Inflation rate*	1.10***	(0.41)	*Inflation rate*	-1.82***	(0.58)
	S&P 500 return	-7.10**	(3.02)	*S&P 500 return*	9.79	(8.48)
	GDP per capita growth	-0.98	(0.64)	*GDP per capita growth*	0.86	(1.41)
	Real interest rate	0.18	(0.32)	*Real interest rate*	-2.57***	(0.50)
	Constant	83.68***	(4.93)	Constant	-2.47	(51.70)
Sector	*Household consumption*	0.92	(0.68)	*Household consumption*	-2.02	(1.48)
	Real Dhutry House	-0.001***	(0.00)	*Death rate crude*	10.05***	(2.78)
				Employment to pop ratio	0.73	(0.71)
	Sigma	2.89**	(0.33)	Sigma	7.88**	(0.80)
	p11	0.88**	(0.04)	p11	0.90**	(0.07)
	p21	0.05**	(0.05)	p21	0.05**	(0.03)
	Observations	51		Observations	51	
	AIC criterion	305.58		AIC criterion	407.84	
	BIC criterion	334.56		BIC criterion	438.75	
	Log likelihood	-137.79		Log likelihood	-187.92	

Note: *** $p<0.01$, ** $p<0.05$.

The results presented in Table 9.9 show a non-significant impact of inflation on the P&C *Loss ratio* in periods of low inflation (State 1) but a positive impact in periods of high inflation (State 2). Insurers face higher *Claims* costs and a slowdown in sales from new businesses due to the decline in customer purchasing power during an inflationary period.

The results presented in Table 9.9 empirically validate a positive and statistically significant impact of inflation on the Life *Loss ratio* in periods of low inflation (State 1) and a contrary significant effect in periods of high inflation (State 2). In other words, the results indicate that rising inflation has a negative impact on the performance of the Life sector during periods of low inflation (State 1) and a positive impact on the performance of the Life sector during periods of high inflation

(State 2). The lower decrease in *Premiums* observed in State 2 seems to have been sufficient to maintain the profitability of Life insurers.

- Estimated impact of inflation on *Expense ratio*

The *Expense ratio* is equal to the ratio of expenses (loss adjustment expenses and selling expenses) to *Premiums* collected. Inflation can cause the *Expense ratio* to increase or decrease, as it affects both components of this ratio.

Table 9.10: Estimated impact of inflation on *Expense ratio* (P&C and Life)
1973 to 2023 period

		P&C *Expense ratio*			Life *Expense ratio*	
	Variable	Coefficient	SE	Variable	Coefficient	SE
State 1	*Inflation rate*	0.04	(0.08)	*Inflation rate*	-1.60***	(0.51)
	S&P 500 return	-1.24	(0.78)	*S&P 500 return*	-24.91***	(4.99)
	GDP per capita growth	-0.18	(0.12)	*GDP per capita growth*	-1.00	(0.77)
	Real interest rate	-0.33***	(0.07)	*Real interest rate*	3.58***	(0.44)
	Constant	26.80***	(0.83)	Constant	131.80***	(28.64)
State 2	*Inflation rate*	0.14***	(0.05)	*Inflation rate*	1.97***	(0.24)
	S&P 500 return	-0.63	(0.78)	*S&P 500 return*	-4.52	(5.40)
	GDP per capita growth	-0.02	(0.16)	*GDP per capita growth*	0.33	(0.63)
	Real interest rate	0.29***	(0.05)	*Real interest rate*	0.10***	(0.26)
	Constant	22.89***	(0.85)	Constant	121.00***	(27.81)
Sector	*Household consumption*	0.24**	(0.11)	*Household consumption*	2.54***	(0.64)
	Real Dhutry House	0.00**	(6.45e-05)	*Death rate crude*	-4.50***	(1.55)
				Employment to pop ratio	-1.22***	(0.36)
	Sigma	0.58**	(0.06)	Sigma	3.29**	(0.42)
	p11	0.89**	(0.06)	p11	0.51**	(0.14)
	p21	0.10**	(0.06)	p21	0.37**	(0.11)
	Observations	51		Observations	51	
	AIC criterion	144.49		AIC criterion	341.46	
	BIC criterion	173.47		BIC criterion	372.37	
	Log likelihood	-57.25		Log likelihood	-154.73	

Note: *** p<0.01, ** p<0.05.

The results presented in Table 9.10 empirically validate a positive and statistically significant impact of inflation on the *Expense ratio* (P&C and Life) in periods of high inflation (State 2). In periods of low inflation (State 1), the results indicate a negative and statistically significant impact of inflation on the *Expense ratio* in the Life sector and a statistically insignificant effect in periods of low inflation in the P&C sector. The sectoral control variables are all significant. Only the macroeconomic variable *Real interest rate* is significant.

- Estimated impact of inflation on insurers' underwriting efficiency measured by the *Combined ratio*

The *Combined ratio* is equal to the sum of the *Loss ratio* and the *Expense ratio*. Each of these two ratios increases the level of the *Combined ratio*. The two ratios are channels through which the impact of inflation can be transmitted to the *Combined ratio*.

The results presented in tables 9.9 and 9.10 allow us to predict the possible statistical link between inflation and the *Combined ratio* through the *Loss ratio* and the *Expense ratio*. Inflation should have a positive influence on the *Combined ratio* in State 2 and no effects in State 1. The prediction of the sign of the influence of inflation on the Life *Combined ratio* appears ambiguous in both states. The results presented in Table 9.11 confirm the positive sign predicted for State 2 in the P&C sector but at only 10%. The result is not significant in State 1. The results suggest that an increase in inflation reduces the underwriting performance of the P&C sector during periods of high inflation (State 2).

The results presented in Table 9.11 empirically validate a positive sign for the *Inflation rate* variable coefficient on the Life *Combined ratio* during periods of low inflation (State 1). They suggest that rising inflation has adverse effects on the performance of the Life sector during periods of low inflation. Another result presented in Table 9.11 empirically validates a negative sign (at 10%) for the coefficient of the *Inflation rate* variable on the Life *Combined ratio* during periods of high inflation (State 2). In other words, rising inflation has small beneficial effects on the performance of the Life sector during periods of high inflation. This slight improvement in performance seems to be attributable to the beneficial effects that inflation has had on the *Loss ratio* during periods of high inflation.

The results obtained for the sectoral control variables indicate that the *Real Dhutry House* variable and the *Death rate* variable have explanatory power over the underwriting profitability of the P&C insurance business and the profitability of the Life insurance business, respectively. An increase in the *Real Dhutry House* variable appears to have a positive effect at 10% on the P&C insurers' business. Further, the *Death rate* variable has a negative impact on the profitability of the Life insurance business. Only the macroeconomic variable *S&P 500 return* is significant in both sectors, with a negative sign in State 2. Moreover, the *GDP per capita growth* is statistically significant at 1% in State 1 with a negative effect in the P&C sector and a positive sign in the Life sector.

Table 9.11: Estimated impact of inflation on insurers' underwriting efficiency (P&C and Life) measured by the *Combined ratio*, 1973 to 2023 period

	P&C *Combined ratio*			Life *Combined ratio*		
	Variable	Coefficient	SE	Variable	Coefficient	SE
State 1	*Inflation rate*	-0.13	(0.43)	*Inflation rate*	4.27***	(1.17)
	S&P 500 return	-2.95	(6.04)	*S&P 500 return*	7.81	(10.92)
	GDP per capita growth	-1.80***	(0.59)	*GDP per capita growth*	3.93***	(1.17)
	Real interest rate	0.06	(0.35)	*Real interest rate*	-2.64**	(1.24)
	Constant	106.00***	(5.76)	Constant	7.00	(38.29)
State 2	*Inflation rate*	0.97*	(0.55)	*Inflation rate*	-0.81*	(0.42)
	S&P 500 return	-8.84**	(3.83)	*S&P 500 return*	-11.82*	(6.43)
	GDP per capita growth	-0.73	(0.82)	*GDP per capita growth*	-0.01	(1.06)
	Real interest rate	0.46	(0.41)	*Real interest rate*	-0.40	(0.38)
	Constant	106.90***	(6.26)	Constant	68.41*	(39.22)
Sector	*Household consumption*	0.75	(0.70)	*Household consumption*	-0.08	(1.10)
	Real Dhutry House	-0.00*	(0.00)	*Death rate crude*	7.43***	(2.11)
				Employment to pop ratio	0.19	(0.53)
	Sigma	3.17**	(0.32)	Sigma	5.99**	(0.60)
	p11	0.89**	(0.08)	p11	0.90**	(0.08)
	p21	0.05**	(0.04)	p21	0.05**	(0.03)
	Observations	51		Observations	51	

	P&C *Combined ratio*			Life *Combined ratio*		
	Variable	Coefficient	SE	Variable	Coefficient	SE
	AIC criterion	309.67		AIC criterion	380.09	
	BIC criterion	338.64		BIC criterion	411.00	
	Log likelihood	-139.83		Log likelihood	-174.04	

Note: *** p<0.01, ** p<0.05, * p<0.1.

- Estimated impact of inflation on *Net investment income to Total assets*

The *Net investment income to Total assets* ratio is equal to the ratio between *Net investment income* (financial income minus financial expenses) and *Total assets*. Again, inflation can increase or decrease the *Net investment income to Total assets* ratio.

We use the Fed interest rate and the NASDAQ index as sector variable to measure the return that P&C insurers receive on their investments. In the case of Life insurance companies, variable annuities may involve investing the *Premiums* collected on behalf of the insured. Interest rates offered on bond investments are generally comparable to those offered on 3-month US Treasury bills. We have therefore selected the NASDAQ Composite Index (*NASDAQCOM*) and the interest rate on 3-month US Treasury bills (*TB3SMFFM*) to estimate the return that Life investors receive on their investments.

The results presented in Table 9.12 empirically validate a positive and statistically significant impact of inflation on Life *Net investment income to Total assets* in periods of both low and high inflation. The coefficients obtained indicate that the effect is greater in periods of high inflation than in periods of low inflation, which is probably explained by higher interest rates. In the P&C sector, the results empirically validate a positive and statistically significant impact of inflation on *Net investment income to Total assets* during periods of high inflation and low inflation with a lower and less significant effect in State 1. Sector-specific interest rate variables have a positive effect on the investment ratio, although this is not significant for the Life sector. The NASDAQ index has a negative effect that is difficult to justify. The effect to Total assets seems to dominate the income effect.

Table 9.12: Estimated impact of inflation on *Net investment income to Total assets* (P&C and Life), 1973 to 2023 period

		P&C *Net investment income to Total assets*			Life *Net investment income to Total assets*	
	Variable	Coefficient	SE	Variable	Coefficient	SE
State 1	*Inflation rate*	0.00**	(0.00)	*Inflation rate*	0.002***	(0.00)
	S&P 500 return	-0.00	(0.002)	*S&P 500 return*	-0.006	(0.004)
	GDP per capita growth	0.00	(0.00)	*GDP per capita growth*	0.001	(0.00)
	Real interest rate	0.002***	(0.00)	*Real interest rate*	0.001***	(0.00)
	Constant	0.03***	(0.001)	Constant	0.04***	(0.002)
State 2	*Inflation rate*	0.002***	(0.00)	*Inflation rate*	0.005***	(0.001)
	S&P 500 return	0.003	(0.006)	*S&P 500 return*	0.006	(0.008)
	GDP per capita growth	0.001**	(0.00)	*GDP per capita growth*	0.001**	(0.001)
	Real interest rate	0.001***	(0.00	*Real interest rate*	-0.00	(0.001)
	Constant	0.04***	(0.003)	Constant	0.050***	(0.01)
Sector	Fed rate	0.00*	(0.00)	*TB3SMFFM*	0.001	(0.002)
	NASDAQCOM	-2.06e-06***	(2.13e-07)	*NASDAQCOM*	-8.94e-07***	(2.28e-07)
	Sigma	0.003**	(0.00)	Sigma	0.004**	(0.00)
	p11	0.95**	(0.04)	p11	0.98**	(0.03)
	p21	0.09**	(0.07)	p21	0.06**	(0.05)
	Observations	51		Observations	51	
	AIC criterion	412.00		AIC criterion	370.37	
	BIC criterion	382.62		BIC criterion	341.40	
	Log likelihood	-220.80		Log likelihood	-200.19	

Note: *** p<0.01, ** p<0.05.

- Estimated impact of inflation on *Operating ratio*

The *Operating ratio* is equal to the sum of the *Combined ratio* and the investment ratio. The *Combined ratio* increases the level of the *Operating ratio*, while the investment ratio reduces the level of the *Combined ratio*. Tables 9.11 and 9.12 show, respectively, a non-significant coefficient for the *Inflation rate* variable for the P&C *Combined ratio* and a positive coefficient for the

Inflation rate variable for *Net investment income to Total assets* in State 1. The net effect on the *Operating ratio* should be negative.

In State 2, tables 9.11 and 9.12 show a positive coefficient for the *Inflation rate* variable for the P&C *Combined ratio* and a positive coefficient for P&C *Net investment income to Total assets*. Consequently, the *Combined ratio* variable should have a negative influence on the *Operating ratio*, and the *Net investment income to Total assets* variable should have a positive influence on the P&C *Operating ratio*.

Tables 9.11 and 9.12 show, respectively, a positive coefficient for the *Inflation rate* variable for the Life *Combined ratio* and a positive coefficient for the *Inflation rate* variable for Life *Net investment income to Total assets* in State 1. Since the two effects are opposite, we could expect inflation to have a positive or negative effect on the Life *Operating ratio* in State 1. In State 2, the *Combined ratio* variable should have a negative influence on the *Operating ratio*, and the *Net investment income to Total assets* variable should also have a negative influence on the Life *Operating ratio*.

The results presented in Table 9.13 confirm a positive effect in both states for the P&C sector. The coefficients obtained suggest that an increase in inflation has a negative effect on the performance of P&C insurers. The positive impact on investment was not sufficiently high to compensate for the negative impact of the *Combined ratio*.

Table 9.13: Estimated impact of inflation on insurers’ operating cost management efficiency (P&C and Life) measured by the *Operating ratio*, 1973 to 2023 period

	P&C *Operating ratio*			Life *Operating ratio*		
	Variable	Coefficient	SE	Variable	Coefficient	SE
State 1	*Inflation rate*	1.13***	(0.42)	*Inflation rate*	-3.84*	(1.99)
	S&P 500 return	-7.74***	(2.59)	*S&P 500 return*	-11.49	(16.47)
	GDP per capita growth	-2.02***	(0.65)	*GDP per capita growth*	1.33	(1.57)
	Real interest rate	1.43***	(0.36)	*Real interest rate*	0.62	(2.13)
	Constant	102.40***	(4.35)	Constant	-12.88	(33.46)
State 2	*Inflation rate*	1.63***	(0.60)	*Inflation rate*	-1.43***	(0.42)
	S&P 500 return	7.89	(6.35)	*S&P 500 return*	12.33***	(4.75)
	GDP per capita growth	0.38	(0.58)	*GDP per capita growth*	0.69	(0.74)
	Real interest rate	0.32	(0.32)	*Real interest rate*	-1.89***	(0.46)
	Constant	103.40***	(5.33)	Constant	29.08	(32.23)
Sector	*Household consumption*	1.76***	(0.66)	*Household consumption*	-2.05**	(0.81)
	Real Dhutry House	-0.003***	(0.00)	*Death rate crude*	-3.11	(2.11)
	Fed rate	-1.90***	(0.40)	*Employment to pop ratio*	1.20***	(0.41)
				TB3SMFFM	-5.08**	(2.37)
	NASDAQCOM	0.00**	(0.00)	*NASDAQCOM*	0.002***	(0.00)
	Sigma	2.47**	(0.30)	Sigma	4.65**	(0.46)
	p11	0.85**	(0.07)	p11	0.86**	(0.12)
	p21	0.25**	(0.14)	p21	0.02**	(0.02)
	Observations	51		Observations	51	
	AIC criterion	299.48		AIC criterion	353.15	
	BIC criterion	332.32		BIC criterion	387.91	
	Log likelihood	-132.74		Log likelihood	-158.57	

Note: *** p<0.01, ** p<0.05, * p<0.1.

The results presented in Table 9.13 empirically validate a negative and statistically significant impact of inflation on the *Operating ratio* during periods of low inflation (State 1) in the Life sector. This improvement in performance appears to be attributable to the beneficial effects that inflation has had on the investment ratio during periods of low inflation. This reflects the presence of natural interest rate hedging on Life insurers’ profitability during periods of low inflation.

The negative and statistically significant sign of the coefficient obtained indicates that an increase in inflation during periods of high inflation (State 2) also has beneficial effects on the performance of Life insurers. This improvement in performance appears to be attributable to the beneficial effects that inflation has had on both the *Combined ratio* and the *Net investment income to Total assets* ratio in periods of high inflation.

The results obtained for the sectoral control variables indicate that the four sector variables have explanatory power over the profitability of P&C insurers' insurance business. Moreover, *Household consumption*, *Employment to pop ratio*, and financial market indices variables each have explanatory power over the profitability of Life insurers' insurance business. These results should affect the effect of inflation on the *ROA*.

- Estimated impact of inflation on *ROA*

ROA is equal to the ratio of net income to Total assets. *ROA* is an increasing function of net income. Since the *Operating ratio* is an indicator of net income, we can deduce that *ROA* is a decreasing function of the *Operating ratio*. Hence, we consider the *Operating ratio* to be the main channel through which inflation impacts *ROA*, although other financial factors may influence *ROA*.

Table 9.14: Estimated impact of inflation on financial profitability measured by the *ROA* indicator, 1973 to 2023 period

	P&C *ROA*			Life *ROA*		
	Variable	Coefficient	SE	Variable	Coefficient	SE
State 1	*Inflation rate*	-0.006 ***	(0.002)	*Inflation rate*	0.004***	(0.00)
	S&P 500 return	-0.03	(0.03)	*S&P 500 return*	-0.02***	(0.009)
	GDP per capita growth	-0.002	(0.002)	*GDP per capita growth*	-0.002	(0.001)
	Real interest rate	-0.002**	(0.001)	*Real interest rate*	0.005***	(0.00)
	Constant	0.016	(0.02)	Constant	0.12**	(0.06)
State 2	*Inflation rate*	-0.004***	(0.001)	*Inflation rate*	0.004	(0.004)
	S&P 500 return	0.01*	(0.009)	*S&P 500 return*	-0.009	(0.03)
	GDP per capita growth	0.009***	(0.002)	*GDP per capita growth*	-0.002	(0.003)
	Real interest rate	-0.006***	(0.001)	*Real interest rate*	0.009**	(0.004)

	P&C *ROA*			Life *ROA*		
	Variable	Coefficient	SE	Variable	Coefficient	SE
	Constant	0.0143	(0.01)	Constant	0.18***	(0.06)
Sector	*Household consumption*	-0.007***	(0.002)	*Household consumption*	0.005***	(0.00)
	Real Dhutry House	5.52e-06***	(1.99e-06)	*Death rate crude*	0.01***	(0.004)
	Fed rate	0.007***	(0.001)	*Employment to pop ratio*	-0.003***	(0.00)
				TB3SMFFM	0.01***	(0.004)
	NASDAQCOM	-2.25e-06**	(1.04e-06)	*NASDAQCOM*	-5.23e-06***	(6.33e-07)
	Sigma	0.009**	(0.001)	Sigma	0.008**	(0.00)
	p11	0.68**	(0.14)	p11	0.98**	(0.02)
	p21	0.15**	(0.07)	p21	0.14**	(0.12)
	Observations	51		Observations	51	
	AIC criterion	276.57		AIC criterion	291.24	
	BIC criterion	243.73		BIC criterion	256.46	
	Log likelihood	-155.28		Log likelihood	-163.62	

Note: *** p<0.01, ** p<0.05, * p<0.1.

The results presented in Table 9.14 indicate a negative sign for each of the two states in the P&C sector. The statistical significance of the coefficients obtained indicates that an increase in inflation has adverse effects on the financial performance of P&C insurers.

The non-statistical significance of the coefficient obtained in State 2 indicates that an increase in inflation during periods of high inflation would not have effect on the performance of Life insurers. It seems that the hedging effect of investment income was efficient. The positive coefficient obtained in State 1 can be explained by the low level of significance obtained for the *Operating ratio* (negative *Inflation rate* coefficient significant only at 10%).

9.5 Conclusion

The objective of this section was to study the effect of inflation on US insurance markets. We analyzed the characteristics of the US *Inflation rate* series observed over the 1973 to 2023 period to model the effects of inflation on the insurance industry. Two important conclusions emerged on the nature of inflation during the period of analysis that included two oil price shocks and the

COVID-19. The US *Inflation rate* series was characterized by a random trend and nonlinear dynamics. These results led us to select the two-regime Markov model for analyzing the effect of inflation on different performance indicators of the insurance industry.

Table 9.15 summarizes the impact of inflation on various fundamental determinants of insurance company performance in the US. The table shows that both Life and P&C insurers were significantly exposed to inflation fluctuations, especially in periods of high inflation (State 2). Inflation in State 1 did not affect significantly the P&C underwriting variables and had a positive effect on investment income at only 5%. It is surprising to observe that the net effect on both the *Operating ratio* and *ROA* generated negative results on profitability. Results in State 2 are more coherent since the negative result on *Premiums* generated a negative performance overall. The positive result on investment did not create a significant hedging effect in this sector.

The table indicates that the impact of inflation on *ROA* in the Life sector was not significant, in State 2. Other factors than the *Operating ratio* seem to have affected the *ROA*. The impact of inflation on Life insurers performance indicators in State 1 was negative for the underwriting activities, but the good performance of investment created a net positive effect on profitability.

In conclusion, the P&C sector seems to have been more affected by inflation during our period of analysis. The negative effect on *Premiums* in State 2, probably explained by a reduction in purchasing power of clients, affected insurance demand and the higher interest rates did not compensate for the negative underwriting results. In the Life sector, the hedging effect of investment was efficient in State 1 and neutral in State 2.

Table 9.15: Summary of inflation estimation results

Panel A: Summary of estimation results in the P&C sector		
Variable	State 1	State 2
Premiums	NS −	N 1%
Claims	NS −	NS −
Loss ratio	NS −	P 1%
Expense ratio	NS −	P 1%
Combined ratio	NS −	P 10%
N. Inv. Income	P 5%	P 1%
Operating ratio	P 1%	P 1%
ROA	N 1%	N 1%
Panel B: Summary of estimation results in the Life insurance sector		
Variable	State 1	State 2
Premiums	N 1%	N 5%
Losses	N 1%	N 10%
Loss ratio	P 1%	N 1%
Expense ratio	N 1%	P 1%
Combined ratio	P 1%	N 10%
N. Inv. Income	P 1%	P 1%
Operating ratio	N 10%	N 1%
ROA	P 1%	NS +

Note: P for positive effect of inflation; N for negative effect of inflation; NS for non-significant effect; X% for degree of significance.

This section, with aggregate annual data, does not take into account the heterogeneity between insurers in each sector. A panel data with individual firms' information could be more appropriate for this purpose. Another issue concerns the difference between the *COVID-19* inflation shock and the previous shocks to the oil price during the 1970's. The *COVID-19* inflation shock was much shorter, probably explained by the recent contractionary move of the Fed monetary policy against inflation. Taking these aspects into consideration would represent a significant extension to our research.

Appendix A9: Variable definitions

Table A9.1: Variables, data sources and descriptions (P&C)

Measure	Description	Variable	Data source
Losses and loss adjustment expenses ($ billion)	Losses and loss adjustment expenses (LAE) include benefit payments and other contract payments	*Claims*	AMBest database
Net *Premiums* written ($ billion)	Net *Premiums* written is the sum of direct *Premiums* written, minus the *Premiums* ceded to reinsurance companies (to affiliates and non-affiliates), plus any reinsurance assumed (from affiliates and non-affiliates)	*Premiums*	AMBest database
Loss ratio (%)	Loss ratio is Losses and loss adjustment expenses to Net *Premiums* written	*Loss ratio*	Our calculations
Operating expenses ($ billion)	Operating expenses include commissions to agents, other commissions, home- and field-office expenses and taxes	*Expenses*	AMBest database
Expense ratio (%)	Expense ratio is Operating expenses to Net *Premiums* written	*Expense ratio*	Our calculations
Combined ratio before dividend to policyholders (%)	*Combined ratio* before dividend to policyholders is the sum of the Loss ratio and Expense ratio. It measures the insurance company's overall underwriting profitability.	*Combined ratio*	AMBest database
Net investment income ($ billion)	*Net investment income* is Total gross investment income less investment expenses, taxes, and deductions	*Net investment income*	AMBest database
Operating ratio (%)	*Operating ratio* is *Combined ratio* less *Net investment income* to *Premiums*	*Operating ratio*	Our calculations

Measure	Description	Variable	Data source
Pretax operating income ($ billion) before dividends to policyholders and federal income taxes	*Pretax operating income* before dividends to policyholders and federal income taxes is the sum of Net underwriting income, other income/expense, and *Net investment income*, minus change in contingency reserve.	*Pretax operating income*	AMBest database
Total assets ($ billion)	Total assets is the sum of cash, invested assets (bonds, stocks, mortgage loans, real estate, contract loans, derivatives and other invested assets), and other items	*Total assets*	AMBest database
Net investment income to Total assets (ratio)	*Net investment income* to Total assets is the ratio of *Net investment income* to Total assets	*Net investment income to Total assets*	Our calculations
ROA (ratio)	*ROA* is *Pretax operating income* to Total assets	*ROA*	Our calculations
Households and NPISHs final consumption expenditure (annual % growth)	Annual percentage growth of households and NPISHs final consumption expenditure based on constant local currency	*Household consumption*	World Bank
Real Dhutry House ($ billion)	Real personal consumption expenditures: services, housing and utilities	*Real Dhutry House*	FRED
S&P500 annual return (%)	Annual index, not seasonally adjusted	*S&P 500 return*	FRED
GDP per capita growth (annual %)	Annual percentage growth rate of GDP per capita based on constant local currency	*GDP per capita growth*	World Bank
Real interest rate (%)	Real interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator	*Real interest rate*	World Bank
Inflation rate	Percentage change of the Consumer Price Index (*CPI*)	*Inflation rate*	World Bank

Table A9.2: Variables, data sources and descriptions (Life)

Variable	Description	Measure	Data source
Losses and loss adjustment expenses ($ billion)	Losses and loss adjustment expenses (LAE) include benefit payments and other contract payments	*Claims*	American Council of Life Insurers (ACLI) database
Premiums earned ($ billion)	*Premiums* receipts - derived from sales of Life insurance, health insurance, and annuities	*Premiums*	ACLI database
Loss ratio (%)	Loss ratio is Losses and loss adjustment expenses to *Premiums* earned	*Loss ratio*	Our calculations
Operating expenses ($ billion)	Operating expenses include commissions to agents, other commissions, home- and field-office expenses and taxes.	*Expenses*	ACLI database
Expense ratio (%)	Expense ratio is Operating expenses to *Premiums* earned	*Expense ratio*	Our calculations
Combined ratio (%)	*Combined ratio* is Losses and losses adjustment to *Premiums*	*Combined ratio*	Our calculations
Net investment income ($ billion)	*Net investment income* is Total gross investment income less investment expenses, taxes, and deductions	*Net investment income*	ACLI database
Operating ratio (%)	*Operating ratio* is *Combined ratio* less *Net investment income* to *Premiums*	*Operating ratio*	Our calculations
Pretax operating income ($ billion)	*Pretax operating income* is Total income (ACLI database) less Total expense (ACLI database) before policyholder dividends, federal income taxes and realized capital gains/losses before dividends to policyholders and federal income taxes	*Pretax operating income*	Our calculations
Total assets ($ billion)	Total assets is the sum of cash, invested assets (bonds, stocks, mortgage loans, real estate, contract loans, derivatives and other invested assets)	*Total assets*	ACLI database

Variable	Description	Measure	Data source
Net investment income to Total assets (ratio)	*Net investment income* to Total assets is the ratio of *Net investment income* to Total assets	*Net investment income to Total assets*	Our calculations
ROA (ratio)	*ROA* is *Pretax operating income* to Total assets	*ROA*	Our calculations
Households and NPISHs final consumption expenditure (annual % growth)	Annual percentage growth of households and NPISHs final consumption expenditure based on constant local currency	*Household consumption*	World Bank
Employment to population ratio (%)	Employment to population ratio is the proportion of a country's population that is employed	*Employment to pop ratio*	World Bank
Crude death rate	Crude death rate indicates the number of deaths occurring during the year, per 1,000 population	*Death rate*	World Bank
S&P500 annual return	Annual index, not seasonally adjusted	*S&P 500 return*	FRED
GDP per capita growth (annual %)	Annual percentage growth rate of GDP per capita based on constant local currency	*GDP per capita growth*	World Bank
Real interest rate (%)	Real interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator	*Real interest rate*	World Bank
Inflation rate	Percentage change of the Consumer Price Index (*CPI*)	*Inflation rate*	World Bank
NASDAQ Composite Index (%)	Annual index, not seasonally adjusted	*NASDAQCOM*	FRED
TB3SMFFM (%)	Series is calculated as the spread between 3-month Treasury Bill and Effective Federal Funds Rate (https://fred.stlouisfed.org/series/EFFRM).	*TB3SMFFM*	FRED

Appendix B9: Economic inflation and its predicted effects on insurance industry

B9.1 Mesure of inflation

Economic inflation is the loss of purchasing power that results in a general and sustainable increase in prices. The *Inflation rate* is the percentage change of a price index during a period, usually a year. Inflation can affect the real economy and the monetary policy.

The price index the most often used is the Consumer Price Index (*CPI*) of a large basket of goods (Bureau of Labor Statistics, BLS). Keeping a constant basket over the years may create a bias, because some goods may become less important for consumption and new goods from innovations may turn into high demand. Moreover, during an inflation period, customers may substitute goods with high inflation in the general basket and consume other goods with lower *CPI*. A US Senate committee concluded that the *CPI* overstated inflation by 1.1% in 1996 (Boskin et al., 1996; see also Gordon, 2006). Since 1999, the BLS updates the index to reduce the potential biases. In this article, we use the corrected official index and we do not consider other measures of inflation. Our main inflation variable is the *Inflation rate*, which is the percentage change of the *CPI*.

B9.2 Causes of recent inflation

Inflation was less important over the 1983-2019 period. The 2007-2009 financial crisis did not accentuate price variations significantly although it affected financial markets. Particularly it increased default and liquidity risks in the banking sector.

The *COVID-19* crisis had a different pattern on prices stability by creating shortage in many markets and inciting many governments to inject money into the economy. Following the recent *COVID-19* pandemic, inflation became an international growing concern. The BLS reported that the inflation for all items in the US rose 7% from December 2020 to December 2021, the largest annual percent change since 1981. The annual *Inflation rate* was 6.5% in 2022 (3.4% in 2023 and 2.9% in 2024).

Bernanke and Blanchard (2025) analyze the causes of the post *COVID-19* inflation. They show that, for the US, the recent inflation period was explained by strong increases in the prices of food and energy. Supply disruptions in key sectors is also a cause, as well labor supply became tight and contributed to wage inflation.

They find that energy prices, food prices, and price spikes due to shortages were the significant drivers of inflation in its early stages, although the second-round effects of these factors, through their effects on other prices and through higher inflation expectations and wages, were limited. The contribution of labor market conditions to inflation was initially modest. But as product market shocks became less significant over time, the labor market conditions and the persistence in nominal wage increases have become the main factors behind wage and price inflation.

The US response to the *COVID-19* pandemic included a series of federal intervention plans which caused roughly $5 trillion in government spending. These programs contributed to strong consumer and business demand, which affected labor markets in mid-2021 and early 2022, causing upward pressure on wages and prices. In summary, rising commodity prices and supply chain disruptions were the principal triggers of the recent inflation. But when these factors became less significant, labor market conditions and wage increases became the main drivers of the rate of price increase.

The resurgence of inflation in 2020 was a surprise in insurance markets (Schanz and Treccani, 2023). The immediate impact of inflation on non-Life insurers’ earnings should be negative according to the report, primarily through rising future claims costs on current insurance policies and the need to protect loss reserves with more capital. The short-run effect on Life insurers’ earnings should be more neutral. Most Life insurance products, e.g. mortality, wealth accumulation and longevity protection, offer benefits that are nominally fixed. Rising interest rates may negatively affect insurers’ balance sheets. Higher interest rates, however, could have a favorable effect on the net present value of future liabilities.

On the investment side, there are two divergent aspects, according to the Geneva Association report. On the one hand, rising interest rates are positive regarding investment yields. On the other hand, escalating anxiety of an economic recession can substantially affect market values and volatility.

According to EIOPA (2023), the key determinants of P&C insurers’ welfare sensitivity to inflation and corresponding higher interest rates are the exposure to interest rate sensitive assets, the relative duration of liabilities and the sensitivity of claims and expenses to inflation.

Inflation may also have an impact on regulated capital. A decrease in the value of fixed income assets leads to a variation in market risks while an increase in exposure to future *Premiums* might lead to a potential increase in underwriting risk. High inflation and interest rates could be beneficial for Life and non-Life insurers in the long run due to the reinvestment of assets at higher yields. In the short term, the impact should be negative mainly due to value losses on interest rate sensitive investments.

When assessing the impact of inflation on profitability, the time horizon needs to be considered. In the short run, the impact of inflation on profitability may be negative, in particular for non-Life insurers with higher share of business in competitive lines of business such as liability insurance. The impact is reflected in higher claims for which insurers must increase their reserves. Moreover, *Premiums* need to be adjusted to maintain the equilibrium combined ratio. In the short run, under market competition, underwriting profitability may be reduced.

Another important component of profitability is investment (EIOPA, 2023). If high inflation generates high interest rates this would result in higher investment returns on the fixed income portfolios. Better investment results would allow non-Life insurers to compensate for lower premium increases and maintain overall profitability. In other words, considering that the pre-tax profitability of a non-Life insurer is the sum of the underwriting result and the investment result, then higher investment results can provide at least a partial offset for the inability to increase *Premiums* in line with inflation. This suggests that the potential partial offset from higher investment results should be significant for long-tail business. Table B9.1 summarizes the main predictions discussed in this literature review and in this appendix.

Table B9.1: Main predictions of inflation effect from literature

Effect	Reference
Positive effect of inflation on claims costs in P&C sector	Schanz and Treccani, 2023; EIOPA, 2023
During inflation periods, *Premiums* must increase to maintain the combined ratio at an equilibrium level	EIOPA, 2023; Schanz and Treccani, 2023
Positive effect of inflation on interest rates, including T-Bills	Masterson, 1968
Positive effect of inflation on investment returns in the long-run	D'Arcy, 1981; EIOPA, 2023
Negative impact on investment returns in short-run because inflation reduces assets values	D'Arcy et al., 2009; EIOPA, 2023; Krivo, 2009
Negative impact of inflation on loss reserves in P&C sector	Lowe and Warren, 2010; D'Arcy et al., 2009
Short-run effect of inflation should be negative on earnings in P&C sector	Schanz and Treccani, 2023

The effects on claims management should be more neutral for Life insurance activities because many variables are long-run activities measured in nominal terms. Investment activities may represent more hedging effects for Life insurers because Life insurers are more involved in financial investments.

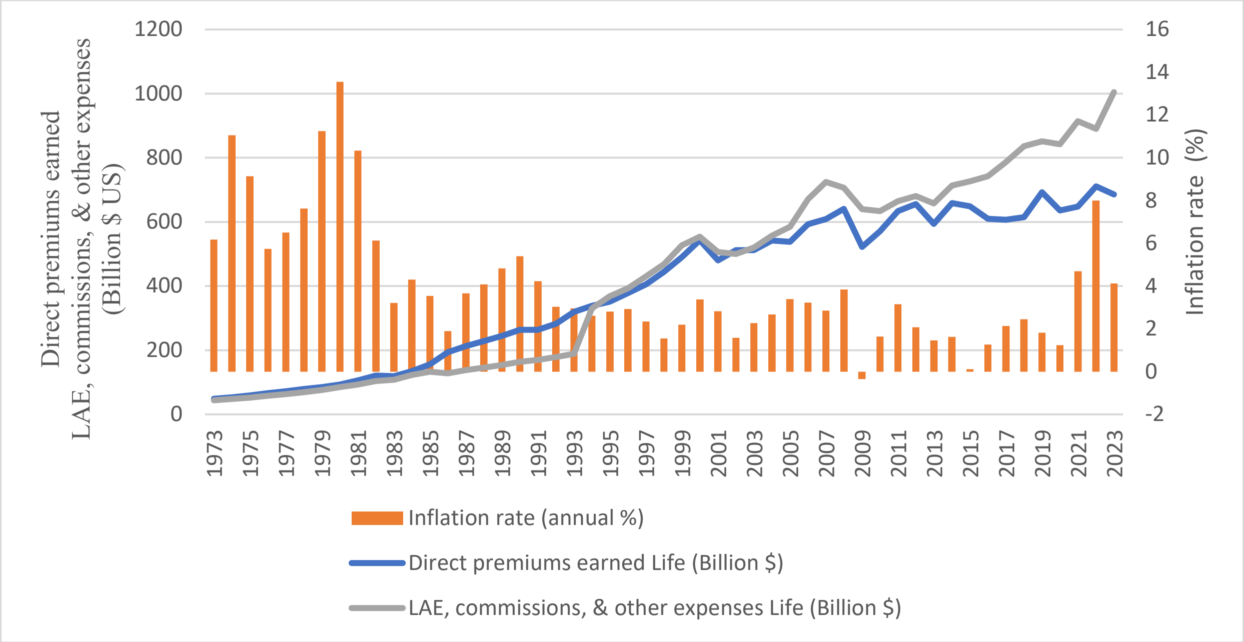
Appendix C9: Insurance business performance indicators

Two accounting indicators are often used by insurance professionals to measure insurance companies' performance: the *Combined ratio* (indicator of efficiency in managing the underwriting activity) and the *Operating ratio* (indicator of efficiency in managing the operating costs of the underwriting activity and investments). These two indicators are widely used in the insurance industry. In addition to these indicators of operating cost management efficiency, there is another indicator traditionally used in the literature to measure the performance of insurance companies: the *ROA*, which measures the accounting profitability of insurers (Dionne and Harrington, 2014). Finally, insurers' capital and investment levels are indicators of their ability to cover more or less anticipated risks.

C9.1 Influence of inflation on the combined ratio

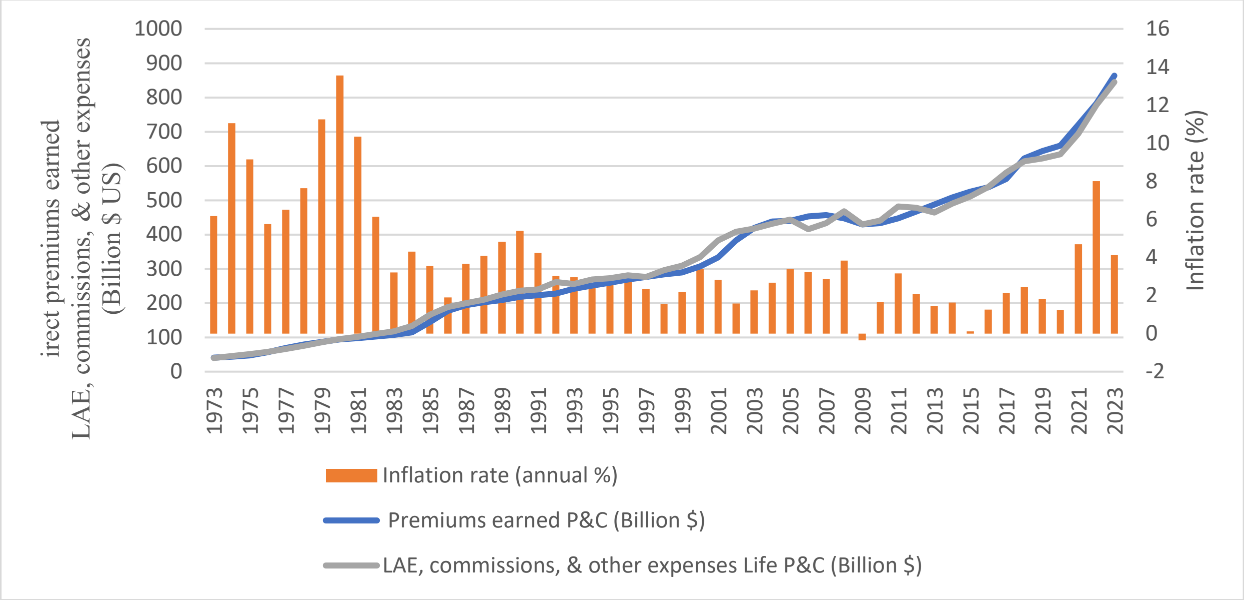
The *Combined ratio* is measured by the ratio of *Total operating expenses* (claims paid + management expenses) to *Premiums* collected (insurance policies sold). This indicator shows whether *Premiums* collected are sufficient to cover all operating expenses. Clearly, the most obvious risk for the insurer is that *Premiums* collected are insufficient to pay policyholder claims and cover management expenses. The less sufficient *Premiums* are to cover claims paid and management expenses, the higher the *Combined ratio* will be, and the more the insurer will experience financial difficulties. Consequently, a high *Combined ratio* will have a negative influence on the profitability of insurers' underwriting business. A *Combined ratio* below 100% means that the insurance company is in a profitable situation.

Figure C9.1: Trends in inflation (*Inflation rate*), *Premiums* collected and total operating expenses in the Life sector, 1973 to 2023 period



Source: American Council of Life Insurers (ACLI).

Figure C9.2: Trends in inflation (*Inflation rate*), *Premiums* collected and total operating expenses in the P&C sector, 1973 to 2023 period



Source: AM-Best.

Generally speaking, the two determinants of the combined ratio—total operating expenses (claims paid + management expenses) and *Premiums* collected—follow the same tendance, as shown in figures C9.1 and C9.2. Figure C9.1, however, points to some difficulties in the Life insurance sector since the financial crisis of 2007-2009, despite the fact that inflation was at a low level before 2021. Inflation can affect each of the two determinants of the combined ratio. In fact, it is difficult to detect the precise influence of inflation on the combined ratio.

The P&C sector appears more stable than the Life sector over the same period, as shown in Figure C9.2. This difference between the two sectors can be explained by low interest rates, such as those observed in Figure 9.1. The Life insurance sector has been more affected by the low interest rate policy of the Fed after the 2007-2009 financial crisis, a monetary policy not related to inflation but to the lack of liquidity in different markets.

C9.2 Influence of inflation on the *Operating ratio*

According to Ahlgrim and D'Arcy (2012), an insurance company has two main sources of revenue, namely *Premiums* and net investment income, and two main sources of costs, namely claims paid and operating expenses (commissions and management fees or operating expenses). These two main sources of income and two main sources of costs are used to determine the *Operating ratio* (Hull, 2023).

An insurance company can be profitable even with a combined ratio of above 100%. This is because the combined ratio does not consider the second source of income for insurance companies: net investment income, which comes from income earned on *Premiums* invested in bonds, equities or other forms of longer-term investment. The inclusion of net investment income should reduce the level of the *Operating ratio* in periods of high financial profitability.

In the remainder of our analysis, we have chosen the *Operating ratio* as the most reliable indicator for measuring the efficiency of operating cost management in the insurance business, since it considers the total level of revenue and the total level of operating expenses. As the *Operating ratio* is an increasing function of the combined ratio, we can deduce that inflation can have a positive or negative influence on the *Operating ratio*.

C9.3 Financial performance indicator for the insurance business

Until now, we have analyzed the performance of insurance companies simply by considering their operating activity, i.e. the net profit generated by their commercial activity, without considering the capital invested by shareholders and creditors to finance this activity. In fact, an insurer's real performance lies in its ability to create value or wealth for the shareholders and creditors who finance its activity. The impact of capital invested by shareholders and creditors on profitability is measured by the *ROA* indicator. *ROA* is obtained by taking the ratio between net income and total assets. This measure indicates profitability per dollar invested. In other words, the financial performance of the insurance business (*ROA*) is an increasing function of the profitability of the insurance business. We have just mentioned that inflation can exert a positive or negative influence on the profitability of the insurance business and that *ROA* is an increasing function of the profitability of the insurance business. It can then be argued that inflation can exert positive or negative effects on the performance of the insurance business.

Appendix D9: ARMA process and EGARCH process

D9.1 Nonlinear stochastic process in variance: ARCH and EGARCH models

D9.1.1 ARCH model

The ARCH model was introduced by Engle (1982). The null hypothesis tested is that of homoscedasticity versus the alternative hypothesis of conditional heteroscedasticity. If the null hypothesis is not rejected, the conditional variance is constant. Conversely, if the null hypothesis is rejected, the residuals may follow an ARCH (q) process. In this appendix, we show there is an ARCH effect in the inflation series of Figure 9.1.

ARCH (q) applications are often used in finance to account for this ARCH effect. However, certain criticisms have been leveled at ARCH models. According to Nelson (1991), ARCH models may prove inadequate for two main reasons. The first is that the choice of a quadratic form for the conditional variance has important consequences for the time path of the series. Choosing a symmetrical quadratic form for the conditional variance does not allow us to model the phenomenon of asymmetry. The second reason is that ARCH models remain strongly constrained to positive conditional variation of variance. This implies that a shock, whatever its sign, always has a positive effect on current volatility: the impact increases with the size of the shock.

These criticisms led to the development of the EGARCH (Exponential GARCH) model. The EGARCH model (Nelson, 1991) takes into account the possibility that variance responds asymmetrically to positive and negative shocks.

D9.1.2 EGARCH (c,q) model

An EGARCH process is given by:

$$y_t = \mu_t + \sigma_t \varepsilon_t \qquad \varepsilon_t \sim N(0, 1) \qquad \text{(D9.1)}$$

where μ_t and σ_t, respectively, denote the conditional mean and standard deviation of y_t (the *Inflation rate* series) for a set of information consisting of the variables observed up to time t-l. ε_t represents the innovation (shock) of an Autoregressive moving-average (ARMA)-type process fitted to the series under study y_t. Nelson (1991) proposed the following model:

$$ln\,\sigma_t^2 = \alpha_0 + \sum_{j=1}^{c} \beta_j \, ln\, \sigma_{t-j}^2 + \sum_{i=1}^{q} \alpha_i \, g(z_{t-i}),\, z_{t-i} = \frac{\varepsilon_{t-\mathrm{i}}}{\sigma_{t-\mathrm{i}}} \sim \mathrm{iid}(0,1). \qquad \text{(D9.2)}$$

where σ_t^2 is the conditional variance of y_t, z_{t-i} represents normalized innovations and $g(.)$ is a function of normalized innovations (z_{t-i}). β_j is the coefficient associated with the EGARCH (c) part and α_i is the coefficient associated with the ARCH (q) part of the EGARCH (c,q) model.

Unlike ARCH (q) models, whose specialization concerns the quadratic nature of the conditional variance, the specification of the EGARCH model concerns the logarithm of the conditional variance and thus avoids positivity constraints on the coefficients α_i and β_j of equation (D2).

D9.1.3 Estimation with the maximum likelihood method

Table D9.1 shows the estimation of the ARMA (1,1)-EGARCH (1,1) model. The table suggests that the negative and statistically significant coefficient of the variable ($\beta_j < 0$) implies that a shock with a negative effect on inflation will have a greater impact on volatility than would a shock with an equivalent positive effect. In other words, inflation reacts more strongly to a negative shock than to a positive one, reflecting the asymmetrical effect. Table D9.1 shows that all the coefficients of the variables in the variance equation are significantly different from zero.

Table D9.1: ARMA (1,1)-EGARCH (1,1) model estimates
1973 to 2023 period

Dependent variable	*Inflation rate*
L1.ar	0.462**
	(0.204)
L1.ma	0.434*
	(0.259)
Constant	2.820***
	(0.394)
Variance equation (σ_t^2)	
L1.egarch (β_j)	-0.696***
	(0.131)
L1.arch (α_i)	0.180***
	(0.057)
Constant	0.940***
	(0.364)
Observations	51

Note: L1.ar and L1.ma represent respectively the AR (1) and MA (1) components of the ARMA (1,1) model. L1.egarch and L1.arch respectively represent the EGARCH (1) and ARCH (1) components of the EGARCH (1,1) model. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Let us assume that the mean equation is described by an Autoregressive moving-average (ARMA) process. Consider the series Y_t generated by the following system of equations:

$$\Phi(L)\, Y_t = \Theta(L)\, \tilde{e}_t \qquad \text{(D9.3)}$$

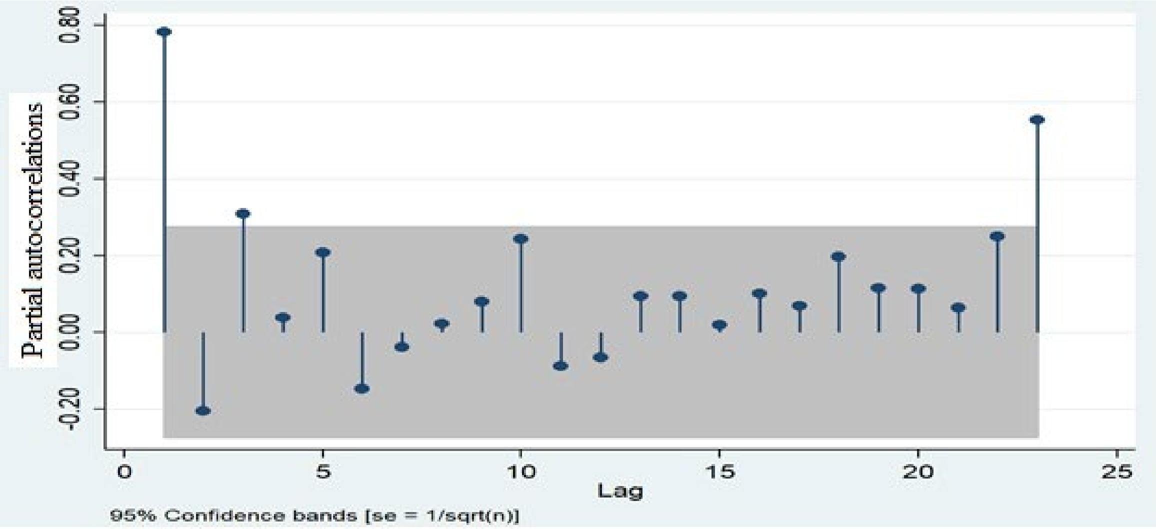
$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \tilde{e}_t^2 \qquad \text{(D9.4)}$$

Y_t represents the *Inflation rate* series and $\tilde{e}_t$ represents the residuals from estimating the mean equation. The parameter $\Phi(L)$ is the lag polynomial of the *Inflation rate* series (Y_t). Parameter $\Theta(L)$ represents the lag polynomial of the residuals from the estimation of the mean equation ($\tilde{e}_t$). σ_t^2 is the variance.

The ARCH model is implemented in three stages from (D9.3) and (D9.4). The first step is to estimate the mean equation. We then recover the estimated residuals $\tilde{e}_t$ and calculate the series $\tilde{e}_t^2$. Second, we regress $\tilde{e}_t^2$ on a constant and its q past values (only significant lags are retained). Third, we calculate the TR^2 statistic, where T is the number of observations and R^2 is the coefficient of determination associated with the regression in step 2. Under the null hypothesis of homoscedasticity, the TR^2 statistic follows a chi-square distribution with q degrees of freedom. The decision rule is as follows: If $TR^2 \leq \chi^2(q)$, the null hypothesis is not rejected. In other words, there is no ARCH effect. Conversely, if $TR^2 > \chi^2(q)$, the null hypothesis is rejected in favor of the alternative hypothesis including conditional heteroscedasticity.

To select the ARMA (c,q) model for our estimation, we apply the method of Box and Jenkins (1970) and Box et al. (2015). The Box and Jenkins method consists, first, in selecting the number of lags *c* and *q* using visual inspection of sampled autocorrelations and partial autocorrelations. ARMA (c,q) processes are a natural extension of AR (c) and MA (q) processes. For an autoregressive process AR (l), the partial autocorrelations cancel out from rank *c*+1. This property is used to identify the order *c* of AR processes. For a moving average process MA (q), the autocorrelations cancel out from rank *q*+1. This second property is used to identify the order *q* of MA processes.

Figure D9.1: Partial *Inflation rate* autocorrelations, 1973 to 2023 period

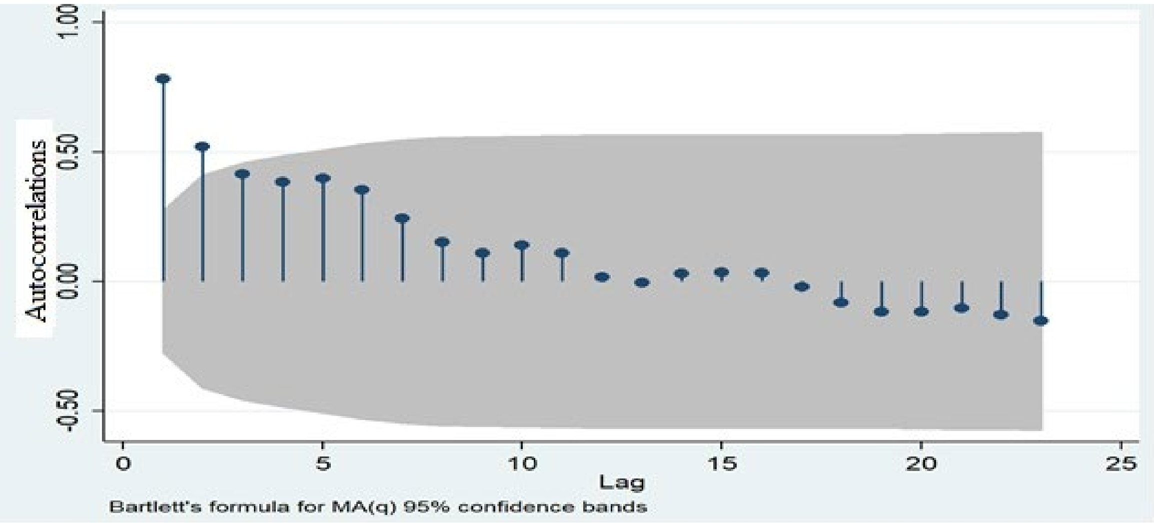


Source: World Bank and our calculations.

The fact that the first partial autocorrelation in Figure D9.1 is highly statistically significant could indicate an AR (1) process, i.e., $c = 1$. Moreover, Figure D9.2 implies that we could choose MA (2) because the autocorrelations are not statistically significant starting from order 3.

To summarize, visual inspection of the sampled autocorrelations and partial autocorrelations enabled us to select the AR (1) and MA (2) models. The AR (2), MA (1), ARMA (1,1), ARMA (1,2), ARMA (2,1) and ARMA (2,2) models, derived from the combination of c and q with a maximum number of lags equal to 2, may also be logical candidates.

Figure D9.2: *Inflation rate* autocorrelations, 1973 to 2023 period



Source: World Bank and our calculations.

Table D9.2: Information criteria for estimated models, 1973 to 2023 period

	AIC	BIC
AR (1)	211.3436	217.1391
AR (2)	211.0094	218.7367
MA (1)	218.4029	224.1984
MA (2)	210.4831	218.2104
ARMA (1,1)	207.1818*	214.9091*
ARMA (1,2)	207.6114	217.2706
ARMA (2,1)	215.2440	224.9031
ARMA (2,2)	209.0835	220.6745

Note: The asterisk indicates the model to be retained according to the selected criterion.

A comparison of the selection criteria between the different models estimated is shown in Table D9.2. This leads us to select the ARMA (1,1) process for the *Inflation rate*. The estimation of this process is shown in Table D9.3.

Table D9.3: Estimation of the mean equation: ARMA (1,1) process,
1973 to 2023 period

Variable	*Inflation rate*
L.ar	0.556***
	(0.151)
L.ma	0.596***
	(0.183)
Constant	3.913***
	(0.927)
Sigma	1.683***
	(0.132)
Adjusted R-squared	0.133
Observations	51

Note: L.ar and L.ma represent respectively the AR (1) and MA (1) components of the ARMA (1,1) model. Robust standard errors in parentheses. *** p<0.01.

The second stage of our ARCH estimation consists in recovering the residuals $\tilde{e}_t$ from the estimation of the ARMA (1,1) mean equation and regressing $\tilde{e}_t^2$ on a constant and its q past values. To estimate the second-stage regression, we first need to determine the number of q lags to be considered. To do this, we selected the number of q lags from the graph of partial autocorrelations shown in Figure D9.3.

Figure D9.3 shows that only the fifth partial autocorrelation is significantly different from zero. We therefore use a number of q lags equal to 5 to perform the ARCH test. The results are shown in Table D9.4.

Figure D9.3: Partial autocorrelations of squared residuals ($\tilde{e}_t^2$)
1973 to 2023 period

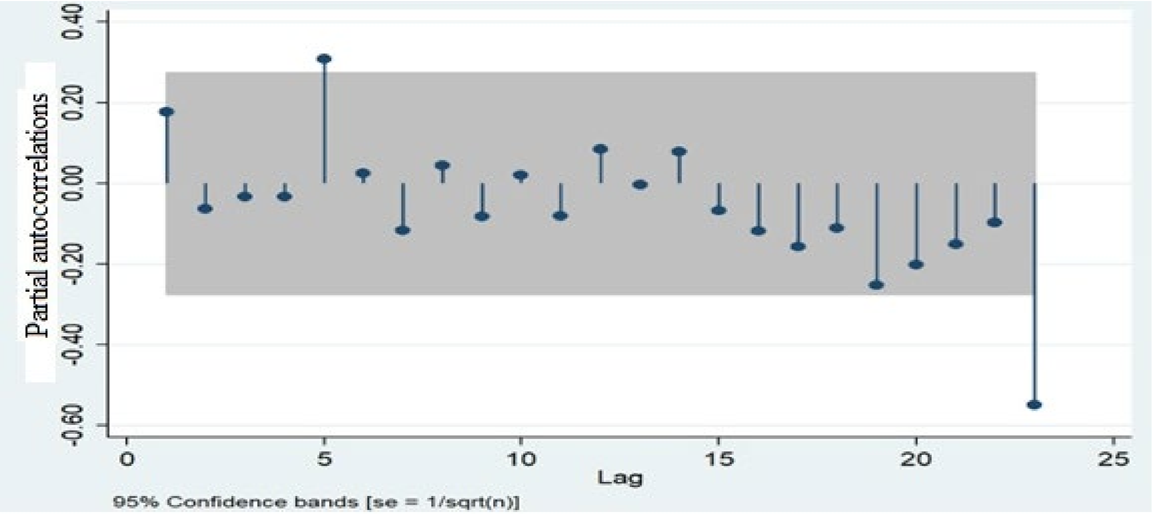


Table D9.4: ARCH test results, 1973 to 2023 period

Variable	${RES_t}^2$
L.1. ${RES_t}^2$	0.293*** (0.048)
L.2. ${RES_t}^2$	-0.039 (0.101)
L.3. ${RES_t}^2$	-0.050 (0.054)
L.4. ${RES_t}^2$	-0.085 (0.059)
L.5. ${RES_t}^2$	0.308 (0.215)
Constant	1.360 (0.989)
Observations	46
R-squared	0.230
Adjusted R-squared	0.133

Note: ${RES_t}^2$ represents the squared residuals from estimating the mean equation. Robust standard errors in parentheses. *** p<0.01.

The results in Table D9.4 allow us to calculate a TR^2 statistic of 10.58 and a $\chi^2(5)$, which gives us a value of 9.236 at the 10% threshold. Given that $TR^2 \geq \chi^2(5)$, we reject the null hypothesis. We find that the autoregressive coefficient associated with one-period lagged squared residuals is significantly different from zero. In other words, there is an ARCH effect in our *Inflation rate* series.

D9.2 Comparison of nonlinear stochastic processes in variance (EGARCH) and nonlinear stochastic processes in the mean (Markov)

The results show that the two forms of nonlinear stochastic process, namely the nonlinear stochastic process in variance (EGARCH (1,1) model) and the nonlinear stochastic process in the mean **(**two-regime Markov model), are well suited to capture the asymmetry observed in the US inflation series. To select the process best suited to our data, we use the selection criteria shown in Table D9.5 to distinguish between the two forms of nonlinear stochastic process.

Table D9.5: Comparison criteria for estimated models, 1973 to 2023 period

	LL	AIC	BIC	Wald
Markov 2 states	-105.14	220.29	229.94	87.91*
EGARCH	-93.82	199.64	211.23	66.77

Note: LL is the log-likelihood value at the optimum, AIC and BIC are the information criteria of Akaike and Schwarz respectively. The asterisk indicates the model to be retained according to the selected criterion.

A comparison of the selection criteria shows, first, that the results obtained differ very little, suggesting that the two models of the GARCH class (nonlinear stochastic process in variance) and Markov (nonlinear stochastic process in the mean) are relevant for modeling the inflation series. However, the comparison shows a slight advantage for the Markov regime-switching model over the EGARCH model.

Despite their many empirical successes, EGARCH models share two major weaknesses. First, they fail to produce unconditional distributions of *Inflation rate* with tails as thick as those observed in reality, even when replacing $z_t \sim N(0, 1)$ by a distribution with thicker tails than $N(0, 1)$, such as the *t*-distribution. Second, in EGARCH models, the conditional variance of the *Inflation rate* (${\sigma_t}^2$) is nonrandom. This is a problem because financial theoretical models now assume that volatility is a random process. The class of models known as random volatility models, such as the case of the Markov model where the conditional variance of the *Inflation rate* (${\sigma_{s_t}}^2$) is random because it depends on the state of the regime $s_t \in (1,2)$, solves both of these problems.

Appendix E9: Effects of control variables on insurers' performance

E9.1 Introduction

Very few academic studies have analyzed the relationship between macroeconomic and insurance variables, and those that did often focused on *Premiums* and claims. This makes it difficult to draw conclusions about profitability effects related to changes in macroeconomic environments such as inflation.

A recent study by Rohman et al. (2023) examined the relationship between macroeconomic indicators and both gross insurance *Premiums* and claims in a sample of 63 countries around the world during the period 2010-2019. The authors do not take into account the *COVID-19* period, so their analysis must be considered to have been made in a low inflation environment. The four studied indicators are GDP, inflation, real interest rates and exchange rates. The authors demonstrate that GDP, inflation and real interest rates have a positive significant effect on *Premiums* in the non-Life sector, but only GDP and inflation have a lasting effect.

Their main hypotheses obtained from the literature are the following:

- GDP has a positive relationship with *Premiums* because more consumers are able to buy more insurance when GDP increases (Beenstock et al, 1988); this relationship is confirmed by the estimations.
- Interest rate has a negative relationship with *Premiums* because higher interest rates lead households to postpone consumption (Li et al, 2007). However, Beck and Webb (2003)

suggest a positive empirical effect because high interest rates drive higher investment opportunities for insurers and make insurance products more attractive.

- Real inflation should have a negative impact on *Premiums* because price stability is an important predictor of insurance consumption (Beck and Webb, 2003, cited in Rohman et al., 2023). However, they obtain a positive relationship in their empirical analysis.
- Regarding the effects of these variables on claims, the static results mentioned for *Premiums* above remain the same. However, the result for interest rate is insignificant.

Christophersen and Jakubik (2014) studied the relationship between gross *Premiums* and economic growth and unemployment in Europe with EIOPA data on 30 countries during the period of 2005 to 2012. They affirmed a strong link between nominal GDP and premium growth, with more sensitivity for Life insurers when unemployment is taken into account.

According to Christophersen and Jakubik (2014), Bianchi et al. (2011) found a positive relationship between real premium growth and growth in the CESEE region of Europe, and Feyen et al. (2011) obtained a positive relationship between *Premiums* and per capita income from a panel of 90 countries during the 2000-2008 period.

Further, Stathopoulos and Vrontos (2022) found that Life insurance demand increases in periods of economic downturn, described by declining GDP, stable interest rates and consumers' preference for spending over saving.

E9.2 Mean and standard error of insurance company performance variables in both regimes

Tables E9.1 and E9.2 present the descriptive statistics for the main variables analyzed.

Table E9.1: Mean and standard error in the P&C sector for both regimes, 1973 to 2023 period

	State 1(N=38)		State 2 (N=13)	
Variable	Mean	SE	Mean	SE
Loss ratio	77.04	6.06	74.62	3.31
Expense ratio	26.77	1.07	26.58	1.08
Combined ratio	103.82	5.88	101.19	3.73
Net investment income to Total assets (ratio)	0.04	0.01	0.05	0.01
Operating ratio	91.55	4.90	91.49	3.28
ROA (ratio)	0.027	0.01	0.04	0.02

Note: State 1: low inflation; State 2: high inflation.

The mean and standard error of the six P&C insurer performance measurement variables in Table E9.1 show different trends between the two states of inflation for some variables. We also note that the mean and standard error of the six variables that measure the performance of Life insurance companies in Table E9.2 show different trends for some variables.

Table E9.2: Mean and standard error in the Life sector in both regimes, 1973 to 2023 period

	State 1 (*N*=38)		State 2 (*N*=13)	
Variable	Mean	SE	Mean	SE
Loss ratio	99.35	21.65	100.00	21.44
Expense ratio	28.74	8.64	31.87	12.65
Combined ratio (%)	128.09	20.29	131.87	11.09
Net investment income to Total assets (ratio)	0.057	0.02	0.058	0.014

	State 1 (*N*=38)		State 2 (*N*=13)	
Variable	Mean	SE	Mean	SE
Operating ratio (%)	59.38	21.94	64.43	15.98
ROA (ratio)	0.06	0.05	0.07	0.05

Note: State 1: low inflation; State 2: high inflation.

E9.3 Indicators for measuring insurance companies' profitability

The objective is to determine the impact of inflation on insurance companies' profitability. We have selected six variables to measure this performance: *Loss ratio*, *Expense ratio*, *Combined ratio*, *Net rate of return to Total assets*, *Operating ratio* and *ROA*. We also analyze *Premiums* and *Claims*.

To understand the impact that inflation can have on insurance companies' profitability, we must first understand insurers' role and how they function. The role of insurance companies is to provide protection to individuals or businesses (policyholders) against adverse events. Policyholders make regular payments (*Premiums*) and receive benefits (*Claims*) from the insurance company when certain predefined events occur. P&C insurance companies cover property (insurable consumption) and personal insurance. Life insurance companies operate in three lines of business: health insurance, Life insurance, and annuity contracts, which are divided into two sub-sections (fixed annuities and variable annuities). The Life insurance and annuity contracts lines of business constitute the first Life sub-sector. It includes savings products. The health insurance line of business constitutes the second Life sub-sector, which covers healthcare. Generally, a distinction is made between the Life insurance sub-sector and the health insurance sub-sector. Savings is an integral part of this Life insurance sub-sector and involves the investment of funds collected (*Premiums*) by insurers on behalf of policyholders. Health insurance, in contrast, is comparable to

P&C insurance since the costs of bodily injury claims, including medical expenses, equipment, or third-party compensation, are short term.

In this subsection, we have selected macroeconomic variables other than inflation that can also influence insurance companies' profitability. These variables depend on the state of the US economy, either low inflation (State 1) or high inflation (State 2). It should be noted that macroeconomic variables generally adjust after being disrupted by a shock. The adjustment of macroeconomic variables refers to the mechanisms by which an economy seeks to return to a state of equilibrium after being disrupted by a shock. These adjustments can be made through changes in economic policy (as in the case of the 1979 monetary policy change) or changes in the behavior of economic agents, particularly consumers and businesses (as in the case of behavioral changes during and after the *COVID-19* pandemic in 2020 and beyond).

To illustrate the adjustment of macroeconomic variables in the context of an inflationary shock, we use the example of the 1979 change in monetary policy. Figure 9.1 in the section shows that there was a change in the direction of monetary policy under the leadership of Paul Volcker at the Federal Reserve in 1979 intended to bring the US economy back to equilibrium after the disruption of the shocks to the oil price of the 1970s. This monetary policy consisted of significantly raising the key interest rate in order to slow down economic activity and dampen inflation. This policy influenced the health of the economy because the key interest rate affects not only consumers' willingness to spend or save, but also companies' investment and risk management decisions. The evolution of inflation (*Inflation rate*) and the nominal rate on long-term government bonds (10-year maturity) moved in the same direction throughout the period (Figure 9.1). This is an example of the adjustment of macroeconomic variables after a shock to the economy.

Since macroeconomic variables generally adjust after being disrupted by an inflationary shock, we have selected a number of macroeconomic variables that can also influence the profitability of insurance companies. Like our *Inflation rate* interest variable*,* the macroeconomic control variables depend on the state of the regime (*s*)*,* namely whether the US economy is in a period of low inflation (State 1) or high inflation (State 2). To choose the macroeconomic control variables to include in our model, we analyzed the correlation between a set of macroeconomic variables and selected those that are less correlated with each other and with inflation (Table E5) in order to avoid any potential multicollinearity issues. Following this analysis, we selected the following three variables: *S&P 500 return, GDP per capita growth*, and *real interest rate.* Sánchez (2015) showed, based on the work of other authors, that the Markov-switching model could be applied in economics to these three macroeconomic variables: *S&P 500 return*, GDP, and interest rate.

E9.4 Independent variable of interest: *Inflation rate*

In theory, in both periods of low inflation (State 1) and periods of high inflation (State 2), when inflation rises, workers' incomes should also rise to keep pace with inflation. Further, as incomes rise, so does insurance consumption. This should increase sales of insurance products (P&C and Life). In this case, the *Premiums* variable is therefore an increasing function of inflation. Rising inflation could also exert downward pressure on the level of *Premiums* collected, as rising inflation reduces the purchasing power of consumers and businesses. However, the lower the purchasing power of consumers and businesses, the less they purchase insurance products (P&C and Life). We can therefore say that in periods of low inflation (State 1) and high inflation (State 2), we should expect a negative or positive sign for the *Premiums* variable in both the P&C and Life sectors.

We have just shown that we could expect a negative or positive sign for the *Premiums* variable in the P&C sector in periods of low inflation (State 1) and high inflation (State 2). In addition, we know that there is a positive relationship between the *Premiums* variable and the *Claims* variable, since repair and replacement costs generally increase with the purchase of insurable consumer goods in the P&C sector. In other words, we should expect a negative or positive sign for the P&C *Claims* variable in periods of low inflation (State 1) as well as in periods of high inflation (State 2). Since the health insurance line of business is comparable to the P&C sector, we should also expect a negative or positive sign for the *Claims* variable in the health insurance line of business of the Life sector in both states.

With regard to the two other lines of business in the Life sector (Life insurance and annuity contracts), we should expect the *Claims* variable to have a negative sign in periods of low inflation (State 1) and a positive sign in periods of high inflation (State 2). Low inflation (State 1) benefits the stock markets, as financial returns increase during periods of low inflation. This increase in financial returns during periods of low inflation in turn leads to an increase in the benefits paid by Life insurers in both the Life insurance and annuity lines of business, thereby increasing Life insurers' expenses. In contrast, high inflation (State 2) is detrimental to the stock markets: financial returns tend to decline. This leads to a decrease in the benefits paid by insurers in both the Life insurance and annuity business lines (decrease in benefits paid).

In conclusion, in periods of low inflation (State 1), we should expect a negative or positive sign for the *Claims* variable for the entire Life sector, since inflation has a positive or negative influence on the *Claims* variable in the health insurance line of business of the Life sector and a negative influence on the *Claims* variable in both lines of business of the Life sector (Life insurance and annuity contracts). In periods of high inflation (State 2), we should expect a negative or positive sign for the *Claims* variable for the entire Life sector, since inflation has a positive or negative influence on the *Claims* variable in the Life sector's health insurance line of business and a positive influence on the *Claims* variable in both lines of business in the Life sector (Life insurance and annuity contracts).

E9.5 Macroeconomic indicator *S&P 500 return*

The variable *S&P 500 return* represents the return on the stock market index based on the shares of 500 large companies listed on US stock exchanges. It affects the profitability of P&C insurance business through individuals' willingness to spend on durable consumer goods. It also affects the profitability of the Life sector through individuals' willingness to save (invest) in Life insurance policies (Life insurance and annuity contracts).

In general, low inflation is beneficial for stock markets because of the negative correlation between inflation and stock market returns. In other words, when the economy is in a period of low inflation (State 1), the return on the S&P 500 increases. Further, stock market returns are positively correlated with consumption because an increase in the return on risky assets can increase investors' purchasing power. This will then increase individuals' willingness to spend on durable consumer goods and thus increase *Premiums* in the P&C sector. We can therefore deduce that in periods of low inflation (State 1), the *S&P 500 return* variable has a positive influence on P&C insurers' profitability via the *Premiums* variable. From a savings perspective, an increase in the return on the S&P 500 will make investments more attractive. This will then have a positive influence on sales in the Life insurance sub-sector (Life insurance and annuity contracts) of the Life sector. We can therefore deduce that in periods of low inflation (State 1), the *S&P 500 return* variable has a positive influence on the profitability of Life insurers' insurance business via the *Premiums* variable.

We have just shown that an increase in the *S&P 500 return* should lead to an increase in the purchase of insurable consumer goods in periods of low inflation. However, we know that the repair and replacement costs paid by P&C insurers rise as purchases of insurable consumer goods increase. Consequently, claims paid by P&C insurers should increase during periods of low inflation. We can therefore say that during periods of low inflation (State 1), the *S&P 500 return* variable has a negative impact on the profitability of P&C insurers via the *Claims* variable. In addition, good management of risky assets can generate returns that increase the funds accumulated by policyholders and therefore increase the benefits payable by Life insurers. We can therefore deduce that the benefits payable by Life insurers (funds accumulated by policyholders) increase with stock market returns. Thus, in periods of low inflation (State 1), the *S&P 500 return* variable has a negative influence on the profitability of Life insurers' insurance business via the *Claims* variable.

In State 2, high inflation tends to lower the return on the S&P 500. This makes investments less attractive and reduces individuals' willingness to save. This will have a negative impact on sales in the Life insurance sub-sector (Life insurance and annuity contracts) of the Life sector and on *Premiums* in the P&C sector (positive correlation between the return on risky assets (equities) and consumption). We can therefore conclude that in periods of high inflation (State 2), the *S&P 500 return* variable has a negative impact on Life insurers' profitability (declining *Premiums*) via the *Premiums* variable, and a negative impact on P&C insurers' profitability via the *Premiums* variable. *R*egarding the benefits to be paid by P&C insurers, as consumption declines during periods of high inflation (State 2), the purchase of insurable consumer goods also declines.

However, we know that the costs of repairs and replacements paid by insurers also decrease as purchases of insurable consumer goods decline. In other words, the *S&P 500 return* variable has a positive influence on P&C insurers' profitability (lower benefits to pay) via the *Claims* variable. In the Life insurance sector, lower returns during periods of high inflation (State 2) also lead to a decrease in benefits paid by Life insurers (positive correlation between the *S&P 500 return* and benefits paid in the Life insurance sector). We can therefore deduce that the *S&P 500 return* variable has a positive influence on Life insurers' profitability (lower benefits paid) via the *Claims* variable.

E9.6 Macroeconomic indicator *GDP*

The *GDP per capita growth* variable (GDP) represents the growth rate of gross domestic product per capita. The GDP variable affects the profitability of the Life insurance sub-sector (Life insurance and annuity contracts) of the Life sector and the profitability of P&C insurers.

Low inflation (State 1) can stimulate economic growth by encouraging consumption and investment. We can therefore deduce that when the economy is experiencing low inflation (State 1), the GDP variable has a positive influence on P&C insurers' profitability via the *Premiums* variable (*Premiums* driven upward by increased consumption) and a positive influence on Life insurers' profitability via the *Premiums* variable (*Premiums* rise due to strong financial market performance). Further, the GDP variable should have a negative influence on P&C insurers' profitability via the *Claims* variable during periods of low inflation (State 1), as the repair and replacement costs paid by insurers increase with the use of insurable consumer goods (rising P&C benefits). Regarding Life insurance benefits, we can also predict an increase in the benefits to be paid. If the financial markets perform well, policyholders will see their accumulated funds (net asset value) increase, leading to an increase in the benefits to be paid by Life insurers.

Further, high inflation can harm economic growth and cause an economic recession. In addition, it is well known that interest rates rise during periods of expansion and fall during periods of recession. Falling interest rates during a recession make investments less attractive (lower interest on bonds). As consumers' willingness to save declines, their tendency to spend increases. In other words, we can say that in periods of high inflation (State 2), the decline in the GDP variable has a negative influence on P&C insurers' profitability (because consumption decreases) and a positive influence on the profitability of Life insurers via the *Premiums* variable (higher saving). In addition, in periods of high inflation, the decline in the GDP variable has a negative impact on P&C insurers' profitability via the *Claims* variable, as the repair and replacement costs paid by insurers increase. Regarding Life benefits, we can also predict a decline in the benefits to be paid. If financial markets perform poorly during a recession (declining GDP), policyholders will see their accumulated funds (net asset value) decline, resulting in a decrease in benefits payable by Life insurers.

E9.7 Macroeconomic indicator *Real interest rate*

The real interest rate measures the return on an investment or the cost of a loan, adjusted for inflation. It affects the profitability of the insurance business of the Life insurance sub-sector (Life insurance and annuity contracts) of the Life sector and the profitability of P&C insurers' insurance business. The real interest rate often measures financial returns such as the *S&P 500 return.* Therefore, the analysis results should be almost the same as in the case of the *S&P 500 return* variable.

In periods of low inflation (State 1), the real interest rate (nominal rate minus inflation) tends to be higher. A high real interest rate indicates that financial markets perform well in periods of low inflation. Saving then becomes more attractive, which could increase Life *Premiums*. Further, as stock market returns are positively correlated with consumption (higher returns on risky assets increase investors' purchasing power), P&C *Premiums* will also increase. As in the case of the *S&P 500 return* variable*,* we can deduce that in periods of low inflation (State 1), the *Real interest rate* variable has a positive influence on the profitability of Life insurers and a positive influence on the profitability of P&C insurers via the *Premiums* variable. Further, as in the case of the *S&P 500 return* variable*,* we can conclude that in periods of low inflation (State 1), the *Real interest rate* variable has a negative influence on the profitability of P&C insurers (increase in benefits paid) and a negative influence on the profitability of Life insurers (increase in benefits paid) via the *Claims* variable.

In periods of low inflation (State 1) when the economy is doing well (high real interest rate and less uncertainty about the future), the analysis results are the same as for the *S&P 500 return* variable. However, in periods of high inflation (low real interest rate and greater uncertainty about the future), the analysis results are not the same as for the *S&P 500 return* variable. Precautionary saving may help explain this.

In periods of high inflation (State 2), inflation erodes real interest rates by reducing economic growth and causing economic recession. However, it is well known that uncertainty decreases during periods of expansion and increases during periods of recession. In other words, the decline in real interest rate in a situation of high inflation increases uncertainty about the future. In this context, households increase their savings to improve their ability to cope with random shocks. This is known as precautionary saving (Leland, 1968). Precautionary saving reduces current consumption and therefore increases savings. As consumers' willingness to save increases at the expense of their willingness to spend during periods of high inflation (State 2), we can conclude that during periods of high inflation (State 2), the *Real interest rate* variable has a positive influence on Life insurers' profitability and a negative influence on P&C insurers' profitability via the *Premiums* variable. With regard to the *Claims* variable, the *Real interest rate* variable has a negative influence on Life insurers' profitability (increase in benefits payable) and a positive influence on the profitability of P&C insurers' insurance business (decrease in benefits payable) via the *Claims* variable. Predictions are summarized in Table E3.

Table E9.3: Summary of expected signs of macroeconomic variables on the profitability of insurance activity (P&C and Life)

	State 1			State 2		
Panel A: P&C	*Premiums*	*Claims*	Perf. Expected	*Premiums*	*Claims*	Perf. Expected
S&P 500 return	+	+	+ or −	−	−	+ or −
GDP per capita growth	+	+	+ or −	−	−	+ or −
Real interest rate	+	+	+ or −	+	+	+ or −
Panel B: Life	*Premiums*	*Claims*	Perf. Expected	*Premiums*	*Claims*	Perf. Expected
S&P 500 return	+	+	+ or −	−	−	+ or −
GDP per capita growth	+	+	+ or −	+	+	+ or −
Real interest rate	+	+	+ or −	−	−	+ or −

Note: Perf. indicates insurer's performance.

E9.8 Sectoral control variables

E9.8.1 Sectoral control variables P&C

To analyze the impact of inflation on the profitability of the P&C insurance business, we identified a number of control variables likely to influence the profitability of P&C insurance companies. We calculated the correlation coefficients for a set of sectoral variables in the P&C insurance sector (Table E9.6) and selected those that were less correlated with each other in order to avoid any potential multicollinearity issues. This approach enabled us to select *Household Consumption* and *Real Dhutry House* as P&C sectoral control variables to be included in our econometric model.

Household Consumption

The *Household Consumption* variable represents the level of total household consumption in the economy. It corresponds to the market value of all goods and services, including durable goods (cars, washing machines, personal computers, etc.), purchased by households. It excludes purchases of housing but includes imputed rents for owner-occupied housing. This variable influences both the P&C *Premiums* variable and the P&C *Claims* variable. With regard to the P&C *Premiums* variable, an increase in consumer spending may lead to an increase in the purchase of insurable consumer goods, which should increase the P&C *Premiums* collected. In other words, the P&C *Premiums* variable is an increasing function of the *Household Consumption* variable. We can therefore say that the *Household Consumption* variable has a positive influence on the profitability of insurance companies in the P&C sector via the *Premiums* variable.

We have just mentioned that an increase in consumer spending implies an increase in the purchase of insurable consumer goods. We also know that repair and replacement costs should also increase with the ownership of insurable consumer goods. We can therefore deduce that the P&C *Claims* variable is also an increasing function of the *Household Consumption* variable. It is therefore possible that the *Household Consumption* variable has a negative influence on the profitability of insurance companies' P&C insurance business via the *Claims* variable.

Real Dhutry House

The second P&C sectoral variable selected is *Real Dhutry House*. The *Real Dhutry House* variable represents the service costs associated with owning a home. It excludes the purchase price of housing. It influences the P&C *Claims* variable since it represents the service costs associated with home ownership, including repair and replacement costs (*Claims*) related to property and casualty insurance policies. As repair and replacement costs increase the P&C *Claims* variable, the P&C *Claims* variable is an increasing function of the *Real Dhutry House* variable. We can therefore say that the *Real Dhutry House* variable has a negative influence (increased benefits paid) on the profitability of insurance companies in the P&C sector via the *Claims* variable. The *Real Dhutry House* variable also has a positive influence (increased *Premiums*) on the profitability of insurance companies in the P&C sector via the *Premiums* variable, as it increases the *Premiums* payable upon renewal of P&C contracts. Indeed, if claims are becoming increasingly expensive due to the service costs associated with property and casualty insurance policies, it is clear that the premium amount will rise.

E9.8.2 Life sectoral variables

To analyze the impact of inflation on the profitability of the Life insurance business, we used the same method of calculating correlation coefficients (see Table E6) as before. This allowed us to identify the following three variables: *Household Consumption, Employment to Pop Ratio*, and *Death Rate* as control variables likely to influence the profitability of insurance companies in the Life sector.

Household Consumption

In general, individuals divide their income between two complementary macroeconomic variables: consumption (represented by our variable *Household Consumption*) and savings.

The *Household Consumption* variable affects the profitability of the insurance business in each of the three lines of business in the Life sector: health insurance, Life insurance, and annuity contracts. It influences the profitability of the health insurance line of business (health insurance policies) through the consumption variable and the profitability of the insurance business in the Life insurance sub-sector (Life insurance and annuity contracts) of the Life sector through the savings variable. Regarding the profitability of the health insurance business line (health insurance policies), we can show that health insurance is comparable to P&C insurance. To do this, note that, as in the case of the P&C sector, the *Household Consumption* variable has a positive influence on *Premiums*. So the *Household Consumption* variable should have a positive effect on *Premiums* and a negative influence on the profitability of the health insurance line of business in the Life sector via the *Claims* variable.

As mentioned, the *Household Consumption* variable affects the profitability of the Life insurance sub-sector (Life insurance and annuity contracts) of the Life sector through the *Savings* variable. Given the inverse relationship between the consumption variable and the savings variable, we should see effects opposite to those expected in the case of the P&C insurance sector and the health insurance line of business in the Life sector. Consequently, we might expect the *Household Consumption* variable to have a negative influence on the profitability of the Life insurance sub-sector (Life insurance and annuity contracts) of the Life sector via the *Premiums* variable. Regarding the *Claims* variable, an increase in the *Household Consumption* variable implies a decrease in savings. Further, a decrease in *Premiums* also leads to a decrease in benefits payable by Life insurers. Consequently, the *Household Consumption* variable has a positive influence on the profitability of the Life insurance sub-sector (Life insurance and annuity contracts) of the Life sector via the *Claims* variable.

Employment

The *Employment* variable represents the proportion of the total population that is employed. It affects the profitability of the insurance business in the annuity contracts line of business (individual and group annuities) and the profitability of the insurance business in the health insurance line of business (group Life insurance) in the Life sector.

The *Employment* variable influences the profitability of the annuity insurance business (individual and group annuities) because *Premiums* are collected throughout the insured's period of employment and benefits are paid to them in the form of a lifetime annuity, generally from age 65 (the legal retirement age in the United States) until their death. An increase in this variable should therefore have a positive impact on the *Premiums* variable, as *Premiums* from the working population should be collected in large numbers. As mentioned, the *Employment* variable also influences the profitability of the group Life insurance line of business (health insurance). Group Life insurance covers many people under a single policy, often managed by a company for its employees. In the vast majority of cases, the *Premiums* paid are shared between the employer and the employees. The higher the proportion of workers within the total population, the more *Premiums* should be collected. This indicates that the *Employment* variable would positively influence the *Premiums* variable in the context of a group policy, as in the case of the annuity business line. We can therefore say unequivocally that the *Employment* variable has a positive influence on the profitability of Life insurers' insurance business via the *Premiums* variable.

Regarding the *Claims* variable, when the *Employment* variable increases, this has a positive influence on the profitability of annuity insurance via the *Claims* variable, as compensation will be paid to a small number of retirees (the retired population is a minority relative to the working population). In the case of group Life insurance (health insurance), the *Employment* variable can have a negative or positive influence on the Life *Claims* variable. This ambiguity can be explained by the fact that group policies combine good and bad risks. Thus, if the increase in the employed population measured by the *Employment* variable is coupled with a decrease in medical claims paid, it can be argued that good risks dominate bad risks. In this context, there are economies of scale in group Life insurance (health insurance) benefits, which could exert downward pressure on medical care benefits. In contrast, if the employed population measured by the *Employment* variable and demand for health services increase simultaneously, particularly due to rising drug prices, a higher risk of overconsumption (bad risks), or a higher risk of fraud (bad risks), then it can be argued that bad risks dominate good risks. Further, if bad risks dominate good risks, the *Employment* variable could exert upward pressure on claims paid for medical care. In conclusion, the *Employment* variable could have a positive or negative influence on the profitability of the Life sector.

Death rate

The *Death rate* variable affects the profitability of the annuity business line (individual and group annuities) and the Life insurance business line in the Life sector. In other words, it affects the Life insurance sub-sector (Life insurance and annuities) of the Life sector.

The *Death rate* variable represents the risk of mortality or longevity (life expectancy) since longevity and mortality risks offset each other. An increase in longevity risk reduces mortality risk and vice versa. An increase in mortality implies a reduction in life expectancy (longevity risk) according to the inverse relationship between these two risks. Thus, an increase in mortality would exert downward pressure on the *Premiums* variable in both the annuity business line and the Life insurance business line, as *Premiums* would have to be collected over a short period (decreasing life expectancy). In other words, the *Premiums variable* is a decreasing function of the *Death rate* variable in the annuity business line and in the Life insurance business line. Thus, the *Death rate* variable has a negative influence on Life insurers' profitability via the *Premiums* variable.

According to Hull (2023), longevity risk has a positive influence on the *Claims variable* in the annuity business line (because the annuity must be paid for a longer period) and a negative influence on the *Claims* variable in the Life insurance business line (because the final payment is delayed). Since there is an inverse relationship between longevity risk and mortality risk, we can say that the *Claims* variable is a decreasing function of the *Death rate* variable in the annuity business line and an increasing function of the *Death rate* variable in the Life insurance business line. We can therefore conclude that the *Death rate* variable has a positive or negative influence on Life insurers' profitability via the *Claims* variable. A summary of the predictions is presented in Table E9.4.

Table E9.4: Summary of expected signs for sectoral control variables (P&C and Life)

Panel A: P&C	Performance *Premiums*	Performance via *Premiums*	Performance *Claims*	Performance via *Claims*	Performance expected
Household Consumption	+	+	+	−	+ or −
Real Dhutry House	+	+	+	−	+ or −

Panel B: Life	Performance *Premiums*	Performance via *Premiums*	Performance *Claims*	Performance via *Claims*	Performance expected
Household Consumption	+ or −	+ or −	+ or −	+ or −	+ or −
Employment	+	+	+ or −	+ or −	+ or −
Death rate	−	−	+ or −	+ or −	+ or −

Table E9.5: Empirical correlations matrices for macroeconomic variables

- P&C sector

	State 1				State 2			
	Premium	*S&P 500 return*	*GDP per capita growth*	*Real interest rate*	*Premium*	*S&P 500 return*	*GDP per capita growth*	*Real interest rate*
Premium	1.0000				1.0000			
S&P 500 return	0.4410	1.0000			-0.2455	1.0000		
GDP per capita growth	0.1367	0.4524	1.0000		0.0386	-0.0638	1.0000	
Real interest rate	0.8244	0.6010	0.2133	1.0000	0.1874	-0.2316	-0.0246	1.0000

- Life sector

	State 1				State 2			
	Premium	*S&P 500 return*	*GDP per capita growth*	*Real interest rate*	*Premium*	*S&P 500 return*	*GDP per capita growth*	*Real interest rate*
Premium	1.0000				1.0000			
S&P 500 return	0.3374	1.0000			-0.0440	1.0000		
GDP per capita growth	-0.1068	0.3298	1.0000		0.0926	-0.0268	1.0000	
Real interest rate	0.8433	0.4439	-0.0896	1.0000	-0.1298	-0.3788	-0.1028	1.0000

Table E9.6: Empirical correlations matrice for sectoral variables

- P&C sector

	Households' consumption	*Real Dhutry House*
Households' consumption	1.000	
Real Dhutry House	-0.165 (0.246)	1.000

- Life sector

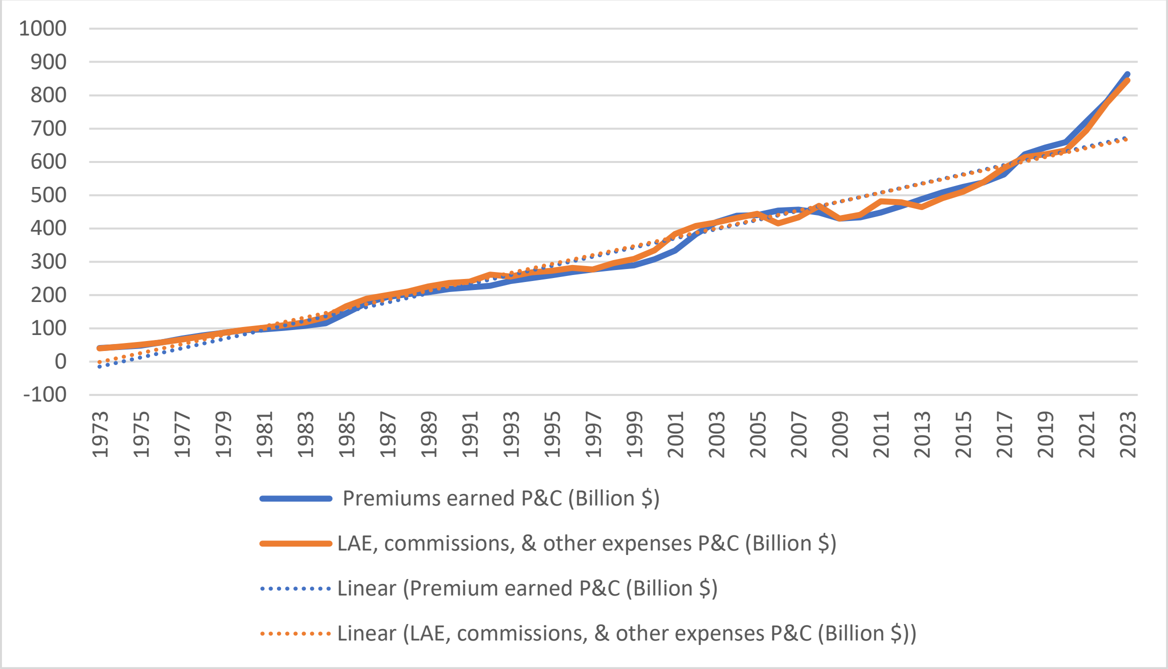
	Households' consumption	*Death rate*	*Employment to pop ratio*
Households' consumption	1.000		
Death rate	0.181	1.000	
Employment to pop ratio	0.193 (0.176)	-0.253 (0.073)	1.000

E9.9 Transformation of original data for the *Claims* and *Premiums* variables into a logarithm

Here, we want to determine the impact of inflation on *Premiums* collected and benefits paid by insurers. As we have shown, the *Premiums* variable and the *Claims* variable can each be an increasing or decreasing function of inflation, so we might expect inflation to have a positive or negative impact on the *Premiums* variable and the *Claims* variable. Before moving on to the empirical validation of this hypothesis, we will transform the original data for the *Claims* and *Premiums* variables into logarithms.

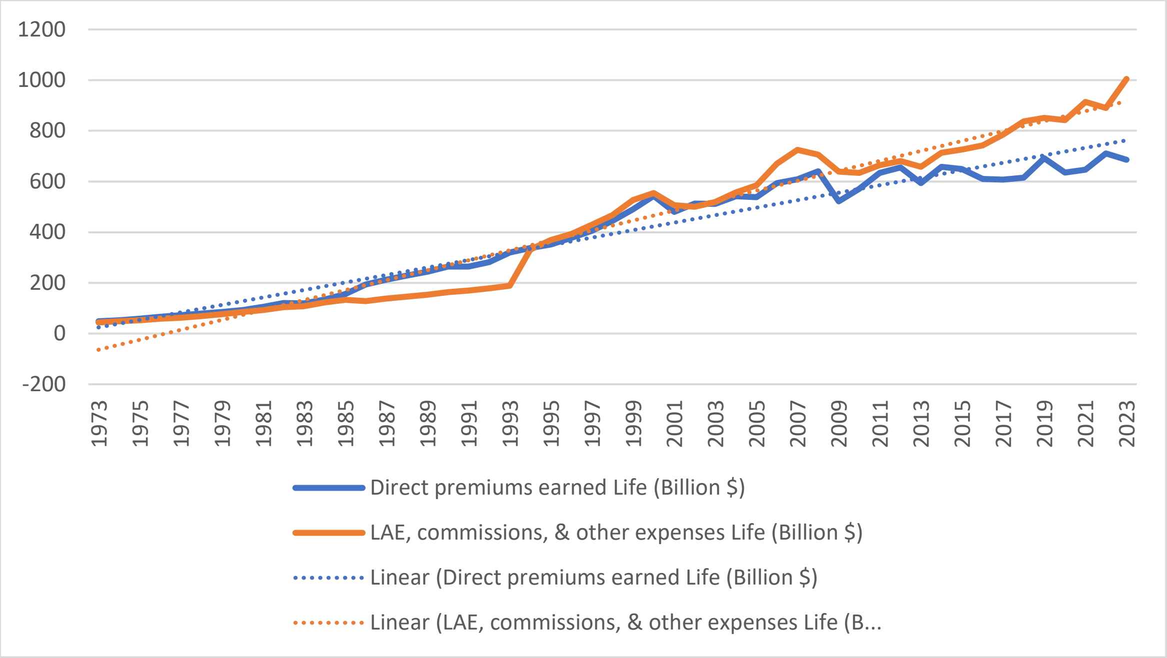
In time series econometrics, when the original variables are linear, it is often useful to transform them to facilitate the interpretation of the results. The appropriate transformation when the linear variable is measured in current dollars (e.g., gross domestic product) is the logarithmic transformation. The logarithmic transformation allows the data to be approximated in terms of growth rate.

Figure E9.1: Trends in inflation (*Inflation rate*), *Premiums* collected and Loss and adjustment expenses (LAE) in the P&C sector, 1973 to 2023 period



Source: AM Best

Figure E9.2: Trends in inflation (*Inflation rate*), *Premiums* collected and Loss and adjustment expenses (LAE) in the Life sector, 1973 to 2023 period



Source: American Council of Life Insurers (ACLI)

Table E9.7: Correlation matrix with *Premiums*

	State 1				State 2			
P&C	*Premiums*	*S&P 500 return*	*GDP per capita growth*	*Real interest rate*	*Premiums*	*S&P 500 return*	*GDP per capita growth*	*Real interest rate*
Premiums	1.00				1.00			
S&P 500 return	0.44	1.00			-0.25	1.00		
GDP per capita growth	0.14	0.45	1.00		0.039	-0.06	1.00	
Real interest rate	0.82	0.60	0.21	1.00	0.19	-0.23	-0.02	1.00

	State 1				State 2			
Life	*Premiums*	*S&P 500 return*	*GDP per capita growth*	*Real interest rate*	*Premiums*	*S&P 500 return*	*GDP per capita growth*	*Real interest rate*
Premiums	1.00				1.00			
S&P 500 return	0.34	1.00			-0.04	1.00		
GDP per capita growth	-0.11	0.33	1.00		0.09	-0.03	1.00	
Real interest rate	0.84	0.44	-0.09	1.00	-0.13	-0.38	-0.10	1.00

Table E9.8: Correlation matrix with *Claims*

	State 1				State 2			
P&C	*Claims*	*S&P 500 return*	*GDP per capita growth*	*Real interest rate*	*Claims*	*S&P 500 return*	*GDP per capita growth*	*Real interest rate*
Claims	1.00				1.00			
S&P 500 return	0.23	1.00			-0.39	1.00		
GDP per capita growth	0.05	0.05	1.00		-0.30	0.12	1.00	
Real interest rate	0.72	0.32	0.11	1.00	0.17	-0.33	-0.02	1.00

	State 1				State 2			
Life	*Claims*	*S&P 500 return*	*GDP per capita growth*	*Real interest rate*	*Claims*	*S&P 500 return*	*GDP per capita growth*	*Real interest rate*
Claims	1.00				1.00			
S&P 500 return	-0.33	1.00			-0.05	1.00		
GDP per capita growth	-0.06	0.22	1.00		0.11	-0.12	1.00	
Real interest rate	-0.07	0.19	0.11	1.00	0.54	-0.18	0.02	1.00

10. Effect of inflation on insurers’ main financial indicators with panel data in the US P&C insurance industry

10.1 Introduction

In this section, our goal is to study the effect of inflation on the insurance industry by using panel data on P&C insurers during the 1993-2023 period.

Protecting against the risks associated with fluctuating inflation may become necessary for insurers. For example, unanticipated variations in inflation may increase claims volatility and total expenses without an increase in *Premiums* in the short run, thus increasing the combined ratio. This will reduce the profitability of the underwriting business. Under competition, increasing *Premiums* to recover the equilibrium profitability may be problematic for insurers. However, higher interest rates can generate higher investment results to compensate losses in underwriting activity in the long run.

Our data make it possible to investigate the causality links between *Liquidity creation ratio*, *Reinsurance demand*, *ROA*, and other important decision variables for insurers, along with their relationships with inflation in a dynamic panel where the number of observations is quite large, and the number of periods is moderately large.

We use observed and forecasted measures of inflation. We compute forecasted rates of inflation from the Bayesian Vector Autoregression (BVAR) model under two different distribution assumptions, the Gaussian distribution and the Student-*t* distribution. The Student-*t* distribution lets us capture the heavy-tailed data and skewness often observed in macroeconomic variables, particularly during periods of high volatility such as the 2007-2009 financial crisis and the *COVID-*

19 pandemic. The Gaussian distribution is used to describe the multivariate normal distribution of the data. By incorporating forecasted inflation, the analysis aligns with the forward-looking nature of financial markets, which are driven by expectations rather than realized values.

For the econometric estimations, we proceed with the Generalized Method of Moments (GMM) with fixed effects. Since the study by Arellano and Bond (1991), the GMM procedure has become a standard method for estimating parameters with dynamic panel data. However, when the number of moment conditions is large, bias estimates can be obtained with the standard GMM estimation method, particularly when the autoregressive parameter of the dependent variable is close to unity (Blundell and Bond, 1998; Doran and Schmidt, 2006; Okui, 2009). We apply the GMM-FOD model to reduce potential bias estimates.

The rest of the section is organized as follows. We present a literature review on the effect of inflation on the insurance sector in Subsection 10.2, along with a description of inflation during our period of analysis. Subsection 10.3 describes the main variables used in this research. The descriptive statistics are summarized in Subsection 10.4. Subsection 10.5 adds more structural analysis with the Generalized Method of Moments (GMM) model. Subsection 10.6 estimates the main relationships between the variables of our study with the GMM-FOD model. Subsection 10.7 illustrates the effect of inflation on *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* in the P&C sector during the 1993-2023 period including the *COVID-19* pandemic. Subsection 10.8 documents inflation results on six additional financial variables that are analyzed in Appendix F10. Subsection 10.9 summarizes the main results and concludes the section.

10.2 Economic inflation and literature review

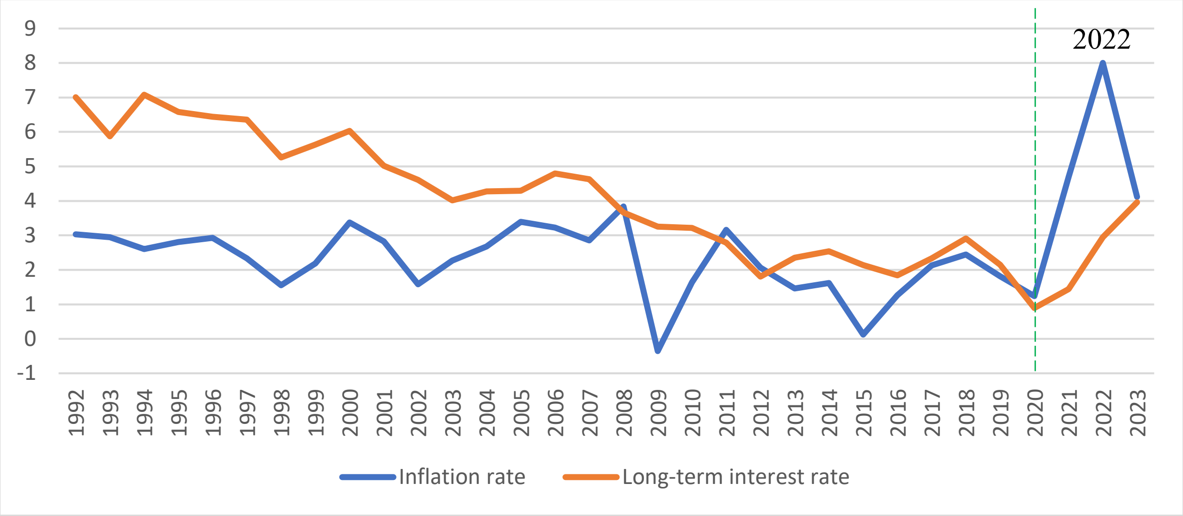
10.2.1 Measuring inflation

The price index most often used to measure inflation is the Consumer Price Index (*CPI*) of a large basket of goods and services (Bureau of Labor Statistics, BLS). For many years, the BLS has updated the index, and no significant bias has been documented in recent years. In this research, to analyze the effect of inflation variation, we use the *Inflation rate,* defined as the annual percentage change of the *CPI*.

10.2.2 Historical inflation rates in US

Understanding historical inflation is important. Stock and Watson (2007) argue that the changing economic conditions in recent decades have made it more difficult to accurately predict inflation. Figure 10.1 presents the trends of *Inflation rate* from 1992 to 2023. Three observations can be made from Figure 10.1. First, the *Inflation rate* reached historically low points in 2009 and 2015. It floated around 0 and 3.8% throughout the post-2000 period and before *COVID-19*. The second observation stems from the specific nature of the post-2000 period, marked by higher volatility. Finally, Figure 10.1 shows that inflation and the nominal rate of LT government bonds (10-year maturity) moved in the same direction over the entire period. We can clearly see that the reduction of inflation observed between 1992 and 2020 has led to a reduction in the interest rates on LT (10-year maturity) government bonds in which insurers invest significantly.

Figure 10.1: Trends in *Inflation rate*
and in the nominal rate of LT (10-year) government bonds, 1992 to 2023 period



Note: The *Inflation rate* is the percentage change of the Consumer Price Index (*CPI*).
Source: World Bank.

10.2.3 Causes of recent inflation

As observed in Figure 10.1, inflation was below 4% over the 1992-2020 period. The 2007-2009 financial crisis did not accentuate price variations significantly, although it affected financial markets. The *COVID-19* crisis had a different pattern on price stability by creating shortages in many markets and inciting many governments to inject money in the economy. Following the recent *COVID-19* pandemic, inflation has become an international growing concern, as observed in the recent data.

Bernanke and Blanchard (2025) analyze the causes of the post-*COVID-19* inflation. They show that, for the US, the recent inflation period was explained by strong increases in the prices of food and energy. Supply disruptions in key sectors also caused inflation. Concomitantly, tightening labor supply contributed to wage inflation.

The US response to the *COVID-19* pandemic included a series of federal intervention plans that caused roughly $5 trillion in US government spending. These programs fueled strong consumer and business demand, which affected labor markets in mid-2021 and early 2022, putting upward pressure on wages and prices.

In summary, rising commodity prices and supply chain disruptions were the principal triggers of the recent inflation. When these factors became less significant, labor market conditions and wage increases enhanced the main drivers of the rate of price increase.

10.2.4 Effect of inflation on the insurance industry

Masterson (1968) measures the impact of inflation on insurers by isolating components that are related to separate lines of business. He shows that during the 1966-1967 years, inflation did not have an isolated impact on insurers' performance.

During the 1951-1976 period, inflation had a negative correlation with underwriting profit margins and investment returns in the P&C insurance industry (D'Arcy, 1982). No significant correlation between underwriting profits and inflation was observed during the 1977-2006 period (Krivo, 2009). A positive relationship between T-Bill yields and inflation was estimated in both the 1951-1976 and 1977-2006 periods. In fact, D'Arcy (1982) recommends using T-Bills to immunize deteriorations in underwriting profit margins due to inflation.

Another potential impact of inflation is on the investment portfolio. An increase in interest rates reduces the value of fixed income holdings in the short run, which make up a significant proportion of investments for property-casualty insurers. Insurance investment returns were significantly negatively correlated with inflation during the period 1933-1981 (D'Arcy, 1982) and 1977-2006

(Krivo, 2009). In addition, stock returns were significantly negatively correlated with inflation during the period 1933-1981 (D'Arcy, 1982), although not during the 1977-2006 period (Krivo, 2009). This discrepancy may be due to the level of inflation and whether it was expected. If inflation rates were to increase sharply, the short-run impact on property-casualty insurers would be significant. Earnings from both underwriting and investments would be reduced, and policyholder surplus would decrease as a result of both increased liabilities and reduced asset values. In the long run, higher interest rates may become an important hedging financial instrument.

Lowe and Warren (2010) describe the negative impact of inflation on property-casualty insurers' claim costs, loss reserves and asset portfolios. They express concern that most recent actuaries, underwriters and claim staff have never experienced severe inflation, so could be slow to adapt to any change in the economic environment.

Social inflation is particular to insurance. It is defined as excessive growth in insurance settlements or excessive inflation in claims (Lynch and Moore, 2023; The Institutes, 2020; Pain, 2020; Badiel and Dionne, 2025). It has increased auto liability claims by more than 20 billion during the period 2010-2019 (Lynch and Moore, 2023). It is also important in other liability markets including medical malpractice (Wellington, 2023). It is difficult to separate social inflation from pure economic inflation. In this research, we assume that social inflation is included in the *Inflation rate*.

Insurers are also likely to experience adverse development on loss reserves if inflation increases. As explained in D'Arcy et al. (2009), loss reserves are commonly set based on the inherent assumption that the inflation experienced in the recent past will continue until these claims are closed. For some liability insurance lines, it can take a decade for losses to close.

The resurgence of inflation in 2021 was a surprise in insurance markets (Geneva Association, 2023). According to the report, the immediate impact of inflation on non-Life insurers' earnings should be negative, primarily through rising future claims costs on current insurance policies and the need to protect loss reserves with more capital.

According to EIOPA (2023), the key determinants of P&C insurers' welfare sensitivity to inflation and corresponding higher interest rates are the exposure to interest rate-sensitive assets, the relative duration of liabilities and the sensitivity of claims and expenses to inflation. Inflation may also have an impact on regulated capital. A decrease in the value of fixed income assets leads to a decrease in market risks, while an increase in exposure to future *Premiums* might lead to a potential increase in underwriting risk. When assessing the impact of inflation on profitability, the time horizon needs to be considered. In the short run, the impact of inflation on profitability is typically negative, in particular for non-Life insurers with a higher share of business in competitive lines of business such as liability insurance.

More recently, Dionne et al. (2025) analyzed the effect of inflation on the US insurance industry during the period 1973-2023 with aggregate data. They show that P&C insurers were significantly affected by inflation fluctuations, especially in periods of high inflation. The negative results on *Premiums*, probably explained by a reduction in clients' purchasing power, caused a negative performance on P&C insurers overall. The positive results on investments did not create a significant hedging effect in this sector. The Life sector was less affected by inflation.

10.3 Data and variables

10.3.1 Data

We first focus on three important financial indicators: *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* in the US property-casualty insurance industry. Other items of financial statements[7] are also analyzed in detail. We use data from the National Association of Insurance Commissioners' (NAIC) annual financial statements. Our data set is a panel of US P&C insurers. Our period of data ranges from 1992 to 2023, which gives us coverage of the 2007-2008 financial crisis, the 2001 recession, and the *COVID-19* crisis. The year 1992 is used for lagged variables.

Several data exclusion criteria are applied. We first remove insurers with nonpositive total admissible assets and *Premiums*. We exclude insurers reporting a value outside the 0 and 1 range for *Reinsurance demand*. The observations are winsorized at the 1% and 99% levels to remove potential outliers. In order to estimate fixed-effect regressions with lagged variables, firms with only one year of observations are also removed. The resulting sample consists of 51,951 firm-year observations, from 3,163 P&C insurers. Insurers entered or left the market during the study period. We thus have an unbalanced panel to permit a comprehensive dynamic evaluation of inflation in the US P&C insurance industry.

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[7] *Premiums to Total assets*, *Losses incurred to Total assets*, *Net gain from operations to Total assets*, *Net investment income to Total assets*, *Net realized capital gains to Total assets*, and *Capital ratio*.

10.3.2 Dependent variables

- Revenue and risk intensity

Reinsurance demand, *Premiums to Total assets*, and *Losses incurred to Total assets* are key metrics that measure an insurer's risk transfer activity, operational volume, and risk burden. We use *Reinsurance demand* (*Reins*) to quantify the extent to which an insurer relies on reinsurance. This metric is calculated as the sum of affiliated reinsurance ceded and non-affiliated reinsurance ceded, divided by the sum of direct business written and reinsurance assumed. *Reinsurance demand* reflects an insurer's capital management strategy and risk appetite—indicating how much risk is transferred to reinsurers versus retained on the insurer's own balance sheet.

Premiums to Total assets measures how intensively a company uses its asset base to generate underwriting revenue, providing insight into the operational scale relative to Total assets. *Losses incurred to Total assets* serves as a measure of the insurer's risk burden, indicating the proportion of claims costs incurred relative to its total assets. *Net gains from operations to Total assets* summarizes the results from underwriting business.

- Liquidity management

The *Liquidity creation ratio*, denoted as Liquid, measures an insurer's liquidity creation in the economy relative to its total admitted assets. It is calculated as LC/Total assets, where LC (liquidity creation) is defined in Table A10.1, Step 3. This ratio reflects the insurer's capacity to meet immediate and short-term obligations through the use of liquid assets, providing an important indicator of financial flexibility and short-term solvency. Usually, LC/Total assets is negative in insurance markets because insurers invest more in short-term assets than in long-term assets (Desjardins et al., 2022).

- Profitability and returns

ROA (return to Total assets), *Net investment income to Total assets*, and *Net realized capital gains to Total assets* are key profitability metrics that measure the returns generated by an insurer's operations and investments relative to its total assets. These metrics focus on returns, providing valuable insights into an insurer's performance, operating efficiency, and financial strength, especially when comparing companies of different sizes.

Net investment income to Total assets and *Net realized capital gains to Total assets* both originate from the investment side and capture different sources of return: *Net investment income to Total assets* reflects income from interest, dividends, and rental income; *Net realized capital gains to Total assets* captures net profits from the sale of investments.

ROA serves as a broad indicator of an insurer's overall accounting profitability. It aggregates the effects of underwriting performance, investment results, and capital gains, offering a single accounting measure of return relative to assets. While generally more stable than other profitability measures, *ROA* is influenced by claims experience, pricing cycles, and investment market conditions. Capital to Total assets (*Capital ratio*) measures financial strength and capital adequacy. Together, these ratios help stakeholders evaluate how effectively an insurer converts its assets into profits.

Reinsurance demand and *Liquidity creation ratio* primarily address aspects of risk transfer and short-term solvency, rather than directly reflecting profitability. In contrast, *ROA* captures the overall financial outcome of an insurer's operations, investment income, and realized capital gains.

Table 10.1 summarizes the definitions and construction of each dependent variable and provides their respective symbols for reference.

Table 10.1: Dependent variables: definition, symbol, and construction

Variable name	Symbol	Variable definition	Variable measurement
Reinsurance demand	*Reins*	Affiliated reinsurance ceded + non-affiliated reinsurance ceded/direct business written plus reinsurance assumed	How much risk is transferred to reinsurers — capital and risk management tool
Liquidity creation ratio	Liquid	LC/Total assets	Ability to meet short-term obligations — liquidity health
ROA (return to Total assets)	*ROA*	Net income before dividends to policyholder, after capital tax and before all others federal and foreign income taxes/Total assets	Overall profitability relative to Total assets — includes underwriting, investment income, capital gains, and other activities
Premiums to Total assets	Pe	*Premiums* earned to Total assets	Revenue from underwriting relative to Total assets — a measure of operational intensity
Losses incurred to Total assets	Li	Claims incurred to Total assets	Measure the cost of claims relative to Total assets, representing the insurer's operational risk burden. It includes claims already paid, claims reported but not yet settled, and estimates for claims incurred but not yet reported (IBNR).
Net gains from operations to Total assets	Nibdt	Net gains earned from operations to Total assets	The insurer's profit from core activities — combining underwriting results and net investment income but excluding realized capital gains. It reflects net income before policyholder dividends, after capital taxes, and before all other federal and foreign income taxes, measured relative to Total assets.
Net realized capital gains to Total assets	Rcg	Net earned capital gains to Total assets	The profit an insurance company records from selling or disposing of investments, such as stocks, bonds, or other assets. These gains or losses are recognized at

Variable name	Symbol	Variable definition	Variable measurement
			the time of sale and are measured relative to the insurer's total assets.
Net investment income to Total assets	Ii	*Net investment income* earned to Total assets	The revenue an insurer earns from its investment portfolio, after deducting related expenses. It primarily consists of recurring earnings such as interest and dividends, measured relative to the insurer's total assets.
Capital ratio	Capital	Policyholders' surplus to Total assets	Measures the financial strength and capital cushion relative to assets. Measures the proportion of a company's total assets financed by shareholder equity and surplus, which is essentially the company's ownership stake in itself. A key indicator of a company's financial health and stability.

Note: This table presents the definitions of the dependent variables analyzed in this study.

10.3.3 *Inflation rate* measures[8]

The inflation measures used in this research consist of one observed annual *Inflation rate* and four forecasted rates generated at different horizons (*t*+1 and *t*+3) using Bayesian Vector Autoregression (BVAR) models. These BVAR models are based on two different assumptions:

- Gaussian distribution without stochastic volatility (*F1-GAUSS*, *F3-GAUSS*);
- Student-*t* distribution with stochastic volatility (*F1-MST*, *F3-MST*)

where F1 and F3 are for forecasted inflation at one- or three-year horizons, respectively. GAUSS is for Multivariate Gaussian distribution, and MST is for Multivariate Skew-*t* distribution.

The Student-*t* distribution captures the heavy-tailed data and skewness often observed in macroeconomic variables, particularly during periods of high volatility such as the 2007-2009

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[8] See Section 11 for a more detailed analysis of these inflation measures.

financial crisis and the *COVID-19* pandemic. The Gaussian distribution is used to describe the multivariate normal distribution of data. By incorporating forecasted inflation, the analysis aligns with the forward-looking nature of financial markets, which are driven by expectations rather than realized values. Table 10.2 presents the different inflation measures used in this study.

F1 measures the expected change in inflation over the next 4 quarters (1 year ahead) compared to the most recent observed inflation over the past 4 quarters. This is forecast data vs. observed data comparison. It reflects how inflation is expected to evolve in the short term relative to current inflation trends, capturing near-term inflation shocks or changes in trend. F3 measures the expected change in inflation between two future periods: from year 3 (quarters *t*+9 to *t*+12) compared to year 2 (quarters *t*+5 to *t*+8). This is forecast data vs. forecast data comparison (all values are predicted). It reflects the anticipated change in the inflation trend between the medium to longer term. Table 10.3 summarizes the differences between the forecasted measures of inflation.

Table 10.2: Inflation measures

Variable description	Variable name	Variable measurement
Observed inflation	*Inflation rate*	*Inflation rate* measured by the variation of the Consumer Price Index (*CPI*) during a period of time, which is the average change in prices for a basket of goods and services over time.
One-year ahead GAUSS	*F1-GAUSS*	Measured as the average of the predicted *Inflation rate* with the Gaussian distribution for the quarters *t*+1 to *t*+4 minus the average of the observed *Inflation rate* during the last previous four quarters (quarters *t*−3 to *t*).
One-year ahead Student-*t*	*F1-MST*	Measured as the average of the predicted *Inflation rate* with the Skew-*t* distribution for the quarters *t*+1 to *t*+4 minus the average of the observed *Inflation rate* during the last previous four quarters (quarters *t*−3 to *t*).
Three-year ahead GAUSS	*F3-GAUSS*	Measured as the average of the predicted *Inflation rate* with the Gaussian distribution for the quarters *t*+9 to *t*+12 minus the average of the predicted *Inflation rate* during the quarters *t*+5 to *t*+8.

Variable description	Variable name	Variable measurement
Three-year ahead Student-*t*	*F3-MST*	Measured as the average of the predicted *Inflation rate* with the Skew-*t* distribution for the quarters *t*+9 to *t*+12 minus the average of the predicted *Inflation rate* during the quarters *t*+5 to *t*+8.

Note: MST refers to the Bayesian VAR with a multivariate skew Student's *t* distribution with stochastic volatility for the innovations. GAUSS refers to the Bayesian VAR with a multivariate Gaussian distribution for the innovations.

Table 10.3: Summary of the difference in forecasted measures

Feature	F1 (1-Year ahead)	F3 (3-Years ahead)
Compared to	Past observed inflation (last 4 quarters)	Future forecasted inflation (quarters *t*+5 to *t*+8)
Horizon	Short-term (next year)	Medium-to-long term (year 3 vs. year 2 ahead)
Measures	Near-term inflation pressure vs. recent past inflation	Change in expected inflation trend over time
Input type	Forecast vs. actual *Inflation rate*	Forecast vs. forecast *Inflation rate*

Note: This table summarizes the differences between the forecasted measures of inflation.

We do not have information about the inflation measures corresponding to each insurer. Our analysis compares different assumptions about potential information insurers may have used on official *Inflation rate* before the year *t* to make predictions on strategic variables in year *t*. As documented in Section 11 statistics and forecasts on inflation are available to the markets such as the Survey of Professional Forecasters (SPF) and the Federal Reserve Bank of Cleveland model. These professional forecasters do not solely rely on models; they use their judgement extensively when forming forecasts. The two forecasters' predictions are compared to F1 and F3 in Section 11.

10.3.4 Control variables

Control variables include standard variables analyzed in the literature on *Reinsurance demand*, *Liquidity creation ratio*, *ROA*, and other analyzed dependent variables (Cole and McCullough, 2006; Mayers and Smith, 1990; Garven and Lamm-Tennant, 2003; Winter, 1994; Sommer, 1996; Weiss and Chung, 2004; Powell and Sommer, 2007; Choi et al, 2013; Alhassan and Biekpe, 2019; Desjardins et al., 2022). Table 10.4 summarizes the definition and construction of each control variable and presents their symbols.

Table 10.4: Control variables: definition, symbol, and construction

Variable name	Variable description	Variable measurement
Insurance leverage	Insurance leverage ratio	Direct business written to surplus
Geographical concentration	Geographical concentration in direct premium written	Herfindahl index defined as $\sum_{l=1}^{55}\left(\frac{PW_l}{TPW}\right)^2$ where PW_l is the value of direct premium written in each US state and TPW represent the insurer's total direct *Premiums* written
Regulatory pressure	Regulatory pressure	Dummy variable equal to 1 if firm's net premium to surplus ratio ≥ 300%, 0 otherwise
Liabilities	Liabilities to liquid assets ratio	Dummy variable equal to 1 if firm's adjusted liabilities to liquid assets ratio ≥ 100%, 0 otherwise
Line concentration	Line of business concentration in direct premium written	Herfindahl index defined as $\sum_{l=1}^{22}\left(\frac{PW_l}{TPW}\right)^2$ where PW_l is the value of direct *Premiums* written in each line of business in the insurers' annual statement and TPW represents the insurer's total direct *Premiums* written
Reinsurance price	Reinsurance price	$\frac{Net\ premium\ written - exp - divp}{D \times losses\ incurred}$ where *exp* = Commissions, expenses paid and aggregate write-ins for deduction *divp* = Dividend paid *D* is the Discount factor used in Winter (1994) to calculate the economic loss ratio Losses incurred is losses incurred in current year
Tax exemption	Tax exemption investment income	Bond interest exempt from federal taxes plus 70% of dividends received from common and preferred stock
Information asymmetry	Information asymmetry	Standard deviation of the firm's ROE over the last 5 years
Loss development	2-yr loss development	Estimated losses and loss expense incurred 2 years before current year and prior year scaled by policyholder's surplus
New York license	New York license	Dummy variable equal to 1 if firm is licensed in New York State, 0 otherwise
Cost of capital	Cost of capital	Average of positive ROE over the last 5 years

Variable name	Variable description	Variable measurement
Firm size	Firm size	Logarithm of total admitted assets
Group affiliation	Firm affiliated with a group	Dummy variable equal to 1 if the insurer is affiliated with a group, 0 otherwise
Mix concentration	Business mix concentration	Herfindahl index of commercial lines short and long tails or personal and commercial lines

Note: This table presents the definitions of the control variables used in different regression models. Note that model specification can change from one dependent variable to another.

10.4 Descriptive statistics

Summary statistics for all insurers are shown in Table 10.5. To capture the variation of the different dependent variables by insurer size, we divide the sample of insurers into two classes:

1. Large insurers, whose total admitted assets are greater than $3 billion;
2. Small insurers, whose total admitted assets are less than $1 billion.

Summary statistics for all variables of large and small insurers are shown in tables A10.2 and A10.3 in Appendix A10. Among the 51,951 insurer-year observations, large insurers account for 2,294 observations and small insurers for 45,909 observations. The sum of the two groups is not equal to 51,951 because we need lagged observations for the estimations, and insurers may change size categories over time.

Table 10.5 indicates that the mean value of *Reinsurance demand* is 37.3%, with a 28.6% standard deviation for all insurers. Small insurers seem to use larger amounts of reinsurance to mitigate risk. On average, the *Reinsurance demand* for large insurers is 30.6%, and is 37.8% for small insurers, as tables A10.2 and A10.3 show. Large insurers control 65.3% of the premium earned in the industry and small insurers control 18.3% of the insurance activity. Medium insurers, not presented in this study, represent 16.4% of the industry.

Table 10.5: Summary statistics for all insurers, 1992-2023

Variable at time *t*	Obs	Mean	Median	Std	Min	Max
Reinsurance demand	51951	0.3732	0.3198	0.2863	0.0000	1.0000
Liquidity creation ratio	51951	-0.5158	-0.5175	0.2136	-3.2730	0.6358
ROA (return on assets)	51951	0.0289	0.0323	0.0773	-2.7319	2.6411
Premiums to Total assets	51951	0.3658	0.3313	0.2524	0.0000	13.8625
Losses incurred to Total assets	51951	0.2059	0.1765	0.1808	0.0000	12.0445
Net gain from operations to Total assets	51951	0.0289	0.0323	0.0773	-2.7319	2.6411
Net investment income to Total assets	51951	0.0311	0.0291	0.0232	-0.1567	2.1969
Net realized capital gains to Total assets	51951	0.0046	0.0009	0.0261	-1.1001	2.4636
Capital ratio	51951	0.4416	0.4015	0.1920	0.0000	1.0000
Insurance leverage ratio	51951	1.8951	1.1457	2.8564	0.0000	33.0000
Geographical concentration	51951	0.5818	0.5823	0.3859	0.0303	1.0000
Regulatory pressure	51951	0.0301	0.0000	0.1710	0.0000	1.0000
Liabilities	51951	0.1129	0.0000	0.3164	0.0000	1.0000
Line concentration	51951	0.5807	0.5181	0.2921	0.0991	1.0000
Reinsurance price	51951	3.7668	3.3591	2.2527	0.0000	12.0000
Tax exemption investment income	51951	0.2490	0.1875	0.2390	0.0000	1.0000
Information asymmetry	51951	0.1146	0.0743	0.1401	0.0020	1.1110
Year loss development	51951	-2.2992	-1.9458	18.8737	-73.7500	80.6200
New York license	51951	0.3202	0.0000	0.4666	0.0000	1.0000
Cost of capital	51951	0.0731	0.0727	0.1313	-0.4648	0.5280
Firm size	51951	18.2447	18.1755	2.0338	11.1758	26.6716
Group affiliation	51951	0.6610	1.0000	0.4734	0.0000	1.0000
Mix concentration	51951	0.6923	0.6409	0.2482	0.2505	1.0000

Note: Variables are defined in tables 10.1 and 10.4. Statistics are for the 1992-2023 period while the analyses are for the 1993-2023 period, due to the use of lagged observations.

The average *Liquidity creation ratio* is -51.6% for all insurers, indicating that insurers generate negative liquidity creation (long-run investments) normalized by total admitted assets. Choi et al. (2013) and Alhassan and Biekpe (2019) obtained -47% and -45%, respectively. The average *Liquidity creation ratio* (standard deviation) is -51.8% (22%) for small insurers; whereas for large insurers, the ratio is -49.9% (15%), indicating that large insurers generate slightly more long-run liquidity creation in the economy than small insurers do. The respective standard deviations indicate, however, much more variability for small insurers.

The average *ROA* is 0.0289 overall, with large insurers achieving a higher average of 0.0376 compared to 0.0281 for small insurers. This disparity can be attributed to differences in size, scale, and operational efficiencies between large and small insurers. Large insurers benefit from economies of scale, which enable them to spread fixed costs, such as administrative expenses, over a broader base of assets or *Premiums*, thereby improving efficiency and *ROA*. They also have better access to investment opportunities, and specialized expertise, allowing for higher returns on their investments and operations. Additionally, large insurers tend to maintain more diversified portfolios, both geographically and across various lines of business, which reduces risk and enhances stability.

On average, key financial metrics for US property-casualty insurers show the following values: *Premiums to Total assets* is 0.3658, *Losses incurred to Total assets* is 0.2059, *Net gain from operations* to Total assets is 0.0289, *Net investment income to Total assets* is 0.0311, *Net realized capital gains to Total assets* is 0.0046, and *Capital ratio* is 0.4416.

When broken down by company size, large insurers report lower *Premiums to Total assets* (0.2996) and *Losses incurred to Total assets* (0.1868), but higher *Net gain from operations to Total assets* (0.0376), *Net investment income to Total assets* (0.0340), and *Net realized capital gains to Total assets* (0.0057) compared to the industry average.

In contrast, small insurers have higher *Premiums to Total assets* (0.3722) and *Losses incurred to Total assets* (0.2075), but lower *Net gain from operations to Total assets* (0.0281), *Net investment income to Total assets* (0.0310), and *Net realized capital gains to Total assets* (0.0045).

Notably, the median value for *Net realized capital gains to Total assets* is considerably lower for small insurers, at 0.0007, while it is much higher for large insurers, at 0.0021. This suggests that although the average capital gains performance appears similar, the distribution is more skewed for small insurers, with typical outcomes falling well below those of larger companies.

The *Capital ratio* variable indicates variations of capital and surplus among the different sizes of insurers. The *Capital ratio* for large insurers is 0.38 and is 0.45 for small insurers. Therefore, small insurers seem to maintain a higher level of capital than large insurers do, which affects liquidity creation because part of the surplus is assigned to illiquid liabilities.

The mean value of the *Insurance leverage* ratio for all insurers is 1.89, and ranges from 0 to 33. This ratio is, on average, 2.0 for small insurers, which is more than double that of large insurers (0.74). On average, small insurers exhibit higher *Concentration ratios* in geographical areas (0.6206 vs. 0.1978), insurance lines (0.5974 vs. 0.4151), and business mix (0.7021 vs. 0.5797) compared to large insurers. These higher concentration levels indicate less diversification, which increases risk and can lead to less stable returns.

Most large insurers are affiliated with a group (96%), compared with 62% of small insurers. Small insurers bear more risk in relation to policyholders' surplus than do large insurers; 3.2% of small insurers have net *Premiums* written to policyholders' surplus greater than 300%, compared with 2.0% for large insurers. For large insurers, 30.2% have a liability to liquid asset ratio greater than 100%, versus only 9.7% for small insurers.

The mean for the two-year *Loss development* ratio is equal to -27.1% and -2.38% for large insurers and small insurers, respectively. Only 27.1% of small insurers held a New York State license, compared with 79.8% of large insurers. Appendix D10 presents the correlation matrix of the nine key financial variables.

10.5 Analysis based on the generalized method of moments

10.5.1 Econometric model

We use a structural equations model to assess the reciprocal relationships between different dependent variables. To this end, we specify a dynamic panel data model that incorporates unobserved heterogeneity. For example, the lagged values of *Liquidity creation ratio* and *ROA* are included as key explanatory variables in the equation for *Reinsurance demand*.

This specification, where the parameters associated with lagged variables capture causal links that take time to materialize, is particularly suitable for our study. Insurers' strategic decisions, including inflation management, investments (liquidity creation) and reinsurance management, are typically made by the board of directors on an annual basis and may take several months to be fully implemented. As a result, these decisions are unlikely to have immediate effects within the same year. Therefore, we focus on annual lagged values of key variables to analyze the relationships between variables. Moreover, this model specification aligns well with Granger causality. We must emphasize that inflation coefficients cannot be interpreted as causal relationships in this model because our annual measures of inflation are aggregate variables not specific to each insurer.

We analyze the causality between different insurance variables and their links with inflation by applying a robust GMM procedure to estimate our parameters. For example, we are going to estimate equations (10.1), where $y_{i,t}$ is for *Reinsurance demand*, $x_{i,t}$ is for the *Liquidity creation ratio*, and $r_{i,t}$ for *ROA*:

$$\mathrm{y}_{i,t} = \beta_y + \beta_1 x_{i,t-1} + \beta_2 y_{i,t-1} + \beta_3 r_{i,t-1} + \delta_1 w_{i,t} + \gamma_1 IR_{t-1} + \alpha_i + \varepsilon_{i,t}$$

$$x_{i,t} = \beta_x + \beta_4 x_{i,t-1} + \beta_5 y_{i,t-1} + \beta_6 r_{i,t-1} + \delta_2 s_{i,t} + \gamma_2 IR_{t-1} + \eta_i + \nu_{i,t}. \tag{10.1}$$

and

$$r_{i,t} = \beta_r + \beta_7 x_{i,t-1} + \beta_8 y_{i,t-1} + \beta_8 r_{i,t-1} + \delta_3 k_{i,t} + \gamma_3 IR_{t-1} + \mu_i + \tau_{i,t}.$$

In equations (10.1), the dependent variables at time *t* are regressed on the control variables at time *t* and on lagged variables. Each equation of the model is in fact a dynamic panel data relationship with a lagged dependent variable, two lagged endogenous variables, individual fixed effects $(\alpha_i, \eta_i, \mu_i)$, vectors of covariates$(w_{i,t}, s_{i,t}, k_{i,t})$, and lagged *Inflation rate* (IR_{t-1}). The terms $\varepsilon_{i,t}$, $\nu_{i,t}$, and $\tau_{i,t}$ are error terms with zero mean and positive variance for $i = 1 \ldots N$ and $t = 1 \ldots T$, where *N* is the number of firms, and *T* the number of periods.

Each equation in (10.1) will be estimated separately from the other equations. We must encounter significant endogeneity issues that have been addressed in the estimation process. The first source of endogeneity arises from the presence of individual fixed effects, which create a correlation between the error term and the lagged value of the dependent variable. As a result, the lagged dependent variable must be treated as an endogenous variable in the estimation process. Consequently, applying the standard OLS method with fixed effects could likely produce biased estimates.

Lagged levels of the explanatory variables serve as instruments. An important advantage of this method is that if a variable at a given period can be used as an instrument, then all its past realizations can also be used in this way. As a result, the number of moment conditions may become quite large, even when the panel's time dimension (T) is finite. This is why we cannot analyze all dependent variables simultaneously. We limit their number to three in each estimation. The presence of a large set of moment conditions can introduce variance bias, commonly referred to as the many instruments problem. Additionally, when the autoregressive parameter is close to unity, the lagged levels of the dependent variable may become weak instruments (Blundell and Bond, 1998).

10.5.2 Model validity and overidentifying restrictions

When the number of moment conditions exceeds the number of unknown parameters estimated by GMM, it is essential to test the model's validity before making inferences. This is typically done by evaluating the overidentifying restrictions. A widely used test for this purpose is the J-test, proposed by Sargan (1958) and Hansen (1982). To ensure that our model is well specified, we apply the modified version of the J-test in the context of dynamic panel data models (Arellano and Bond, 1991).

As Roodman (2006) explains, the choice between Hansen's J-test and Sargan's test for overidentifying restrictions depends on the error structure. Sargan's test assumes homoscedasticity, whereas Hansen's J-test remains valid under heteroscedasticity. If heteroscedasticity is present, the Sargan test may incorrectly reject the null hypothesis, making it inconsistent for robust GMM estimation. The Sargan test for one-step GMM also imposes stricter assumptions about the error term than necessary.

10.5.3 Instrument count problem

GMM estimators can generate a large number of moment conditions, with the instrument count increasing quadratically with the panel's time dimension (T). This poses challenges in finite samples. First, because the number of elements in the estimated variance matrix of the moments is quadratic in the instrument count, the matrix itself grows quadratically in T. In small samples, this can lead to poor estimation of the variance matrix, potentially rendering it singular and necessitating the use of a generalized inverse. While this does not affect consistency, it can weaken the Hansen test, sometimes yielding implausibly high *p*-values, such as 1.0.

To select the number of instruments, we ensure that the number of observations exceeds the number of instruments. While adding more instruments may improve efficiency, beyond a certain point it reduces the excess of observations over instruments, leading to increased bias. Thus, the number of instruments in our model is determined based on the *p*-value of the Hansen test, ensuring it remains above 0.1 and below 0.9.

10.5.4 Forward orthogonal deviation (FOD) transformation

We apply the forward orthogonal deviation (FOD) transformation, introduced by Arellano and Bover (1995). This transformation removes fixed effects problems while minimizing data loss, making it a preferred alternative to first differencing. One key advantage of FOD is that it preserves the structure of the error term, reducing serial correlation issues that often arise with first differencing. By maintaining the integrity of the error structure, FOD helps improve the efficiency of estimations in dynamic panel models.

Additionally, FOD reduces serial correlation in the error term. First differencing often introduces a moving average structure in errors, which can weaken the effectiveness of instrumental variables. In contrast, FOD mitigates this issue by transforming the data in a way that better maintains the integrity of the error term, improving the reliability of estimation results.

10.5.5 Checking overidentification with the Hansen J-test

The Hansen J-test assesses whether the instruments used in GMM estimation are valid, meaning they are not correlated with the error term. Potential issues with the Hansen J-test include the risk of using too many instruments, which can lead to weak identification and excessively high *p*-values (e.g., > 0.9), reducing the test's reliability. Conversely, a low *p*-value (e.g., < 0.10) may suggest that some instruments are endogenous, indicating potential overfitting and weak test performance.

10.6 Econometric results with the GMM-FOD model

In this section, we estimate dynamic models for the three dependent variables: *Reinsurance demand*, *Liquidity creation ratio*, and *ROA*. Other dependent variables are analyzed in Appendix F10 and results are discussed in Subsection 10.8.

We examine the relationship between *Reinsurance demand*, *Liquidity creation ratio* and *ROA*, controlling for different insurers' financial statement variables, the financial crisis in 2007-2008, the 2001 recession, the 2020 *COVID-19* pandemic and inflation measures by applying the two-step Generalized Method of Moment (GMM) procedure to estimate our parameters with forward orthogonal deviation (FOD) transformation. The analyses are performed using Stata xtdpdgmm for two-step GMM-FOD. The two-step estimator is efficient and robust, regardless of the pattern of heteroscedasticity and cross-correlation of the sandwich covariance estimator models (Windmeijer, 2005). Results on control variables are presented in Table A10.4. Those for large insurers and small insurers are in tables A10.5 and A10.6. In Appendix E, we present the OLS estimation results with fixed effects as reference regressions.

10.6.1 Basic estimation results

Table 10.7 presents the estimation results of the two-step GMM-FOD model using 1,395 instruments in each equation, with Windmeijer-corrected standard errors. For brevity, control variables are not displayed in the table. The dataset consists of an unbalanced panel, with a maximum of 31 periods per insurer. The number of instruments is computed as 31×30 divided by 2, equal to 465 per variable, resulting in a total of 1,395 instruments for the model.

Table 10.7: Two-Step GMM-FOD Estimates of *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* for all insurers, 1993-2023

Variable	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t-1}$	0.7838	0.0435	-0.0221
	(0.000)	(0.000)	(0.032)
$Liquid_{t-1}$	0.0873	0.6877	0.1101
	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.0666	-0.0341	0.2411
	(0.000)	(0.068)	(0.000)
Number of observations	46,816	46,816	46,816
Number of firms	3,163	3,163	3,163
Number of instruments	1,395	1,395	1,395
p-value Hansen J-test	0.1455	0.0000	0.0000

Note: Two-step GMM-FOD regression model with same numbers of instruments between equations and Windmeijer-corrected standard errors. The corresponding *p*-values are reported in parentheses. Results on control variables are not presented.

The *p*-values of the Hansen J-test for instrument validity are 0.1455, 0.0000, and 0.0000, respectively. The low *p*-values (0.0000) indicate a rejection of the null hypothesis of instrument validity, suggesting that some instruments may be endogenous. This raises concerns about potential overfitting and weak test performance.

Table 10.8 presents the estimation results of all insurers of the two-step GMM-FOD model with Windmeijer-corrected standard errors and different numbers of instruments between the equations. The *p*-value of the Hansen J-test is greater than 0.10 in each column, indicating that the null hypothesis of instrument validity cannot be rejected. This suggests that the instruments used in the model are valid, meaning they are uncorrelated with the error term and not overidentified. Therefore, the instruments appear to be appropriate for the estimation process.

Table 10.8: Two-Step GMM-FOD estimates of *Reinsurance Demand*, *Liquidity creation ratio*, and *ROA* using different instrument sets for all insurers, 1993-2023

Variable	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t-1}$	0.7837	0.0365	-0.0197
	(0.000)	(0.001)	(0.052)
$Liquid_{t-1}$	0.0894	0.7185	0.0733
	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.0570	-0.2010	0.3566
	(0.000)	(0.000)	(0.000)
Number of observations	46,816	46,816	46,816
Number of firms	3,163	3,163	3,163
Number of instruments	1,860	2,436	2,436
p-value Hansen J-test	0.3225	0.3620	0.2757

Note: Two-step GMM-FOD regression model with different numbers of instruments between the equations and Windmeijer-corrected standard errors. The corresponding *p*-values are reported in parentheses. Results on control variables are not presented here. They are available in Appendix B.

The two-step GMM-FOD estimates for the lagged *Reinsurance demand*, lagged *Liquidity creation ratio*, and lagged *ROA* are 0.7837, 0.7185, and 0.3566, respectively. These values are higher than OLS estimates of Table E10.1 for both *Reinsurance demand* and *ROA*, suggesting that the instrumentation is not biased due to weak instruments. However, the estimate for the lagged

Liquidity creation ratio is slightly lower, which may indicate potential bias, but the *p-value* of the Hansen J-test is greater than 0.10. Table A10.11 and Table A10.12 present the estimation results for large and small insurers respectively.

10.6.2 Bicausality

Table 10.8 presents findings for all insurers, indicating a highly significant positive relationship between *Reinsurance demand* and *Liquidity creation ratio*. Specifically, an increase in the *Liquidity creation ratio* is associated with a higher *Reinsurance demand*, and vice versa. This pattern is also observed among small insurers, as shown in Table A10.12. However, for large insurers, Table A10.11 shows no statistically significant relationship between *Reinsurance demand* and *Liquidity creation ratio*.

The positive association in Table 10.8 suggests that as insurers engage in more liquidity creation, they may seek additional reinsurance to mitigate the increased liquidity risk. This strategy allows them to maintain financial stability while continuing to provide the economy with liquidity. Conversely, obtaining more reinsurance can enable insurers to create more liquidity by freeing up capital that would otherwise be reserved for potential claims (see Desjardins et al., 2022, for more details).

Additionally, Table 10.8 reveals a significant inverse relationship between *Reinsurance demand* and *ROA* across all insurers. Specifically, an increase in *ROA* is associated with a decrease in *Reinsurance demand*. This inverse relationship suggests that more profitable insurers tend to rely less on reinsurance, possibly due to their sufficient capital reserves; they can thus absorb risks internally.

For large insurers, Table A10.11 indicates that the lag of *ROA* is positively related to *Reinsurance demand*, while the lag of *Reinsurance demand* is negatively correlated with *ROA*. This suggests that as large insurers become more profitable, they may increase their reinsurance purchases to protect their earnings. However, increased *Reinsurance demand* may subsequently lead to a decrease in *ROA*, possibly due to the costs associated with reinsurance *Premiums*.

The results in Table 10.8 indicate a significant relationship between *Liquidity creation ratio* and *ROA* for all insurers. An increase in liquidity creation is associated with a higher *ROA*, suggesting that greater liquidity creation allows insurers to take advantage of investment opportunities and improve overall returns. However, the relationship appears to be asymmetric: while higher liquidity creation enhances profitability, an increase in *ROA* tends to reduce liquidity creation. This may be because firms with higher profitability rely less on illiquid assets and instead allocate more resources to lower-yield, more liquid investments.

Table A10.4 presents the results of the two-step GMM-FOD model with control variables and three binary variables representing three financial crises: the 2007-2008 financial crisis, the 2001 recession, and the *COVID-19* pandemic and other control variables. *Reinsurance demand* is not affected by the three variables, while liquidity creation is positively related to the 2001 recession and the financial crisis period and negatively affected by the 2020 *COVID-19* crisis. *ROA* is negatively affected by the 2001 recession, an anticipated result. Additional results are presented in Appendix C.

10.7 *Inflation rate* measures results

10.7.1 Inflation measures

In this subsection, we examine the relationship between inflation and key indicators of insurance company performance. Inflation is measured with five distinct measures—one observed and four forecasted. The measure observed is based on actual data from the *Inflation rate*, reflecting the real inflation experienced in the economy. The forecasted measures are derived using two different statistical models across two forecast horizons: a Bayesian Vector Autoregression (BVAR) model that incorporates either a multivariate skewed Student-*t* distribution (MST) or a multivariate GAUSS distribution.

To assess the impact of inflation on key financial metrics within insurance companies specifically, we rely on lagged values of both observed and forecasted inflation. For example, if *t* is 1992, the observed *Inflation rate* ($IR_{t\text{-}1}$) in 1991 is used as the lagged observed *Inflation rate*. The one-year-ahead forecasts (F1) corresponds to the expected change in inflation estimated in 1991 for the 1992 period. These are denoted as $F1\text{-}MST_{t\text{-}1}$ and $F1\text{-}GAUSS_{t\text{-}1}$, depending on the statistical model used. Similarly, the three-year-ahead forecast (F3) refers to the expected change in *Inflation rate* from forecasts made in 1990 for the period between 1992 and 1993, labeled as $F3\text{-}MST_{t\text{-}3}$ and $F3\text{-}GAUSS_{t\text{-}3}$. Once the lagged forecast of F3 is used in the analysis, it reflects how insurers responded in the past to their medium- to long-term inflation expectations.

10.7.2 Predicted relationships

- Predicted relationship between *Reinsurance demand* and inflation

The predicted relationship between *Reinsurance demand* and inflation is positive. Inflation increases the cost of claims in a competitive world, particularly in long-tail lines such as liability, health, and property insurance, where payouts may occur several years after the policy is written. This creates greater uncertainty around future liabilities and exposes insurers to inflation risk. To manage this uncertainty and preserve capital stability, insurers are likely to cede more risk to reinsurers during the next year, using reinsurance as a strategic tool to reduce exposure. In a longer period, they have more time to adjust their underwriting activities and may not require as much reinsurance if it is costly.

- Predicted relationship between *Liquidity creation ratio* and inflation

The expected relationship between liquidity creation and inflation is positive in the short run (ratio less negative). Inflation is often accompanied by higher interest rates, which reduce, in the short run, the market value of fixed-income securities that dominate insurance investment portfolios. So, insurers should reduce the short-run investments in bonds. Higher interest rates will generate more investments in bonds in the long run, however, and less liquidity creation in the economy is anticipated.

- Predicted relationship between *ROA* and inflation

The expected relationship between *ROA* and inflation should be negative in the short run. Inflation erodes the real value of investment income, especially when insurers hold fixed-income instruments with long maturities and fixed payouts. Additionally, if inflation causes claims to rise faster than insurers can adjust their *Premiums*, underwriting profitability shrinks, reducing underwriting operating returns. In the long run, insurers may have more time to adjust their portfolio by raising *Premiums* and investing in bonds. Table 10.9 presents the predicted relationships between inflation with *Reinsurance demand*, *Liquidity creation ratio*, and *ROA*.

Table 10.9: Predicted relationships in the short run and long run between inflation and *Reinsurance demand*, *Liquidity creation* ratio, and *ROA*

Variable	Predicted relationship	Rationale
Panel A: Predicted relationships in short run (one year)		
Reinsurance demand	Positive	Rising claim uncertainty encourages risk transfer.
Liquidity creation ratio	Positive	Falling bond values reduce investments in bonds in the short run.
ROA	Negative	Inflation reduces real returns when claims outpace pricing adjustments and investments lose value.
Panel B: Predicted relationships in long run (three years)		
Reinsurance demand	Negative	Potential adjustments in *Premiums* may reduce demand for reinsurance if costly.
Liquidity creation ratio	Negative	Higher expected interest rates may have a positive effect on bonds in the long run.
ROA	Neutral	Fixed-income instruments can hedge underwriting potential losses.

Note: This table presents the short-run and long-run predicted relationships between inflation and different dependent variables.

10.7.3 Results

Table 10.10 summarizes the two-step GMM-FOD estimation results, examining the impact of various inflation measures across different groups of insurers: all insurers, large insurers, and small insurers. The scores of the different inflation measures are higher with F3 and $IR_{t\text{-}1}$ at 10%. $F3\text{-}MST_{t\text{-}3}$ and $F3\ GAUSS_{t\text{-}3}$ are about equivalent with a small advantage for MST. A score value is equal to one when the inflation variable is significant at the 10% level or stronger level (5%, 1%) with the good sign.

We assess the impact of inflation while controlling additional explanatory variables. Detailed results are presented in Appendix A10. Specifically, Table A10.7 presents findings based on observed inflation, while Tables A10.8, A10.9, and A10.10 provide results based on forecasted inflation for all insurers, large insurers, and small insurers, respectively. We now discuss the results obtained with emphasis on all insurers.

Table 10.10: Two-step GMM-FOD summary results of the effect of inflation on *Reinsurance demand*, *Liquidity creation ratio*, and *ROA*, control variables included but not reported

Dependent variable	$IR_{t\text{-}1}$	$F1\text{-}MST_{t\text{-}1}$	$F1\text{-}GAUSS_{t\text{-}1}$	$F3\text{-}MST_{t\text{-}3}$	$F3\text{-}GAUSS_{t\text{-}3}$
All insurers					
Reinsurance demand	+	NS	NS	−	−
Liquidity creation ratio	+	+	+	−	−
ROA	NS	+*	+	NS	+
Large insurers					
Reinsurance demand	NS	NS	+*	NS	NS
Liquidity creation ratio	NS	+	+	NS	−
ROA	−	−	NS	NS	NS
Small insurers					
Reinsurance demand	+	−	NS	−	−
Liquidity creation ratio	+	+	+	−	−
ROA	−*	NS	NS	NS	+
Score at 10%	6	4	4	7	6

Note: *Significant at 10%. All other coefficients are significant at 5% (+,-) or not significant (NS).

- *Reinsurance demand*

As expected, a positive relationship is observed with the lagged value of actual inflation ($IR_{t\text{-}1}$), indicating that higher past inflation tends to be associated with increases in *Reinsurance demand*.

This suggests that insurers react in short time to realized inflation after inflation has materialized. This response is consistent with the industry’s need to maintain profitability and solvency in the face of rising costs.

In contrast, a negative relationship is found with the lagged three-years-ahead inflation forecasts ($F3\text{-}MST_{t\text{-}3}$ and $F3\text{-}GAUSS_{t\text{-}3}$). These variables reflect expectations, formed three years prior, about how inflation would evolve between the second and third years following the forecast. The observed negative association implies that when insurers previously anticipated long-term inflation increases, they may have adopted more strategic financial or underwriting strategies at that time, limiting the need for reinsurance in the long run. These adjustments—such as strengthening capital positions or reducing exposure to inflation-sensitive lines—could be reflected in improved or more stable current financial outcomes.

Further, no statistically significant relationship is detected with the lagged one-year-ahead inflation forecasts ($F1\text{-}MST_{t\text{-}1}$ and $F1\text{-}GAUSS_{t\text{-}1}$), which represent short-term expectations formed just one year prior. This suggests that recent short-term forecasts have had limited impact on current insurer performance. One possible explanation is that short-term expectations are either too volatile to guide meaningful short-term decisions or have already been incorporated into earlier operational responses, rendering their marginal effect at time t negligible.

Taken together, these findings suggest that insurers are more responsive to observed inflation and to long-term expectations formed well in advance, rather than to recent short-term forecasts. This likely reflects the structural lag in many insurance-related decisions, where strategic responses to anticipated long-term inflation are implemented early, while short-term inflation pressures are managed through ongoing operational adjustments.

When examining small insurers, overall patterns remain similar, with one notable exception: a surprising significant negative relationship is found with the lagged one-year-ahead forecast ($F1\text{-}MST_{t\text{-}1}$). This indicates that even recent short-term inflation expectations prompted a more cautious response among smaller insurers. Such responses may include reducing risk exposure or adjusting investment allocations because reinsurance may be too costly in periods of inflation. Given their more limited pricing power with narrower margins, small insurers are likely more sensitive to short-term inflation signals and may adopt defensive strategies accordingly.

For large insurers, most inflation variables do not show statistically significant associations with performance. The sole exception is a positive relationship with the lagged one-year-ahead GAUSS forecast ($F1\text{-}GAUSS_{t\text{-}1}$), which is significant at the 10% level. This finding suggests that large insurers may have responded to inflation expectations with proactive strategies—such as repricing policies, repositioning portfolios, or enhancing cost controls—that ultimately maintain their performance.

- *Liquidity creation ratio*

The relationship between inflation and insurers' liquidity creation reveals a nuanced, time-sensitive dynamic. A positive association is observed when inflation is measured using lagged values of actual inflation ($IR_{t\text{-}1}$) and the one-year-ahead forecasts formed in the previous year ($F1\text{-}MST_{t\text{-}1}$ and $F1\text{-}GAUSS_{t\text{-}1}$). In contrast, when inflation is proxied by lagged three-years-ahead forecasts made three years earlier ($F3\text{-}MST_{t\text{-}3}$ and $F3\text{-}GAUSS_{t\text{-}3}$), the relationship turns negative.

This pattern confirms the short run theoretical expectations, which generally anticipate a positive relationship between inflation and liquidity creation. In theory, higher inflation—often accompanied by rising interest rates—erodes the value of insurers' fixed-income portfolios and exerts upward pressure on liquidity creation (fewer bond investments). However, interest rates for new investments may increase over a longer period and reduce liquidity creation (increase more liquid investments).

When examining smaller insurers, the results align with the broader sample: a positive response to recent inflation and a negative response to past long-term expectations. Due to their limited pricing power and smaller capital capacity, these firms may be more exposed to inflationary pressures and thus more likely to make visible liquidity adjustments in response.

In contrast, for larger insurers, the relationships are less pronounced. No significant association is found with either observed inflation or lagged long-term forecasts ($F3\text{-}MST_{t\text{-}3}$), suggesting that large insurers may rely on more sophisticated strategies—such as diversified portfolios, advanced asset-liability matching, or greater market influence—to navigate inflation without substantial shifts in liquidity creation.

Overall, these findings suggest that insurers' liquidity management is horizon dependent. Realized inflation and short-term expectations tend to reduce short-term investments, whereas long-term expectations formed in the past continue to increase liquidity over time.

- *ROA*

A positive relationship is observed between *ROA* and lagged one-year-ahead inflation forecasts, both for $F1\text{-}MST_{t\text{-}1}$ (significant at the 10% level) and $F1\text{-}GAUSS_{t\text{-}1}$ (significant at the 5% level). A similar positive association is found with the lagged three-year-ahead forecast ($F3\text{-}GAUSS_{t\text{-}3}$). These surprising findings suggest that insurers who previously anticipated inflation were able to enhance profitability in the short run, possibly by adjusting pricing, reallocating investment portfolios or using more reinsurance. By incorporating inflation expectations into strategic planning, firms appear to have improved their returns relative to Total assets.

In contrast, no statistically significant effect is found between lagged observed inflation ($IR_{t\text{-}1}$) and *ROA* across the full sample. This indicates that profitability is more closely tied to anticipated inflation than to realized inflation, which may be harder to react to effectively given operational and regulatory constraints.

Among small insurers, a different pattern emerges. A negative relationship is observed between *ROA* and lagged observed inflation ($IR_{t\text{-}1}$), significant at the 10% level. This result aligns with theoretical expectations: realized inflation can erode real investment returns, increase claims costs, and compress underwriting margins, especially for smaller firms with limited pricing flexibility. At the same time, small insurers exhibit a positive relationship with lagged three-year-ahead inflation forecasts ($F3\text{-}GAUSS_{t\text{-}3}$), indicating that forward-looking strategies such as implementing inflation-aware pricing may have improved profitability when inflation was anticipated. The contrast between the negative effect of realized inflation and the positive effect of prior expectations highlights the importance of timing, particularly for resource-constrained firms.

For large insurers, the results are more nuanced. A negative association is found between *ROA* and both lagged observed inflation ($IR_{t\text{-}1}$) and the lagged one-year-ahead forecast ($F1\text{-}MST_{t\text{-}1}$). This suggests that large, well-capitalized firms, may face profitability challenges during inflationary periods, particularly when inflation is either recently realized or had been anticipated over a short horizon. These pressures may stem from rising operational costs, adverse claim developments, or the underperformance of interest-sensitive investments. However, no significant relationship is observed between *ROA* and the lagged three-year-ahead forecast, possibly reflecting large insurers' greater ability to hedge, diversify, or adjust strategically over longer timeframes.

Table 10.10 highlights the critical role of realized inflation IR_{t-1}. Insurers that used past observed inflation are, surprisingly, making appropriate decisions according to the score results at 10%. F3 models are also performing well without important differences between the two statistical distributions. These results underscore the importance of adaptive, anticipatory strategies in safeguarding insurer profitability amid inflationary environments in the long run. One-year forecast models are less accurate; this may be explained by the surprise *COVID-19* pandemic crisis.

10.8 Summary concerning *Inflation rate* results on six core financial indicators

This subsection examines the direct effects of inflation on six key financial indicators: *Premiums to Total assets*, *Losses incurred to Total assets*, *Net gain from operations to Total assets*, *Net investment income to Total assets*, *Net realized capital gains to Total assets*, and *Capital ratio*. The analysis incorporates both observed inflation and lagged inflation expectations—specifically, one-year-ahead and three-year-ahead forecasts generated by the MST and GAUSS models. Detailed results are presented in Appendix F10.

Findings indicate that large insurers adapt more quickly and systematically to inflation. They tend to raise *Premiums to Total assets* in response to current inflation and short-term expectations, likely to protect underwriting margins against rising claims and operational costs. In contrast, small insurers exhibit weaker and less consistent premium adjustments, possibly due to regulatory constraints, limited pricing power, or slower internal decision-making processes.

Losses incurred to Total assets rise with inflation for large insurers, reflecting inflation's upward pressure on claims-related expenses such as medical care, auto repairs, and construction. Large insurers' losses are more strongly tied to recent observed inflation.

Net gains from operations to Total assets are generally neutral with inflation (NS). This trend suggests that rising costs does not seem to outpace premium adjustments. The effect is more pronounced among large insurers, likely due to their broader operational footprint and fixed cost structures.

Net realized capital gains to Total assets tend to decline with observed and near-term forecasted inflation, consistent with rising interest rates eroding bond and equity values. Interestingly, a positive relationship sometimes emerges with lagged three-year-ahead forecasts—especially for small insurers—suggesting that long-term inflation expectations may inform strategic investment decisions in bonds.

Net investment income to Total assets increases with short-term inflation, as insurers reinvest maturing assets into higher-yielding instruments in a rising rate environment. This effect is visible across firm sizes when using one-year-ahead lagged forecasts. However, the relationship weakens over longer horizons.

Capital ratio generally declines in response to short-term inflation, as the real value of assets erodes while liabilities rise with inflation-driven claims and expenses. However, this trend reverses over longer horizons: lagged three-year-ahead inflation expectations are positively associated with capital ratios, particularly for small insurers.

In summary, both observed inflation and lagged inflation expectations significantly influence insurer financial performance, but effects vary by firm size and inflation horizon. Large insurers respond more immediately to recent inflation pressures, while small insurers are more affected by past expectations, reflecting differing operational agility and strategic planning horizons. These findings highlight the importance of robust inflation risk management—incorporating forward-looking pricing, disciplined underwriting, proactive capital planning, and dynamic investment strategies tailored to evolving macroeconomic conditions.

10.9 Conclusion

This section evaluates the impact of inflation—both observed and expected—on *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* for US insurers from 1993 to 2023, with particular attention to differences across firm size. Other financial indicators are analyzed. The methodology distinguishes between lagged observed inflation ($IR_{t\text{-}1}$) and inflation forecasts made one and three years prior (F1 and F3), capturing how insurers react to realized inflation and how prior expectations affect inflation management. Forecasts from Gaussian and the Student-*t* distributions give similar results in the long run while observed inflation performs better in the short run.

For *Reinsurance demand*, the findings reveal a clear positive relationship with lagged observed inflation, suggesting that insurers react to actual inflation through reinsurance protection. In contrast, long-term inflation expectations formed three years earlier are negatively associated with current *Reinsurance demand*. This implies that when insurers anticipated prolonged inflation in the past, they likely adopted more conservative strategies which manifest in more stable financial positions. Short-term forecasts ($F1_{t\text{-}1}$), however, show no significant impact on *Reinsurance demand* across the full sample, indicating that recent expectations may have had a limited influence on current decisions. Short-term forecasts may be too volatile, particularly those following the *COVID-19* pandemic.

Liquidity creation ratio demonstrates a time-sensitive dynamic. Insurers increase liquidity creation in response to realized inflation and short-term forecasts, likely as a response to manage near-term uncertainty in bond values. Conversely, long-term inflation forecasts are associated with decreasing liquidity creation in the economy and investing more in liquid assets. These patterns are more pronounced among small insurers, who are more exposed to inflationary risks and show clearer adjustments. Large insurers, by contrast, do exhibit less significant changes *in Liquidity creation ratio*, likely due to their greater diversification, stronger asset-liability matching, and broader access to financial instruments.

Regarding profitability, *ROA* improves with prior inflation expectations, a surprising result obtained, particularly with lagged one- and three-year-ahead forecasts, suggesting that insurers who planned for inflation were better positioned to adjust pricing, reallocate investments, or take advantage of higher interest rates. In contrast, realized inflation does not significantly affect *ROA* at the aggregate level. Firm-level differences are notable.

Overall, the findings indicate that insurers are responsive to long-term inflation expectations as well to realized inflation. Proactive strategies—particularly those based on long-term forecasts—appear to enhance profitability and stabilize operations, while reactions to realized inflation are more defensive.

This section also examines the direct effects of inflation on six key financial indicators: *Premiums to Total assets*, *Losses incurred to Total assets*, *Net gain from operations to Total assets*, *Net investment income to Total assets*, *Net realized capital gains to Total assets*, and *Capital ratio*.

Findings indicate that large insurers adapt more quickly and systematically to inflation. They tend to raise *Premiums* in response to current inflation and short-term expectations, likely to protect underwriting margins against rising claims and operational costs. In contrast, small insurers exhibit weaker and less consistent premium adjustments, possibly due to regulatory constraints, limited pricing power, or slower internal decision-making processes.

In summary, both observed inflation and lagged inflation expectations significantly influence insurer financial performance, but effects vary by firm size and inflation horizon. Large insurers respond more immediately to recent inflation pressures, while small insurers are more affected by past expectations, reflecting differing operational agility and strategic planning horizons. These findings highlight the importance of robust inflation risk management—incorporating forward-looking pricing, disciplined underwriting, proactive capital planning, and dynamic investment strategies tailored to evolving macroeconomic conditions.

According to the Geneva Association (2023), there is a wide range of management actions insurers can take to respond to the new macroeconomic environment. In terms of product design, insurers could offer more low-cost products with an increased focus on risk and loss prevention. With tight labor markets and increasing wage pressure, insurers can also improve operational cost efficiency and overall productivity.

One underwriting response to inflation is to reset the insurance price of risks that exhibit high claims costs. This activity depends on the competitive environment in insurance markets, insurers' anticipation about central banks' ability to reduce inflation and the degree of public policy and regulatory constraints.

In investment management, inflation protection on asset allocation can be achieved by moving the investment portfolio away from bonds toward commodities, equities and real estate. For many insurers, however, such potential activity is constrained by their very high solvency capital requirements.

In general, effective insurer responses to inflation would have to occur ex-ante, rather than ex-post. This is why inflation anticipation remains a key issue. Once inflation occurs, the value of inflation-linked securities and the level of interest rates reflect capital markets' inflation expectations, which drive up the cost of any hedging strategy. More research is still needed to match aggregate information on inflation and individual behavior.

Appendix A10: Additional data and variables

Table A10.1: Liquidity creation measure for an insurer

Step 1: We classify all items in *Total assets*, liabilities, and surplus as liquid and illiquid
Step 2: Assign weights to the activities
Step 3: Combine insurance activities as classified in step 1 and as weighted in step 2 to construct the liquidity creation (LC) measure

LC = + ½ × illiquid *Total assets* – ½ × liquid *Total assets*
+ ½ × liquid liabilities – ½ × illiquid liabilities
– ½ × surplus

Total assets	
Illiquid *Total assets* (weight = ½)	Liquid *Total assets* (weight = -½)
Mortgage loan	Cash, cash equivalents, and short-term investments
Real estate	Investments in stock and bonds
Other invested *Total assets*	
Uncollected *Premiums* and agents' balances	
Electronic data processing equipment and software	
Furniture and equipment	
Liabilities and surplus	*Liabilities* and surplus
Liquid *Liabilities* (weight = ½)	Illiquid *Liabilities* plus surplus (weight = -½)
Loss reserves within one year (Net losses and unpaid expenses)	Loss reserves with more than one year
Reinsurance payable on paid losses and loss adjustment expenses	Funds held by company under reinsurance treaties
Other expenses	Provision for reinsurance
Taxes, licenses, and fees	Amounts withheld or retained by company on others' behalf
Current federal and foreign income taxes	Draft outstanding
Net deferred tax liability	Liability for amounts held under uninsured accident and health plans
Unearned *Premiums*	Surplus
Dividends declared unpaid	

Source: Desjardins et al. (2022).

Table A10.2: Summary statistics for large insurers, 1992-2023

Variable at time *t*	Obs	Mean	Median	Std	Min	Max
Reinsurance demand	2294	0.3057	0.2434	0.2548	0.0000	0.9486
Liquidity creation ratio	2294	-0.4989	-0.4979	0.1543	-0.9949	0.2610
ROA (return on assets)	2294	0.0376	0.0368	0.0462	-0.4568	0.3989
Premiums to Total assets	2294	0.2996	0.2795	0.1639	0.0002	0.9528
Losses incurred to Total assets	2294	0.1868	0.1690	0.1117	0.0001	0.6503
Net gain from operations to Total assets	2294	0.0376	0.0368	0.0462	-0.4568	0.3989
Net investment income to Total assets	2294	0.0340	0.0318	0.0178	-0.0184	0.2954
Net realized capital gains to Total assets	2294	0.0057	0.0021	0.0238	-0.4082	0.3824
Capital ratio	2294	0.3819	0.3456	0.1519	0.0172	0.9893
Insurance leverage	2294	0.7366	0.5559	0.7884	0.0000	9.4944
Geographical concentration	2294	0.1978	0.0758	0.2794	0.0327	1.0000
Regulatory pressure	2294	0.0201	0.0000	0.1402	0.0000	1.0000
Liabilities	2294	0.3017	0.0000	0.4591	0.0000	1.0000
Line concentration	2294	0.4151	0.3213	0.2574	0.1038	1.0000
Reinsurance price	2294	3.6136	3.4514	1.5064	0.0000	12.0000
Tax exemption	2294	0.3431	0.3309	0.2086	0.0000	0.9782
Information asymmetry	2294	0.0846	0.0587	0.0965	0.0028	1.1110
Loss development ratio	2294	-0.2714	-1.4032	14.7483	-73.7500	80.6200
New York license	2294	0.7977	1.0000	0.4018	0.0000	1.0000
Cost of capital	2294	0.1069	0.0990	0.0999	-0.4648	0.5280
Firm size	2294	22.8284	22.5941	0.8438	21.8226	26.6716
Group affiliation	2294	0.9621	1.0000	0.1911	0.0000	1.0000
Mix concentration	2294	0.5797	0.5141	0.2109	0.2567	1.0000

Note: This table provides summary statistics for the period 1992-2023. Variables are defined in tables 10.1 and 10.4.

Table A10.3: Summary statistics for small insurers, 1992-2023

Variable at time *t*	Obs	Mean	Median	Std	Min	Max
Reinsurance demand	45909	0.3782	0.3235	0.2892	0.0000	1.0000
Liquidity creation ratio	45909	-0.5179	-0.5196	0.2192	-3.2730	0.6358
ROA (return on assets)	45909	0.0281	0.0318	0.0799	-2.7319	2.6411
Premiums to Total assets	45909	0.3722	0.3382	0.2608	0.000	13.8625
Losses incurred to Total assets	45909	0.2075	0.1770	0.1875	0.000	12.0445
Net gain from operations to Total assets	45909	0.0281	0.0318	0.0799	-2.7319	2.6411
Net investment income to Total assets	45909	0.0310	0.0289	0.0238	-0.1567	2.1969
Net realized capital gains to Total assets	45909	0.0045	0.0007	0.0269	-1.1001	2.4636
Capital ratio	45909	0.4506	0.4108	0.1958	0.0000	1.0000
Insurance leverage	45909	2.0055	1.2271	2.9847	0.0000	33.0000
Geographical concentration	45909	0.6206	0.6847	0.3750	0.0303	1.0000
Regulatory pressure	45909	0.0315	0.0000	0.1748	0.0000	1.0000
Liabilities	45909	0.0970	0.0000	0.2960	0.0000	1.0000
Line concentration	45909	0.5974	0.5332	0.2899	0.1139	1.0000
Reinsurance price	45909	3.7793	3.3418	2.3293	0.0000	12.0000
Tax exemption	45909	0.2381	0.1698	0.2391	0.0000	1.0000
Information asymmetry	45909	0.1180	0.0764	0.1433	0.0020	1.1110
Loss development ratio	45909	-2.3773	-1.9042	19.2975	-73.7500	80.6200
New York license	45909	0.2706	0.0000	0.4443	0.0000	1.0000
Cost of capital	45909	0.0692	0.0698	0.1334	-0.4648	0.5280
Firm size	45909	17.7733	17.8647	1.6262	11.1758	20.7227
Group affiliation	45909	0.6233	1.0000	0.4846	0.0000	1.0000
Mix concentration	45909	0.7021	0.6619	0.2489	0.2505	1.0000

Note: This table provides summary statistics for the period 1992-2023. Variables are defined in tables 10.1 and 10.4.

Table A10.4: Two-Step GMM-FOD estimates of *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* for all insurers, 1993-2023

Variable	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t-1}$	0.7835	0.0338	-0.0210
	(0.000)	(0.001)	(0.038)
$Liquid_{t-1}$	0.0906	0.7374	0.0645
	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.0578	-0.2121	0.3517
	(0.000)	(0.000)	(0.000)
2007-2008	0.0019	0.0077	-0.0013
	(0.276)	(0.000)	(0.325)
2001 recession	0.0031	0.0533	-0.0168
	(0.260)	(0.000)	(0.000)
2020 COVID-19	0.0033	-0.0137	0.0023
	(0.122)	(0.000)	(0.145)
Insurance leverage	0.0105		-0.0045
	(0.000)		(0.004)
Geographical concentration			0.0630
			(0.000)
Liabilities	0.0062		-0.0395
	(0.404)		(0.000)
Line concentration	0.0240		-0.1081
	(0.034)		(0.000)
Reinsurance price	-0.0061	0.0062	0.0116
	(0.000)	(0.000)	(0.000)
Tax exemption	-0.0067	-0.0304	
	(0.531)	(0.000)	
Loss development	-0.0003	0.0002	0.0001
	(0.011)	(0.028)	(0.133)
Firm size			-0.0121
			(0.000)
Group affiliation			-0.0082
			(0.436)
Mix concentration			0.0394
			(0.089)
Capital ratio	0.1899		
	(0.000)		
Number of observations	46,816	46,816	46,816
Number of firms	3,163	3,163	3,163
Number of instruments	1,860	2,436	2,436
p-value Hansen J-test	0.3152	0.2525	0.2676

Note: This table provides the results of two-step GMM-FOD, with Windmeijer-corrected standard errors. The corresponding *p*-values are reported in parentheses. *p*-values lower the 0.01 and 0.05 mean the coefficient is significant at 1% and 5% respectively.

Table A10.5: Two-step GMM-FOD estimates of *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* for large insurers, 1993-2023

Variable	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t\text{-}1}$	0.7730	-0.0233	-0.0608
	(0.000)	(0.642)	(0.205)
$Liquid_{t\text{-}1}$	0.0363	0.8057	-0.0252
	(0.585)	(0.000)	(0.735)
$ROA_{t\text{-}1}$	0.2046	-0.0168	0.3002
	(0.119)	(0.870)	(0.003)
2007-2008	0.0045	0.0177	-0.0180
	(0.461)	(0.004)	(0.074)
2001	0.0219	0.0642	-0.0324
	(0.031)	(0.000)	(0.001)
2020 COVID-19	0.0007	-0.0058	-0.0007
	(0.890)	(0.241)	(0.877)
Insurance leverage	0.0238		0.0084
	(0.103)		(0.709)
Liabilities	0.0233		-0.0407
	(0.251)		(0.025)
Line concentration	0.0224		-0.1369
	(0.307)		(0.006)
Reinsurance price	-0.0028	-0.0012	0.0222
	(0.543)	(0.849)	(0.000)
Tax exemption	0.0164	-0.1122	
	(0.537)	(0.000)	
Loss development ratio	0.0002	-0.0002	0.0001
	(0.683)	(0.526)	(0.725)
Firm size			-0.0175
			(0.170)
Mix concentration			0.1194
			(0.160)
Capital ratio	0.2122		
	(0.021)		
Number of observations	2,078	2,078	2,078
Number of firms	152	152	152
Number of instruments	110	110	98
p-value Hansen J-test	0.4286	0.2067	0.3896

Note: This table provides the results of two-step GMM-FOD, with Windmeijer-corrected standard errors. Corresponding *p*-values are reported in parentheses. *p*-values lower the 0.01 and 0.05 mean the coefficient is significant at 1% and 5% respectively.

Table A10.6: Two-step GMM-FOD estimates of *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* for small insurers, 1993-2023

Variable	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t-1}$	0.7918	0.0376	-0.0272
	(0.000)	(0.001)	(0.064)
$Liquid_{t-1}$	0.0881	0.7269	0.1082
	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.0560	-0.2038	0.3796
	(0.001)	(0.000)	(0.000)
2007-2008	0.0012	0.0065	0.0007
	(0.584)	(0.000)	(0.632)
2001	0.0041	0.0503	-0.0127
	(0.190)	(0.000)	(0.000)
2020 COVID-19	0.0039	-0.0144	0.0040
	(0.144)	(0.000)	(0.038)
Insurance leverage	0.0092		-0.0049
	(0.000)		(0.016)
Geographical concentration			0.0599
			(0.001)
Liabilities	0.0059		-0.0503
	(0.468)		(0.000)
Line concentration	0.0286		-0.1027
	(0.039)		(0.000)
Reinsurance price	-0.0059	0.0064	0.0112
	(0.000)	(0.000)	(0.000)
Tax exemption	0.0028	-0.0297	
	(0.806)	(0.000)	
Loss development ratio	-0.0001	0.0003	0.0002
	(0.452)	(0.051)	(0.042)
Firm size			-0.0131
			(0.000)
Group affiliation			-0.0058
			(0.636)
Mix concentration			0.0472
			(0.121)
Capital ratio	0.1807		
	(0.000)		
Number of observations	41,005	41,005	41,005
Number of firms	3,030	3,030	3,030
Number of instruments	1860	2030	1950
p-value Hansen J-test	0.2511	0.2356	0.3256

Note: This table provides the results of two-step GMM-FOD, with Windmeijer-corrected standard errors and the corresponding *p*-values in parentheses. *p*-values lower the 0.01 and 0.05 mean the coefficient is significant at 1% and 5% respectively.

As indicated in Table A10.4, the coefficients of *Capital ratio*, *Insurance leverage*, and *Line concentration* are positively and significantly associated with the *Reinsurance demand* at the 5% level of significance. This suggests that insurers with higher capital ratios, greater leverage and concentrated business lines tend to demand more reinsurance. Such relationships imply the following interpretation: Insurers with higher capital ratios, reflecting a stronger financial foundation relative to their total admitted assets, are more likely to demand more reinsurance to further protect their surplus and ensure financial stability in the face of large losses or catastrophic events.

Firms with higher *Insurance leverage*, meaning they write more direct business relative to their capital and surplus, tend to have a greater need for reinsurance to manage the elevated risk exposure tied to their underwriting capacity. A higher value of *Line concentration*, indicating a less diversified portfolio with higher exposure to specific lines of business, increases the possibility of correlated risks. Such firms are likely to demand more reinsurance to mitigate these risks and stabilize their financial performance.

The coefficients of *Reinsurance price* and *Loss development ratio*—defined as the estimated losses and loss expenses incurred two years before the current year and the prior year, scaled by policyholders' surplus—are negatively and significantly associated with the *Reinsurance demand* at the 5% level of significance. This suggests that insurers reduce their reinsurance purchases when prices rise or when past loss developments indicate higher retained losses, possibly to manage costs.

Also from Table A10.4, the coefficients of *Reinsurance price* and *Loss development ratio* are positively and significantly associated with *the Liquidity creation ratio* at the 5% level of significance, highlighting the role of external pressures and market dynamics in shaping firms' liquidity strategies.

In contrary, *Tax-exempt* is negatively associated with liquidity creation. Tax-exempt firms often operate with distinct cost structures and financial strategies compared to taxable firms, reducing their motivation to engage in liquidity-creating activities. Their unique financial frameworks provide them with more flexibility, limiting their reliance on liquidity-driven measures.

Firm size is another important determinant. Larger firms typically may benefit from economies of scale and possess significant internal resources, which reduce their dependence on external liquidity. Their robust financial position and operational efficiencies enable them to manage liabilities and growth internally, minimizing the need for liquidity creation. *Reinsurance price* also drives liquidity creation. Rising reinsurance prices compel firms to generate additional liquidity to alleviate financial strain that necessitates proactive liquidity management.

Loss development is another significant factor. Firms with substantial loss development—unexpected claim obligations or reserve adjustments—require enhanced liquidity creation to address these financial challenges. Liquidity creation in such cases is essential to maintain solvency and fulfill policyholder obligations during periods of heightened claims activity.

Finally, Table A10.4 indicates that the relationship between various financial and operational metrics and a firm's *ROA* provides significant insights. *Insurance leverage*, *Liabilities*, *Line concentration*, and *Firm size* are negatively associated with *ROA*. Conversely, *Reinsurance price* and *Geographical concentration* are positively associated with *ROA*, both at a 5% significance level. These findings illustrate how specific financial strategies and structural characteristics influence profitability.

A higher *Liquidity creation ratio* suggests that a firm allocates substantial resources to liquidity-enhancing activities, such as maintaining excess reserves or investing in high-yield illiquid assets. While these actions may improve financial stability, they can divert resources from other investments, ultimately reducing returns and impacting *ROA*.

Firms whose liabilities exceed their liquid assets are more susceptible to liquidity pressures and heightened financial risks. This financial strain can reduce operational flexibility and profitability, leading to a negative effect on *ROA*. Similarly, a high *Line concentration*, which reflects a less diversified portfolio, increases a firm's exposure to risks concentrated in specific lines of business. This lack of diversification often results in unstable revenue streams and lower profitability.

Larger firms may face diminishing returns to scale, as operational complexities and inefficiencies increase with size. These firms may also adopt less aggressive profit-maximizing strategies, further reducing *ROA*. Firms affiliated with larger groups may prioritize stability and resources sharing across the group over individual profitability. Although this approach enhances overall group resilience, it can suppress the standalone profitability of individual firms, negatively affecting their *ROA* (but not significant).

Higher reinsurance prices can incentivize firms to optimize their risk management strategies. By carefully evaluating reinsurance arrangements, firms allocate resources more efficiently, ensuring that risk transfer mechanisms align with their financial goals. This strategic optimization of risk and capital contributes to improved profitability and positively influences *ROA*.

Loss development, defined as estimated losses and loss expenses incurred two years before the current year and prior year, scaled by the policyholder's surplus, provides critical insight into a firm's underwriting performance. Firms that effectively manage loss development demonstrate strong risk assessment and operational control capabilities. By minimizing unexpected adjustments and stabilizing claims outcomes, these firms mitigate financial volatility and support consistent profitability, positively influencing *ROA* (but not significant).

Table A10.7: *Inflation rate* and its effect on *Reinsurance demand*, *Liquidity creation ratio*, and *ROA*, 1993-2023

	All insurers			Large insurers			Small insurers		
Variable	$Reins_t$	$Liquid_t$	ROA_t	$Reins_t$	$Liquid_t$	ROA_t	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t-1}$	0.7838	0.0376	-0.0198	0.7823	-0.0100	-0.0880	0.7927	0.0386	-0.0241
	(0.000)	(0.000)	(0.052)	(0.000)	(0.846)	(0.088)	(0.000)	(0.001)	(0.100)
$Liquid_{t-1}$	0.0909	0.7162	0.0734	0.0113	0.8008	-0.0103	0.0877	0.7056	0.1174
	(0.000)	(0.000)	(0.000)	(0.869)	(0.000)	(0.898)	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.0548	-0.1873	0.3561	0.2681	0.0818	0.1852	-0.0529	-0.1849	0.3928
	(0.000)	(0.000)	(0.000)	(0.046)	(0.451)	(0.065)	(0.002)	(0.000)	(0.001)
IR_{t-1}	0.0009	0.0018	-0.0002	0.0011	-0.0003	-0.0020	0.0011	0.0019	-0.0006
	(0.017)	(0.000)	(0.502)	(0.329)	(0.739)	(0.034)	(0.013)	(0.000)	(0.084)
Number of observations	46,816	46,816	46,816	2,078	2,078	2,078	41,005	41,005	41,005
Number of firms	3,163	3,163	3,163	152	152	152	3,030	3,030	3,030
Number of instruments	1,860	2,436	2,436	110	110	98	1,860	2,030	1,950
p-value Hansen J-test	0.3383	0.3862	0.2620	0.4617	0.2214	0.4295	0.2049	0.2134	0.3178

Note: This table provides the results of the two-step GMM-FOD. The dependent variables are *Reinsurance demand*, *Liquidity creation ratio* and *ROA*. Control variables results are not presented. Heteroscedasticity-consistent standard errors clustered at the firm level are computed and the corresponding *p*-values are reported in parentheses. *p*-values lower the 0.01 and 0.05 mean the coefficient is significant at 1% and 5% respectively.

Table A10.8: Forecasted *Inflation rate* and its effect on *Reinsurance demand*, *Liquidity creation ratio*, and *ROA*, for all insurers, 1993-2023

Variable	$Reins_t$	$Liquid_t$	ROA_t	$Reins_t$	$Liquid_t$	ROA_t	$Reins_t$	$Liquid_t$	ROA_t	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t\text{-}1}$	0.7836	0.0373	-0.0198	0.7839	0.0379	-0.0194	0.7807	0.0345	-0.0187	0.7779	0.0313	-0.156
	(0.000)	(0.000)	(0.052)	(0.000)	(0.000)	(0.058)	(0.000)	(0.001)	(0.068)	(0.000)	(0.004)	(0.123)
$Liquid_{t\text{-}1}$	0.0860	0.7207	0.0741	0.0884	0.7171	0.0735	0.0792	0.7130	0.0749	0.0736	0.7092	0.0771
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ROA_{t\text{-}1}$	-0.0562	-0.2188	0.3514	-0.0574	-0.1970	0.3563	-0.0585	-0.2044	0.3593	-0.0565	-0.2029	0.3667
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$F1\text{-}MST_{t\text{-}1}$	-0.0008	0.0032	0.0006									
	(0.106)	(0.000)	(0.089)									
$F1\text{-}GAUSI_{t\text{-}1}$				-0.0002	0.0025	0.0006						
				(0.594)	(0.000)	(0.032)						
$F3\text{-}MST_{t\text{-}3}$							-0.0011	-0.0012	0.0005			
							(0.001)	(0.002)	(0.130)			
$F3\text{-}GAUSS_{t\text{-}3}$										-0.0003	-0.0007	0.0005
										(0.000)	(0.000)	(0.000)
Number of observations	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816
Number of firms	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163
Number of instruments	1,860	2,436	2,436	1,860	2,436	2,436	1,860	2,436	2,436	1,860	2,436	2,436
p-value Hansen J-test	0.3046	0.3243	0.2882	0.3241	0.3360	0.2952	0.3064	0.3539	0.2743	0.3079	0.3626	0.3176

Note: This table provides the results of the two-step GMM-FOD. The dependent variables are *Reinsurance demand*, *Liquidity creation ratio* and *ROA*. Control variables results are not presented. Heteroscedasticity-consistent standard errors clustered at the firm level are computed and the corresponding *p*-values are reported in parentheses. *p*-values lower the 0.01 and 0.05 mean the coefficient is significant at 1% and 5% respectively.

Table A10.9: Forecasted *Inflation rate* and its effect on *Reinsurance demand*, *Liquidity creation ratio*, and *ROA*, for large insurers, 1993-2023

Variable	$Reins_t$	$Liquid_t$	ROA_t	$Reins_t$	$Liquid_t$	ROA_t	$Reins_t$	$Liquid_t$	ROA_t	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t-1}$	0.7836 (0.000)	0.0101 (0.852)	-0.0958 (0.048)	0.7896 (0.000)	0.0166 (0.737)	-0.0979 (0.041)	0.7843 (0.000)	-0.0182 (0.729)	-0.0904 (0.056)	0.7828 (0.000)	-0.0217 (0.668)	-0.1034 (0.027)
$Liquid_{t-1}$	0.0232 (0.713)	0.8410 (0.000)	-0.0362 (0.636)	0.0316 (0.605)	0.8271 (0.000)	-0.0233 (0.757)	0.0113 (0.870)	0.7936 (0.000)	0.0005 (0.995)	0.0059 (0.924)	0.7911 (0.000)	-0.0218 (0.763)
ROA_{t-1}	0.2312 (0.059)	0.0065 (0.948)	0.2819 (0.011)	0.2550 (0.040)	0.1017 (0.358)	0.2039 (0.045)	0.2606 (0.060)	0.0785 (0.440)	0.2180 (0.027)	0.2524 (0.043)	0.0690 (0.501)	0.2073 (0.060)
$F1\text{-}MST_{t-1}$	0.0014 (0.401)	0.0070 (0.000)	-0.0055 (0.003)									
$F1\text{-}GAUSI_{t-1}$				0.0022 (0.086)	0.0051 (0.000)	-0.0016 (0.152)						
$F3\text{-}MST_{t-3}$							-0.0003 (0.859)	-0.0010 (0.403)	0.0028 (0.106)			
$F3\text{-}GAUSS_{t-3}$										-0.0004 (0.212)	-0.0008 (0.014)	0.0003 (0.250)
Number of observations	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078
Number of firms	152	152	152	152	152	152	152	152	152	152	152	152
Number of instruments	110	110	98	110	110	98	110	110	98	110	110	98
p-value Hansen J-test	0.4161	0.2903	0.4638	0.4102	0.2914	0.3592	0.4065	0.2010	0.3794	0.4590	0.2034	0.3122

Note: This table provides the results of the two-step GMM-FOD. The dependent variables are *Reinsurance demand*, *Liquidity creation ratio* and *ROA*. Control variables results are not presented. Heteroscedasticity-consistent standard errors clustered at the firm level are computed and the corresponding *p*-values are reported in parentheses. *p*-values lower the 0.01 and 0.05 mean the coefficient is significant at 1% and 5% respectively.

Table A10.10: Forecasted *Inflation rate* and its effect on *Reinsurance demand*, *Liquidity creation ratio*, and *ROA*, for small insurers, 1993-2023

Variable	$Reins_t$	$Liquid_t$	ROA_t	$Reins_t$	$Liquid_t$	ROA_t	$Reins_t$	$Liquid_t$	ROA_t	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t-1}$	0.7923	0.0386	-0.0243	0.7924	0.0393	-0.0243	0.7883	0.0369	-0.0255	0.7858	0.0340	-0.0229
	(0.000)	(0.001)	(0.097)	(0.000)	(0.001)	(0.097)	(0.000)	(0.002)	(0.085)	(0.000)	(0.005)	(0.117)
$Liquid_{t-1}$	0.0825	0.7103	0.1168	0.0855	0.7072	0.1174	0.0767	0.7044	0.1139	0.0697	0.7015	0.1216
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.0552	-0.2133	0.3969	-0.0568	-0.1967	0.3965	-0.0586	-0.2035	0.3928	-0.0553	-0.2026	0.3974
	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
$F1\text{-}MST_{t-1}$	-0.0013	0.0026	-0.0002									
	(0.034)	(0.000)	(0.652)									
$F1\text{-}GAUSI_{t-1}$				-0.0003	0.0021	-0.0005						
				(0.490)	(0.000)	(0.168)						
$F3\text{-}MST_{t-3}$							-0.0011	-0.0011	-0.0007			
							(0.002)	(0.012)	(0.137)			
$F3\text{-}GAUSS_{t-3}$										-0.0004	-0.0006	0.0005
										(0.000)	(0.000)	(0.000)
Number of observations	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005
Number of firms	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030
Number of instruments	1,860	2,030	1,950	1,860	2,030	1,950	1,860	2,030	1,950	1,860	2,030	1,950
p-value Hansen J-test	0.2377	0.2114	0.3213	0.2444	0.1565	0.3303	0.2367	0.2140	0.3096	0.2801	0.1798	0.3332

Note: This table provides the results of the two-step GMM-FOD. The dependent variables are *Reinsurance demand*, *Liquidity creation ratio* and *ROA*. Control variables results are not presented. Heteroscedasticity-consistent standard errors clustered at the firm level are computed and the corresponding *p*-values are reported in parentheses. *p*-values lower the 0.01 and 0.05 mean the coefficient is significant at 1% and 5% respectively.

Table A10.11: Two-Step GMM-FOD Estimates of *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* using different instrument sets for large insurers, 1993-2023 period

Variable	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t-1}$	0.7852	-0.0107	-0.0982
	(0.000)	(0.832)	(0.042)
$Liquid_{t-1}$	0.0143	0.7989	-0.0185
	(0.811)	(0.000)	(0.803)
ROA_{t-1}	0.2655	0.0857	0.2115
	(0.048)	(0.406)	(0.045)
Number of observations	2,078	2,078	2,078
Number of firms	152	152	152
Number of instruments	110	110	98
p-value Hansen J-test	0.4186	0.2291	0.3475

Note: Two-step GMM-FOD regression model, with Windmeijer-corrected standard errors. The corresponding *p*-values are reported in parentheses. Results on control variables are not presented.

Table A10.12: Two-Step GMM-FOD Estimates of *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* using different instrument sets for small insurers, 1993-2023 period

Variable	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t-1}$	0.7928	0.0386	-0.0245
	(0.000)	(0.001)	(0.095)
$Liquid_{t-1}$	0.0862	0.7088	0.1170
	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.0561	-0.1996	0.3950
	(0.001)	(0.000)	(0.000)
Number of observations	41,005	41,005	41,005
Number of firms	3,030	3,030	3,030
Number of instruments	1,860	2,030	1,950
p-value Hansen J-test	0.2272	0.2249	0.3257

Note: Two-step GMM-FOD regression model, with Windmeijer-corrected standard errors. The corresponding *p*-values are reported in parentheses. Results on control variables are not presented.

Appendix B10: Results of two-step GMM-FOD models with control variables

B10.1 *Premiums to Total assets*

The relationship between *Reinsurance demand* and *Premiums to Total assets*, as indicated in Table B10.1, is negative, meaning that insurers that cede more risk to reinsurers tend to report lower levels of net *Premiums* relative to their *Total assets*. This reflects the fact that purchasing reinsurance reduces the amount of premium retained by the ceding company, as a portion is transferred to the reinsurer in exchange for risk relief.

This result holds consistently across insurer size categories. For large insurers (Table B10.2) and small insurers (Table B10.3), the negative relationship is also observed, suggesting that regardless of firm size, greater reliance on reinsurance is associated with lower reported premium income on an asset-adjusted basis. This may reflect a broader strategic choice by insurers to manage underwriting risk through reinsurance, even at the cost of reduced top-line revenue, particularly in competitive markets.

These findings underscore the trade-off between risk transfer and premium retention in reinsurance decisions and highlight how this trade-off shapes reported financial performance across the industry.

For large insurers, firm size (measured as the logarithm of total assets) exhibits a negative relationship with the premium ratio, while the *Liquidity creation ratio* shows a positive relationship. This suggests that as insurers become larger, they tend to generate proportionally less premium income, possibly because they diversify into a broader range of financial activities or allocate more resources to investment and asset management rather than core underwriting.

Conversely, the positive association between *Liquidity creation* and the *Premiums ratio* indicates that insurers with greater liquidity creation capacity are more focused on underwriting activities, supporting a higher proportion of premium revenue relative to their total assets. This may reflect a strategic trade-off between pursuing underwriting growth and utilizing the balance sheet to enhance liquidity through financial channels. Overall, these findings highlight the differing business models that large insurers can adopt — either leveraging size for greater financial flexibility or emphasizing traditional insurance operations to drive premium income.

Insurance leverage shows a positive relationship with the *Premiums* ratio across all insurer, large insurers, and small insurers. However, for both large and small insurers, this relationship is statistically significant only at the 10% level, indicating a weaker but still meaningful association. This suggests that insurers with higher leverage—meaning they write more *Premiums* relative to their surplus—tend to generate more premium income relative to their *Total assets*. This pattern reflects a more aggressive underwriting strategy, where insurers take on more risk to drive growth. The weaker significance for large and small insurers may point to heterogeneity in risk appetite, regulatory constraints, or strategic focus within those groups compared to the broader industry.

B10.2 *Losses incurred to Total assets*

The relationships between *Reinsurance demand*, *ROA*, *Reinsurance price*, *Tax exemption*, *Two-year loss development* losses (defined as estimated losses and loss adjustment expenses incurred two years before the current year and the prior year, scaled by policyholders' surplus), and *Mix concentration* offer valuable insights into the dynamics of risk-taking behavior and financial performance in the insurance industry.

As shown in Table B10.1 for all insurers, and Table B10.3 for small insurers, all six variables are negatively and significantly associated with *Losses incurred to Total assets*. These findings suggest that when insurers increase their use of reinsurance, achieve higher profitability (*ROA*), face higher reinsurance prices, benefit from tax exemptions, or report greater adverse loss development, they tend to exhibit lower current losses relative to their asset base.

This pattern could imply greater reinsurance utilization and may reflect effective risk transfer strategies, reducing retained losses. Higher *ROA* indicates stronger underwriting discipline or operational efficiency. Higher reinsurance prices may force insurers to be more selective about the risks they underwrite, thus improving underwriting quality.

Tax exemption could ease capital constraints, reducing the incentive to pursue aggressive, high-risk underwriting strategies. Greater *Loss development* may prompt more conservative reserving and underwriting practices, lowering future incurred losses. Lower *Mix concentration* implies a more diversified underwriting portfolio, mitigating risks specific to individual insurance lines.

Collectively, these relationships highlight the complex interplay between financial strength, risk management, and external market pressures, offering a nuanced view of how insurers adjust their behavior to safeguard profitability and reduce loss exposure.

Additionally, *Insurance leverage*, *Geographical concentration*, *Regulatory pressure* (measured as a dummy equal to 1 if net *Premiums* written to surplus are ≥ 300%, 0 otherwise), and *Line concentration* are all positively associated with *Losses incurred to Total assets* for both all insurers and small insurers—with the exception that geographical concentration is not significant for small insurers.

These positive relationships suggest that higher insurance leverage exposes insurers to greater underwriting risk, increasing loss volatility relative to Total assets. Greater *Geographical concentration* increases vulnerability to region-specific shocks such as natural disasters or economic downturns. *Regulatory pressure*, as indicated by high premium-to-surplus ratios, may reflect aggressive growth strategies or undercapitalization, resulting in reduced resilience to losses. Higher *Line concentration* implies less diversification across product lines, heightening the impact of adverse developments in specific lines of business.

Overall, these findings demonstrate that activity risk—whether geographic, regulatory, or underwriting-based—alongside aggressive leverage strategies, materially heightens insurers' operational loss burden.

While the results are broadly consistent across all insurers and small insurers, the lack of significance for geographical concentration among small insurers suggests that smaller firms may be better adapted to local market conditions or possess more targeted risk management practices, insulating them from regional volatility.

For large insurers (Table B10.2), the results reveal that *Reinsurance demand*, *ROA*, and *Reinsurance price* remain negatively related to the losses incurred ratio, similar to the findings for all insurers and small insurers. *Regulatory pressure* remains positively related to losses incurred.

However, divergences are also observed such as *Tax exemption* and *Mix concentration* are not statistically significant for large insurers, even though they are negatively associated with losses incurred for all insurers and small insurers. *Insurance leverage* is not significant for large insurers, whereas it is positively related to losses incurred for both all insurers and small insurers.

These differences suggest that large insurers may have more diversified risk profiles, making their losses less sensitive to factors like tax exemptions or underwriting concentration. *Insurance leverage* may exert less influence on large firms, potentially because of their superior access to capital markets, diversified business models, or stronger internal risk controls.

B10.3 *Net gains from operations to Total assets*

Table B10.1 presents the regression results for *Net gain from operations to Total assets* for the full sample of insurers. The analysis reveals positive and statistically significant relationships with *Geographical concentration*, *Reinsurance price*, *Tax exemption*, and *Two-year loss development* losses.

These findings suggest that insurers with greater geographical concentration may benefit from operational efficiencies or market specialization in specific regions, potentially enhancing underwriting profitability. Higher reinsurance prices could reflect a harder market environment, in which reinsurers and insurers are able to charge higher *Premiums*, thus improving their operational margins. *Tax exemption* can ease financial pressure and improve net operating outcomes by reducing the tax burden on core insurance activities. A positive link with two-year loss development losses may indicate that firms with higher historical adverse development are responding with corrective actions—such as improved pricing, stricter underwriting, or reserve strengthening—which ultimately lead to better operational performance going forward.

Overall, these results highlight how a combination of market conditions, regulatory factors, and firm-specific strategic responses contribute to stronger operational returns relative to Total assets.

In addition, we find negative relationships between *Net gain from operations to Total assets* and the variables *Regulatory pressure*, *Line concentration*, and *Group affiliation*.

These findings suggest that insurers facing regulatory pressure—i.e., those flagged by a high net *Premiums* written to surplus ratio (≥ 300%)—may be operating under tighter capital constraints or closer regulatory scrutiny, which can limit their flexibility and reduce their operational profitability. High line concentration, reflecting a lack of diversification across lines of business, increases vulnerability to volatility in specific underwriting segments, making earnings from core operations less stable. Meanwhile, group affiliation may lead to strategic practices—such as group reinsurance, centralized expense sharing, or tax strategies—that reduce reported profits at the individual entity level, even if they benefit the group as a whole.

Together, these results highlight the importance of capital adequacy, diversification in underwriting, and corporate structure in supporting sustainable profitability from core insurance operations.

For small insurers, as shown in Table B10.3, the results are largely consistent with those for the overall sample, with a few notable differences. Specifically, for small insurers, there is no statistically significant relationship between *Net gain from operations to Total assets* and the variables *Regulatory pressure*, *Tax exemption*, and *Two-year loss development*.

This suggests that these factors—while impactful at the industry level—may exert a more limited influence on the operational performance of smaller firms. The absence of significance could reflect structural or strategic differences. For example, small insurers may adopt more conservative growth strategies that avoid regulatory pressure, be less affected by tax exemptions due to lower taxable income or narrower eligibility and have less exposure to long-tail or complex lines, reducing the role of loss development trends in their financial outcomes.

For large insurers, as shown in Table B10.2, *Liquidity creation ratio* is negatively related to the *Net gain from operations to Total assets*, while *Line concentration* is positively related. This suggests that a higher *Liquidity creation ratio*—indicating that insurers hold a greater proportion of illiquid assets relative to Total assets—can discourage active trading, as these insurers must maintain more stable, long-term portfolios to meet liquidity obligations. This reduces their capacity to frequently rebalance investments and recognize capital gains.

In contrast, the positive relationship with *Line concentration* implies that large insurers that specialize in a narrower set of insurance lines may achieve more stable underwriting results. Greater underwriting predictability enables them to manage their investments more strategically and opportunistically, allowing for better timing of capital gains realization or the mitigation of losses.

Overall, these findings highlight how both external market factors (such as tax policy) and internal strategic choices (such as liquidity management and underwriting focus) jointly shape the investment performance of large insurers, particularly in terms of their ability to realize gains or minimize losses on their asset portfolios.

B10.4 *Net realized capital gains to Total assets*

As shown in Table B10.4, for all insurers, several variables exhibit statistically significant relationships with *Net realized capital gains to Total assets*. Specifically, *ROA*, *Two-year loss development*, *Group affiliation*, and *Capital ratio* are positively related, while *Reinsurance price*, *Tax exemption*, and *New York license* are negatively related to this metric. In contrast, there is no statistically significant relationship between *Net realized capital gains to Total assets* and *Reinsurance demand*, *Line concentration*, or *Business mix concentration*.

These results suggest that higher *ROA* is associated with greater realized investment gains, reflecting a strong overall financial performance that may include strategic asset sales. A positive relationship with two-year loss development may indicate that insurers experiencing adverse reserve developments are more likely to liquidate investments to meet claim obligations, thereby realizing gains or losses. *Group affiliation* may facilitate internal capital optimization strategies, leading to more frequent realization of gains. Higher capital levels may provide greater financial flexibility, enabling firms to engage in proactive investment management, including profit-taking on appreciated securities.

Conversely, a negative relationship with *Reinsurance price* may reflect a market environment where higher reinsurance costs (indicative of heightened risk) coincide with more conservative investment strategies or fewer opportunities to realize gains. *Tax exemption* may increase the incentive to realize capital gains, as exempt entities may prefer to defer recognition of such income. *New York license*, which often comes with more stringent regulatory oversight, could be associated with more conservative investment practices, resulting in fewer realized gains.

Overall, these findings highlight how profitability, capital strength, reserve dynamics, and regulatory environments influence insurers' decisions to realize gains or losses on their investment portfolios, shaping this important component of overall financial performance.

For small insurers, as shown in Table B6, the relationships with *Net realized capital gains to Total assets* differ in several keyways from those observed for all insurers. Specifically, for small insurers, there is a positive relationship with *ROA*, *Line concentration*, *Group affiliation*, and *Capital ratio*, while a negative relationship is found with *Reinsurance price* and *New York license*. In contrast, there is no statistically significant relationship with *Reinsurance demand*, *Tax exemption*, or *Two-year loss development*.

These findings suggest that for small insurers, higher *ROA* continues to be linked to stronger investment performance, possibly reflecting better overall financial health and more active portfolio management. A positive relationship with line concentration may indicate that small insurers focused on specific lines might manage more targeted investment portfolios, potentially enabling them to realize capital gains more effectively. Being part of a group may offer small insurers access to shared investment strategies or liquidity support, increasing their ability to realize gains. Greater capital reserves may provide small firms with the flexibility needed to realize investment gains strategically, particularly during periods of market opportunity.

Meanwhile, a negative relationship with *Reinsurance price* could reflect cost pressures that limit small insurers' ability to buy reinsurance. The negative impact of *New York license* may suggest costs on small firms in that jurisdiction.

The absence of a significant relationship with *Tax exemption*, *Two-year loss development*, and *Reinsurance demand* may reflect differences in scale and complexity — small insurers might face less exposure to tax-based investment planning or reserve volatility.

Comparison with all insurers, *Two-year loss development* and *Tax exemption* showed significant relationships with realized gains, whereas these were not significant for small insurers — possibly due to differences in portfolio size, claim volatility, or tax exposure. *Line concentration*, which was not significant for the full sample, is significant for small insurers — suggesting that concentration risk plays a more pronounced role in shaping investment strategies in smaller firms. The consistent positive relationships with *ROA*, *Group affiliation*, and *Capital ratio* across both groups highlight shared underlying dynamics, though their magnitude or strategic implications may vary by size.

For large insurers, as shown in Table B10.5, reinsurance price and *Liquidity creation ratio* are negatively related to the *Net realized capital gains to Total assets*, while *Line concentration* is positively related.

This suggests that when reinsurance prices rise, large insurers may be less willing or able to realize capital gains, possibly because higher reinsurance costs tighten overall profitability and reduce investment flexibility. Similarly, a higher *Liquidity creation ratio*—indicating that insurers are taking on more illiquid liabilities relative to Total assets—could lead them to hold investments longer, as they prioritize liquidity management overactive portfolio rebalancing.

In contrast, the positive relationship with line concentration implies that large insurers that focus more heavily on a narrower set of insurance lines may experience more stable underwriting results, allowing them to manage their investments more opportunistically. Specialization could lead to greater predictability in cash flows and reserve requirements, enabling insurers to time the realization of capital gains or limit realized losses more effectively.

Overall, these findings highlight how external market factors (like reinsurance pricing) and internal strategic choices (like liquidity management and underwriting focus) jointly influence large insurers' investment performance, particularly in terms of realizing gains or minimizing losses on their asset portfolios.

B10.5 ***Net investment income to Total assets***

From Table B10.4 (all insurers) and Table B10.6 (small insurers), we observe that the coefficients for *Liabilities*, *Line concentration*, *Reinsurance price*, *Two-year loss development*, and *Group affiliation* are all negatively and significantly related to *Net investment income to Total assets*. This suggests that insurers with high liabilities relative to liquid *Total assets* may face liquidity constraints or be forced to adopt more conservative investment strategies, which reduce their ability to generate returns on their assets portfolios. Similarly, high line concentration reflects limited diversification across lines of business, which may be correlated with less diversified or risk-averse investment approaches, leading to lower investment income.

Reinsurance price and *Two-year loss development*—as indicators of recent risk exposure or market stress—may also prompt insurers to rebalance portfolios toward safer, lower-yielding assets, again suppressing investment returns. *Group affiliation* may reflect centralized investment management at the group level, where individual entities report lower income despite broader group-level performance, due to intercompany transactions or capital pooling arrangements.

While *Geographical concentration* shows a positive relationship with *Net investment income* for all insurers, this may suggest that regionally focused firms are able to capitalize on localized investment opportunities or better align investment decisions with regional economic conditions.

The *New York license* is negatively related to net investment income for all insurers but is not statistically significant for small insurers. This could reflect stricter investment rules or higher costs in New York that affect larger or more complex insurers while smaller firms may be less present.

The *Two-year loss development* is negatively related to *Net investment income* for both all insurers and small insurers, but the relationship is not statistically significant for large insurers. This could reflect the fact that higher loss development weakens financial stability, prompting insurers—particularly smaller ones—to adopt more conservative investment strategies that yield lower returns. For small insurers, adverse loss development may also signal weaker reserve practices or greater exposure to long-tail lines, increasing uncertainty and risk aversion in portfolio management. In contrast, large insurers may be better equipped to absorb reserve adjustments without significantly altering their investment strategy, which could explain the lack of significance in that group.

Lastly, *Tax exemption* is not statistically significant for all insurers, positively related for large insurers (Table B10.5), and negatively related for small insurers (Table B10.6). This suggests that larger tax-exempt insurers may benefit from more efficient investment management or favorable regulatory treatment that supports higher investment returns. In contrast, smaller tax-exempt insurers might adopt more conservative investment strategies to maintain compliance or reduce risk exposure, which could lead to lower investment income relative to Total assets.

B10.6 ***Capital ratio***

Table B10.4 presents the results for all insurers, showing that the *Capital ratio* is positively associated with *Reinsurance demand*, *Reinsurance price*, and *Tax exemption*. In contrast, the liability variable (a dummy equal to 1 if a firm's adjusted liabilities to liquid *Total assets* ratio is ≥100%) shows a negative and significant relationship with the *Capital ratio*. Other variables — including *Geographical concentration*, *Two-year loss development*, and *New York license* — do not exhibit statistically significant relationships.

For large insurers (Table B10.5), *Capital ratio* is positively associated with *Reinsurance demand*, *Geographical concentration*, and *Reinsurance price*, while *Liabilities* again shows a negative relationship. However, there is no significant relationship with *Tax exemption*, *Two-year loss development*, or *New York license*, marking a distinction from the full sample.

In contrast, for small insurers (Table B10.6), the pattern differs more substantially. The *Capital ratio* is positively associated with *Tax exemption* and *New York license*, while it is negatively related to *Liabilities*, *Reinsurance price*, and *Two-year loss development*. Notably, there is no significant relationship with *Reinsurance demand* or *Geographical concentration* — both of which were significant for all or large insurers.

These findings suggest that *Liabilities* is consistently negatively related to the *Capital ratio* across all insurer groups, indicating that firms with higher liability exposure relative to liquid *Total assets* tend to hold lower levels of capital. This pattern highlights the adverse impact of tight liquidity positions on capital strength.

Reinsurance demand is positively associated with capital for all and large insurers, but not for small insurers. This could reflect that larger firms use reinsurance more strategically to manage capital efficiently, while smaller firms may face high price constraints or different regulatory incentives.

Reinsurance price is positively related to capital for all and large insurers, but negatively for small insurers. This divergence may suggest that rising reinsurance costs constrain smaller firms' capital positions, while larger firms can absorb the cost or price into their underwriting.

Tax exemption shows a positive relationship with *Capital ratio* for all and small insurers, but not for large insurers. This could mean that tax incentives play a more meaningful role in bolstering capital levels for smaller, potentially more tax-sensitive firms.

Geographical concentration positively relates to capital only for large insurers, suggesting that regionally focused large insurers may face lower diversification risk or benefit from more predictable regional markets, leading to stronger capital positions.

Two-year loss development is negatively related to capital only for small insurers, indicating that reserve volatility or claims uncertainty may more heavily affect their capital adequacy compared to larger peers.

New York license has no significant effect for all and large insurers but is positively associated with capital for small insurers. This may reflect either regulatory discipline or strategic positioning among smaller firms operating in New York.

Large insurers show more strategic and diversified drivers of capital, with factors like reinsurance use and geographical focus playing a stronger role. Small insurers appear more sensitive to regulatory and financial pressures, such as tax benefits, loss development, and reinsurance pricing, which influence their capital positioning more acutely. All insurers reflect a blended view, but the distinctive patterns between large and small firms underscore the importance of firm size and operational complexity in shaping capital strategies within the property-casualty insurance sector.

Table B10.1: *Inflation rate* and its effect on *Premiums to Total assets*,
Losses incurred to Total assets, and *Net gain from operations to Total assets*
for all insurers, 1993-2023

Variable	*Premiums to Total assets*	*Losses incurred to Total assets*	*Net gain from operations to Total assets*
Premiums to Total assets$_{t-1}$	0.6422		
	(0.000)		
Losses incurred to Total assets$_{t-1}$		0.4703	
		(0.000)	
Net gain from operations to Total assets$_{t-1}$			0.3560
			(0.000)
Inflation rate$_{t-1}$	0.0004	0.0005	-0.0001
	(0.509)	(0.274)	(0.790)
Reins$_t$	-0.2297	-0.1826	
	(0.000)	(0.000)	
ROA$_t$	0.1191	-0.3928	
	(0.398)	(0.000)	
Insurance leverage$_t$	0.0164	0.0157	-0.0040
	(0.008)	(0.000)	(0.078)
Geographical concentration$_t$	-0.0155	0.0567	0.1104
	(0.608)	(0.015)	(0.000)
Regulatory pressure$_t$	0.0998	0.0750	-0.0265
	(0.011)	(0.001)	(0.010)
Line concentration$_t$	0.0772	0.0932	-0.0858
	(0.020)	(0.000)	(0.000)
Reinsurance price$_t$	-0.0051	-0.0093	0.0136
	(0.052)	(0.000)	(0.000)
Tax exemption$_t$	-0.0103	-0.0152	0.0164
	(0.237)	(0.050)	(0.046)
Loss development ratio$_t$	0.0001	-0.0005	0.0003
	(0.633)	(0.000)	(0.001)
New York license$_t$	0.0111	-0.0185	-0.0173
	(0.687)	(0.421)	(0.264)
Group affiliation$_t$	-0.0131	-0.0079	-0.0240
	(0.132)	(0.283)	(0.005)
Mix concentration$_t$	-0.0780	-0.0997	
	(0.049)	(0.002)	
Capital ratio$_t$	-0.0904	0.0560	0.0308
	(0.030)	(0.077)	(0.281)
Number of observations	46,816	46,816	46,816
Number of firms	3,163	3,163	3,163
Number of instruments	2,268	2,268	2,100
p-value Hansen J-test	0.3230	0.2574	0.6554

Note: This table provides the results of two-step GMM with orthogonal deviations and different number of instruments. Windmeijer-corrected standard errors are computed, and the corresponding *p*-values are reported in parentheses.

Table B10.2: *Inflation rate* and its effect on *Premiums to Total assets*,
Losses incurred to Total assets, and *Net gain from operations to Total assets*
for large insurers, 1993-2023

Variable	*Premiums to Total assets*	*Losses incurred to Total assets*	*Net gain from operations to Total assets*
Premiums to Total assets$_{t-1}$	0.4911		
	(0.000)		
Losses incurred to Total assets$_{t-1}$		0.1622	
		(0.025)	
Net gain from operations to Total assets$_{t-1}$			0.2161
			(0.019)
Inflation rate$_{t-1}$	0.0012	0.0021	-0.0016
	(0.004)	(0.005)	(0.214)
Reins$_t$	-0.1913	-0.2662	-0.0532
	(0.001)	(0.000)	(0.255)
Liquid$_t$	0.2681		-0.1866
	(0.000)		(0.007)
ROA$_t$		-0.6229	
		(0.000)	
Insurance leverage$_t$	0.0304	0.0396	0.0292
	(0.090)	(0.113)	(0.058)
Line concentration$_t$			-0.0346
			(0.333)
Regulatory pressure$_t$		0.0855	-0.0628
		(0.014)	(0.175)
Geographical concentration$_t$	-0.1083	-0.0558	0.0997
	(0.048)	(0.258)	(0.429)
Reinsurance price$_t$	-0.0022	-0.0130	0.0209
	(0.418)	(0.015)	(0.000)
Tax exemption$_t$		-0.0295	0.0241
		(0.344)	(0.467)
Mix concentration$_t$		-0.0361	
		(0.361)	
Capital ratio$_t$		-0.1777	
		(0.247)	
Size$_t$	-0.0319		
	(0.001)		
Number of observations	2,078	2,078	2,078
Number of firms	152	152	152
Number of instruments	102	102	98
p-value Hansen J-test	0.3792	0.5071	0.5235

Note: This table provides the results of two-step GMM-FOD and different number of instruments. Windmeijer-corrected standard errors are computed, and the corresponding *p*-values are reported in parentheses.

Table B10.3: *Inflation rate* and its effect on *Premiums to Total assets*, *Losses incurred to Total assets,* and *Net gain from operations to Total assets* for small insurers, 1993-2023

Variable	*Premiums to Total assets*	*Losses incurred to Total assets*	*Net gain from operations to Total assets*
Premiums to Total assets$_{t-1}$	0.5766		
	(0.000)		
Losses incurred to Total assets$_{t-1}$		0.4563	
		(0.000)	
Net gain from operations to Total assets$_{t-1}$			0.3741
			(0.000)
Inflation rate$_{t-1}$	0.0004	0.0004	-0.0002
	(0.560)	(0.353)	(0.638)
Reins$_t$	-0.2545	-0.1743	
	(0.000)	(0.000)	
ROA$_t$	0.1394	-0.3867	
	(0.443)	(0.000)	
Insurance leverage$_t$	0.0145	0.0130	-0.0043
	(0.054)	(0.003)	(0.115)
Geographical concentration$_t$	-0.0154	0.0355	0.1092
	(0.696)	(0.205)	(0.000)
Regulatory pressures$_t$	0.1191	0.0954	-0.0171
	(0.018)	(0.001)	(0.172)
Line concentration$_t$	0.0548	0.0776	-0.0929
	(0.062)	(0.002)	(0.000)
Reinsurance price$_t$	-0.0052	-0.0088	0.0124
	(0.162)	(0.000)	(0.000)
Tax exemption$_t$	-0.0106	-0.0217	0.0047
	(0.347)	(0.012)	(0.629)
Loss development ratio$_t$	0.0000	-0.0005	0.0002
	(0.877)	(0.000)	(0.127)
New York license$_t$	0.0116	-0.0199	-0.0105
	(0.749)	(0.481)	(0.599)
Group affiliation$_t$	-0.0118	-0.0106	-0.0331
	(0.268)	(0.171)	(0.008)
Mix concentration$_t$	-0.0510	-0.0867	
	(0.180)	(0.011)	
Capital ratio$_t$	-0.1212	-0.0601	0.0180
	(0.009)	(0.095)	(0.561)
Number of observations	41,005	41,005	41,005
Number of firms	3,030	3,030	3,030
Number of instruments	1,950	1,950	1,771
p-value Hansen J-test	0.4095	0.3677	0.6255

Note: This table provides the results of two-step GMM-FOD and different number of instruments. Windmeijer-corrected standard errors are computed, and the corresponding *p*-values are reported in parentheses.

Table B10.4: *Inflation rate* and its effect on *Net realized capital gains to Total assets*, *Net investment income to Total assets*, and *Capital ratio* for all insurers, 1993-2023

Variable	*Net realized capital gains to Total assets*	*Net investment income to Total assets*	*Capital ratio*
Net realized capital gains to Total assets$_{t-1}$	0.0644 (0.082)		
Net investment income to Total assets$_{t-1}$		0.6498 (0.000)	
Capital ratio$_{t-1}$			0.7992 (0.000)
Inflation rate$_{t-1}$	-0.0007 (0.000)	0.0009 (0.000)	-0.0011 (0.000)
Reins$_t$	-0.0068 (0.107)		0.0345 (0.010)
ROA$_t$	0.0900 (0.002)		
Insurance leverage$_t$		0.0001 (0.777)	
Geographical concentration$_t$		0.0116 (0.001)	0.0098 (0.527)
Liabilities$_t$		-0.0064 (0.000)	-0.0786 (0.000)
Line concentration$_t$	0.0158 (0.196)	-0.0053 (0.021)	
Reinsurance price$_t$	-0.0020 (0.000)	-0.0005 (0.003)	0.0013 (0.057)
Tax exemption$_t$	-0.0066 (0.006)	-0.0012 (0.423)	0.0306 (0.000)
Loss development ratio$_t$	0.0001 (0.044)	-0.0001 (0.000)	-0.0001 (0.469)
Size$_t$			0.0029 (0.160)
New York$_t$	-0.0133 (0.075)	-0.0168 (0.002)	-0.0105 (0.480)
Group affiliation$_t$	0.0066 (0.002)	-0.0044 (0.002)	
Mix concentration$_t$	-0.0020 (0.904)		
Capital ratio$_t$	0.0271 (0.000)	-0.0017 (0.763)	
Number of observations	46,816	46,816	46,816
Number of firms	3,163	3,163	3,163
Number of instruments	2,268	2,100	2,268
p-value Hansen J-test	0.3427	0.3539	0.3767

Note: This table provides the results of two-step GMM with orthogonal deviations and different number of instruments. Windmeijer-corrected standard errors are computed and the corresponding *p*-values are reported in parentheses.

Table B10.5: *Inflation rate* and its effect on *Net realized capital gains to Total assets*, *Net investment income to Total assets*, and *Capital ratio* for large insurers, 1993-2023

Variable	*Net realized capital gains to Total assets*	*Net investment income to Total assets*	*Capital ratio*
Net realized capital gains to Total assets$_{t-1}$	0.2553 (0.007)		
Net investment income to Total assets$_{t-1}$		0.3280 (0.001)	
Capital ratio$_{t-1}$			0.6649 (0.000)
Inflation rate$_{t-1}$	-0.0033 (0.001)	0.0008 (0.001)	-0.0021 (0.048)
Reins$_t$	-0.0208 (0.385)		0.2155 (0.031)
Liquid$_t$	-0.1300 (0.000)		
ROA$_t$		0.1498 (0.025)	
Regulatory pressures$_t$	-0.0973 (0.253)		
Liabilities$_t$			-0.1238 (0.000)
Geographical concentration$_t$			0.2036 (0.095)
Line concentration$_t$	0.0657 (0.015)		
Reinsurance price$_t$		-0.0021 (0.225)	0.0116 (0.001)
Tax exemption$_t$	-0.0568 (0.006)	0.0327 (0.014)	0.0644 (0.222)
Loss development ratio$_t$		-0.0000 (0.715)	0.0002 (0.602)
Size$_t$			0.0084 (0.568)
New York$_t$	-0.0835 (0.349)		0.0834 (0.418)
Capital ratio$_t$		-0.0630 (0.033)	
Number of observations	2,078	2,078	2,078
Number of firms	152	152	152
Number of instruments	98	102	98
p-value Hansen J-test	0.3354	0.3852	0.4715

Note: This table provides the results of two-step GMM-FOD and different number of instruments. Windmeijer-corrected standard errors are computed, and the corresponding *p*-values are reported in parentheses.

Table B10.6: *Inflation rate* and its effect on *Net realized capital gains to Total assets*, *Net investment income to Total assets*, and *Capital ratio* for small insurers, 1993-2023

Variable	*Net realized capital gains to Total assets*	*Net investment income to Total assets*	*Capital ratio*
Net realized capital gains to Total assets$_{t-1}$	0.0439		
	(0.150)		
Net investment income to Total assets$_{t-1}$		0.5640	
		(0.000)	
Capital ratio$_{t-1}$			0.7591
			(0.000)
Inflation rate$_{t-1}$	-0.0009	0.0011	-0.0013
	(0.000)	(0.000)	(0.000)
Reins$_{t-1}$	-0.0019		-0.0093
	(0.686)		(0.287)
ROA$_{t-1}$	0.0630		
	(0.057)		
Insurance leverage$_{t}$		0.0002	
		(0.791)	
Geographical concentration$_{t}$		0.0119	0.0054
		(0.001)	(0.685)
Liabilities$_{t}$		-0.0043	-0.0352
		(0.017)	(0.000)
Line concentration$_{t}$	0.0146	-0.0104	
	(0.010)	(0.000)	
Reinsurance price$_{t}$	-0.0014	-0.0003	-0.0021
	(0.013)	(0.063)	(0.001)
Tax exemption$_{t}$	-0.0017	-0.0039	0.0513
	(0.557)	(0.009)	(0.000)
Loss development ratio$_{t}$	0.0001	-0.0001	-0.0001
	(0.178)	(0.011)	(0.097)
New York$_{t}$	-0.0182	0.0014	0.0277
	(0.031)	(0.797)	(0.041)
Group affiliation$_{t}$	0.0076	-0.0051	
	(0.008)	(0.001)	
Capital ratio$_{t}$	0.0153	-0.0016	
	(0.047)	(0.818)	
Number of observations	41,005	41,005	41,005
Number of firms	3,030	3,030	3,030
Number of instruments	1,950	1,617	2,325
p-value Hansen J-test	0.4410	0.3817	0.2132

Note: This table provides the results of two-step GMM-FOD and different number of instruments. Windmeijer-corrected standard errors are computed and the corresponding *p*-values are reported in parentheses.

Appendix C10: Results of two-step GMM-FOD models on financial crises variables

The research also examines the relationship between *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* during major economic crises: the 2001 recession, the 2007-2008 financial crisis, and the *COVID-19* pandemic.

From Table C10.1, the three economic crises do not significantly influence *Reinsurance demand*. The 2001 recession and the 2007-2008 financial crisis both enhance liquidity creation, while *COVID-19* reduces it. The 2001 recession lowers *ROA*, while *COVID-19* and 2007-2008 financial crisis have no significant effect on *ROA*.

Table C10.1: Financial crises and their effects on *Reinsurance demand*, *Liquidity creation ratio*, and *ROA*, for all insurers, 1993-2023

Variable	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t-1}$	0.7835	0.0338	-0.0210
	(0.000)	(0.001)	(0.038)
$Liquid_{t-1}$	0.0906	0.7374	0.0645
	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.0578	-0.2121	0.3517
	(0.003)	(0.000)	(0.000)
2007-2008	0.0019	0.0077	-0.0013
	(0.276)	(0.000)	(0.325)
2001 recession	0.0031	0.0533	-0.0168
	(0.260)	(0.000)	(0.000)
2020 *COVID-19*	0.0033	-0.0137	0.0023
	(0.122)	(0.000)	(0.145)
Number of observations	46,816	46,816	46,816
Number of firms	3,163	3,163	3,163
Number of instruments	1,860	2,436	2,436
p-value Hansen J-test	0.3152	0.2525	0.2676

Note: Two-step GMM-FOD regression model, with Windmeijer-corrected standard errors, the corresponding *p*-values are reported in parentheses. Results on control variables are not presented. Dummy variables were added for the 2007-2008 financial crisis, the 2001 recession, and 2020 *COVID-19* pandemic.

Table C10.2 presents the impact of major economic crises on large insurers' financial metrics. The 2001 recession significantly increased *Reinsurance demand* among large insurers, suggesting a heightened need for risk mitigation during that period. In contrast, other major economic crises, including the *COVID-19* pandemic, did not have a statistically significant effect on *Reinsurance demand* for these insurers.

Table C10.2: Financial crises and their effects on *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* for large insurers, 1993-2023

Variable	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t-1}$	0.7730	-0.0233	-0.0608
	(0.000)	(0.642)	(0.205)
$Liquid_{t-1}$	0.0363	0.8057	-0.0252
	(0.585)	(0.000)	(0.735)
ROA_{t-1}	0.2046	-0.0168	0.3002
	(0.119)	(0.870)	(0.003)
2007-2008	0.0045	0.0177	-0.0180
	(0.461)	(0.004)	(0.074)
2001 recession	0.0219	0.0642	-0.0324
	(0.031)	(0.000)	(0.001)
2020 *COVID-19*	0.0007	-0.0058	-0.0007
	(0.890)	(0.241)	(0.877)
Number of observations	2,078	2,078	2,078
Number of firms	152	152	152
Number of instruments	110	110	98
p-value Hansen J-test	0.4286	0.2067	0.3896

Note: Two-step GMM-FOD regression model, with Windmeijer-corrected standard errors, the corresponding *p*-values are reported in parentheses. Results on control variables are not presented. Dummy variables were added for the 2007-2008 financial crisis, the 2001 recession, and the 2020 *COVID-19* pandemic.

During the 2001 recession and 2007-2008 financial crises, large insurers enhanced their liquidity creation efforts, possibly as a strategic response to the economic downturn. However, the *COVID-19* pandemic did not have a significant impact on the *Liquidity creation ratio* for these insurers.

The 2001 recession was associated with a decrease in *ROA* for large insurers, reflecting reduced profitability during that time. In contrast, the *COVID-19* pandemic did not have a statistically significant effect on *ROA* for these insurers.

Table C10.3 reveals that, for small insurers, major economic crises have varying impacts on financial metrics. *Reinsurance demand* remains largely unaffected across these periods. Both the 2001 recession and the 2007-2008 financial crisis led to increased liquidity creation, suggesting a strategic move to bolster financial stability during economic downturns. Conversely, the *COVID-19* pandemic results in a reduction in liquidity creation, potentially due to unique challenges posed by the pandemic.

Table C10.3: Financial crises and their effects on *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* for small insurers, 1993-2023

Variable	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t-1}$	0.7918	0.0376	-0.0272
	(0.000)	(0.001)	(0.064)
$Liquid_{t-1}$	0.0881	0.7269	0.1082
	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.0560	-0.2038	0.3796
	(0.001)	(0.000)	(0.000)
2007-2008	0.0012	0.0065	0.0007
	(0.584)	(0.000)	(0.632)
2001 recession	0.0041	0.0503	-0.0127
	(0.190)	(0.000)	(0.000)
2020 *COVID-19*	0.0039	-0.0144	0.0040
	(0.144)	(0.000)	(0.038)
Number of observations	41,005	41,005	41,005
Number of firms	3,030	3,030	3,030
Number of instruments	1,860	2,030	1,950
p-value Hansen J-test	0.2511	0.2356	0.3256

Note: Two-step GMM-FOD regression model, with Windmeijer-corrected standard errors, the corresponding *p*-values are reported in parentheses. Results on control variables are not presented. Dummy variables were added for the 2007-2008 financial crisis, the 2001 recession and the 2020 *COVID-19* pandemic.

Regarding profitability, the 2001 recession is associated with a decrease in *ROA*, while the *COVID-19* pandemic corresponds with an increase in *ROA*. The 2007-2008 financial crisis does not have a significant effect on *ROA* for small insurers. These findings highlight that small insurers adjust their liquidity strategies differently in response to various economic crises, reflecting the distinct nature and impact of each event.

Appendix D10: Correlations matrix of the key financial variables

Table D10.1 presents the correlation matrix of the nine key financial variables. The strength and direction of these relationships reveal several important patterns. The *Liquidity creation ratio* is negatively and strongly correlated with *Capital ratio* (-0.6333), while showing strong positive correlations with *Premiums to Total assets* (0.4529) and *Losses incurred to Total assets* (0.4295). These correlations suggest that when *Premiums* and losses incurred rise, insurers tend to increase their liquidity creation activities, possibly to ensure sufficient resources for claim payments and operational needs. Conversely, as capital levels increase, liquidity creation tends to decrease, implying that well-capitalized insurers may face less pressure to generate additional liquidity.

The correlation coefficient between *ROA* and *Net gain from operations to Total assets* is 1, indicating a perfect positive relationship, as expected, since *ROA* incorporates the net gain from operations as a key component. Additionally, *ROA* is negatively correlated with *Losses incurred to Total assets* (-0.2281) and positively correlated with *Net realized capital gains to Total assets* (0.2264). This suggests that higher incurred losses tend to reduce profitability, while realized capital gains improve it.

Premiums to Total assets is positively correlated with *Losses incurred to Total assets* (0.8743), reflecting the direct relationship between business volume and associated claim costs — as insurers write and earn more *Premiums*, the volume of claims naturally increases. Meanwhile, *Premiums to Total assets* is negatively correlated with *Capital ratio* (-0.2354), indicating that insurers operating with relatively higher premium volumes tend to have proportionally lower capital positions, potentially reflecting higher leverage or more aggressive underwriting strategies.

Reinsurance demand is negatively correlated with *Premiums to Total assets* (-0.2349) and *Losses incurred to Total assets* (-0.1584). This suggests that insurers with higher business volumes and claims costs tend to rely less on reinsurance, possibly retaining more risk in-house or indicating that highly reinsured insurers manage smaller, less volatile books of business.

Lastly, *Losses incurred to Total assets* is negatively correlated with *Net gain from operations to Total assets* (-0.2281) and with *Capital ratio* (-0.2678). These relationships imply that higher claims costs erode operational profitability and tend to be associated with weaker capital positions, reinforcing the critical role of underwriting performance in preserving both profitability and capital strength in the property-casualty insurance sector.

Table D10.1: Correlations between nine financial variables, 1992-2023

	Reins	*Liquid*	*ROA*	*Pe*	*Li*	*Nibdt*	*Ii*	*Rcg*	*Capital*
Reins	1.0000	0.0680	-0.0859	-0.2349	-0.1584	-0.0859	-0.0474	-0.0259	-0.0495
		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Liquid		1.0000	-0.1725	0.4529	0.4295	-0.1725	-0.2062	-0.0389	-0.6333
			(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
ROA			1.0000	0.0114	-0.2281	1.0000	0.1807	0.2264	0.1687
				(0.0095)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Pe				1.0000	0.8743	0.0114	0.1282	-0.0011	-0.2354
					(<0.0001)	(0.0095)	(<0.0001)	(0.7993)	(<0.0001)
Li					1.0000	-0.2281	0.1574	0.0297	-0.2678
						(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Nibdt						1.0000	0.1807	0.2264	0.1687
							(<0.0001)	(<0.0001)	(<0.0001)
Ii							1.0000	0.0998	0.0279
								(<0.0001)	(<0.0001)
Rcg								1.0000	0.0360
									(<0.0001)
Capital									1.0000

Note: *Reins*: *Reinsurance demand*; *Liquid: Liquidity creation ratio*; *ROA*: Return to Total assets; Pe: *Premiums to Total assets*; Li*: Losses incurred to Total assets*; Nibdt: *Net gain from operations to Total assets*; Ii: *Net investment income to Total assets*; Rcg : *Net realized capital gains to Total assets*; *Capital*: *Capital and surplus to Total assets*.
The values in parentheses represent the *p*-values testing the null hypothesis that each correlation coefficient is equal to zero.
Almost all correlations are statistically significant at the 1% level, with one exception.

Appendix E10: OLS estimation results

Estimations are made using Stata xtreg for OLS fixed effect. The OLS fixed effects parameters for lagged *Reinsurance demand*, lagged *Liquidity creation ratio* and lagged *ROA* are respectively 0.7493, 0.7391, 0.2360, which should be considered as a lower-bound estimate. If the two-step GMM-FOD estimates obtained are close to or below the fixed-effects estimates, this suggests that the GMM-FOD estimates are downward biased due to weak instrumentation.

Table E10.1: OLS Estimation Results for *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* for all insurers, 1993-2023

Variable	$Reins_t$	$Liquid_t$	ROA_t
$Reins_{t-1}$	0.7493	0.0299	-0.0052
	(0.000)	(0.000)	(0.160)
$Liquid_{t-1}$	0.0748	0.7391	0.0437
	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.0566	-0.0473	0.2360
	(0.000)	(0.001)	(0.000)
Number of observations	46,816	46,816	46,816
Number of firms	3,163	3,163	3,163
R-Square (within)	0.6282	0.5562	0.2188

Note: OLS fixed effects regression model, results on control variables are not presented. Heteroscedasticity-consistent standard errors clustered at the firm level are computed and the corresponding *p*-values are reported in parentheses. *p*-values lower than 0.01 and 0.05 mean the coefficient is significant at 1% and 5% respectively.

Appendix F10: Analysis based on two-step GMM-FOD for additional financial variables

F10.1 Variables and predictions

In Subsection 10.7, we examined the reciprocal relationships between reinsurers' *Liquidity creation ratio*, their profitability (measured by *ROA*), and their *Reinsurance demand*. These analyses aim to capture how these core operational and financial metrics influence one another within the property-casualty insurance industry.

In addition to these reciprocal relationships, we also included inflation as a control variable in the analysis. While we did not explore the reciprocal effect of inflation itself, its role was important in accounting for broader macroeconomic conditions that could impact the relationships among these decision variables.

In this section, we shift our focus to examine the relationship between inflation and a broader set of six financial variables within the P&C insurance industry. Table F10.1 describes the variables and presents their short-term predicted relationships with inflation.

Table F10.1: Predicted relationships between inflation and six financial variables

Variable	Predicted relationship	Explanation
Premiums to Total assets	Positive	As inflation rises, insurers typically adjust premium rates upward to cover higher expected claims costs and expenses. However, premium increases often lag behind inflation due to pricing regulations, competition, or multiyear policy terms. Demand for insurance can also decrease, driving a negative effect on *Premiums*.
Losses incurred to Total assets	Positive	Inflation increases the cost of claims — especially for property repairs, medical expenses, and liability settlements. This leads to higher loss ratios and incurred losses relative to Total assets. Insurance coverage may also decrease.

Variable	Predicted relationship	Explanation
Net gain from operations to Total assets	Negative	Claims costs usually increase faster than *Premiums* (due to inflation lag), which reduces underwriting profits. Unless offset by investment income growth, operational profitability should weaken under inflationary pressure.
Net realized capital gains to Total assets	Mixed	In inflationary environments, bond prices usually fall (leading to potential capital losses if sold), while equities and real assets might perform better. Realized gains depend on asset mix, timing of sales, and portfolio strategy in response to inflation expectations.
Net investment income earned to Total assets	Mixed	Inflation typically leads to rising interest rates in the long run, which increase yields on new fixed-income investments. However, existing portfolios may have locked-in at lower rates, so the benefit of net investment income appears gradually as portfolios turn over.
Capital ratio	Negative	Rising inflation erodes asset values (especially fixed income) and raises liabilities (higher claim costs), putting downward pressure on capital to Total assets. Unless offset by strong investment returns or premium adjustments, surplus tends to shrink in inflationary periods.

Note: This table presents the predicted relationships between inflation and additional financial variables.

In summary, inflation directly affects both sides of the insurance balance sheet: liabilities increase through higher claim costs, and *Total assets*, especially fixed-income securities, can lose value in the short run. *Premiums* adjustments often lag behind inflation, so profitability and surplus are pressured to decrease in the short run. Investment performance becomes crucial in inflationary environments, as insurers may rely more on realized gains and recurring investment income to offset underwriting strain. Company size and risk appetite also influence the degree of exposure. Large insurers might manage inflation risk better through diversification, hedging, or faster pricing adjustments.

F10.2 Results of two-step GMM-FOD on inflation measures

Table F10.2 presents the summary results of two-step GMM-FOD models among the six financial indicators and lagged values of both observed and forecasted inflation, for all insurers. Tables F10.3 and F10.4 present respectively the results on large insurers and small insurers. Additional results are presented in tables F10.5 to F10.10.

Table F10.2: Two-Step GMM-FOD summary results of the effect of inflation on six core financial indicators, all insurers, control variables included but not reported

Dependent variable	IR_{t-1}	$F1\text{-}MST_{t-1}$	$F1\text{-}GAUSI_{t-1}$	$F3\text{-}MST_{t-3}$	$F3\text{-}GAUSS_{t-3}$
Premiums to Total assets	NS	NS	+*	+*	NS
Losses incurred to Total assets	NS	+	NS	+	NS
Net gain from operations to Total assets	NS	NS	NS	-	+
Net realized capital gains to Total assets	-	-	-	+	+
Net investment income to Total assets	+	+	+	+	NS
Capital ratio	-	-	-	NS	+

*Significant at 10%. All other coefficients are significant at 5% (+,-) or not significant (NS).

Table F10.3: Two-Step GMM-FOD summary results of the effect of inflation on six core financial indicators, large insurers, control variables included but not reported

Dependent variable	IR_{t-1}	$F1\text{-}MST_{t-1}$	$F1\text{-}GAUSI_{t-1}$	$F3\text{-}MST_{t-3}$	$F3\text{-}GAUSS_{t-3}$
Premiums to Total assets	+	+	+	NS	NS
Losses incurred to Total assets	+	+	+	NS	NS
Net gain from operations to Total assets	NS	-*	NS	NS	NS
Net realized capital gains to Total assets	-	NS	NS	+*	NS
Net investment income to Total assets	+	+	+	NS	NS
Capital ratio	-	-	-	NS	+*

*Significant at 10%. All other coefficients are significant at 5% (+,-) or not significant (NS).

Table F10.4: Two-Step GMM-FOD summary results of the effect of inflation on six core financial indicators, small insurers, control variables included but not reported

Dependent variable	IR_{t-1}	$F1\text{-}MST_{t-1}$	$F1\text{-}GAUSI_{t-1}$	$F3\text{-}MST_{t-3}$	$F3\text{-}GAUSS_{t-3}$
Premiums to Total assets	NS	NS	+*	NS	NS
Losses incurred to Total assets	NS	+	NS	+	NS
Net gain from operations to Total assets	NS	NS	+	-	NS
Net realized capital gains to Total assets	-	-	-	+	+
Net investment income to Total assets	+	+	+	NS	NS
Capital ratio	-	-	-	+*	+*

*Significant at 10%. All other coefficients are significant at 5% (+,-) or not significant (NS).

Table F10.5: Forecasted *Inflation rate* and its effect on *Premiums to Total assets*, *Losses incurred to Total assets*, and *Net gain from operations to Total assets* for all insurers, 1993-2023

Variable	Pe_t	Li_t	$Nibdt_t$	Pe_t	Li_t	$Nibdt_t$	Pe_t	Li_t	$Nibdt_t$	Pe_t	Li_t	$Nibdt_t$
Pe_{t-1}	0.6428			0.6427			0.6403			0.6432		
	(0.000)			(0.000)			(0.000)			(0.000)		
Li_{t-1}		0.4763			0.4715			0.4606			0.4718	
		(0.000)			(0.000)			(0.000)			(0.000)	
$Nibdt_{t-1}$			0.3584			0.3538			0.3386			0.3625
			(0.000)			(0.000)			(0.000)			(0.000)
$F1\text{-}MST_{t-1}$	0.0008	0.0017	-0.0002									
	(0.186)	(0.000)	(0.724)									
$F1\text{-}GAUSI_{t-1}$				0.0009	0.0005	0.0003						
				(0.051)	(0.219)	(0.315)						
$F3\text{-}MST_{t-3}$							0.0016	0.0026	-0.0028			
							(0.079)	(0.000)	(0.000)			
$F3\text{-}GAUSS_{t-3}$										-0.0001	-0.0000	0.0003
										(0.213)	(0.868)	(0.008)
Number of observations	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816
Number of firms	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163
Number of instruments	2,268	2,268	2,100	2,268	2,268	2,100	2,268	2,268	2,100	2,268	2,268	2,100
p-value Hansen J-test	0.3363	0.2648	0.6700	0.3504	0.2544	0.6584	0.3388	0.2294	0.7031	0.3305	0.2441	0.6566

Note: This table provides the results of the GMM-FOD. Heteroscedasticity-consistent standard errors clustered at the firm level are computed and the corresponding *p*-values are reported in parentheses. *p*-values lower the 0.01 and 0.05 mean the coefficient is significant at 1% and 5% respectively. Pe: *Premiums to Total assets*; Li: *Losses incurred to Total assets*; Nibdt: *Net gain from operations to Total assets.*

Table F10.6: Forecasted *Inflation rate* and its effect on *Premiums to Total assets*, *Losses incurred to Total assets*, and *Net gain from operations to Total assets* for large insurers, 1993-2023

Variable	Pe_t	Li_t	$Nibdt_t$	Pe_t	Li_t	$Nibdt_t$	Pe_t	Li_t	$Nibdt_t$	Pe_t	Li_t	$Nibdt_t$
Pe_{t-1}	0.5089 (0.000)			0.4964 (0.000)			0.4934 (0.000)			0.4867 (0.000)		
Li_{t-1}		0.2476 (0.001)			0.1879 (0.004)			0.2104 (0.003)			0.2117 (0.005)	
$Nibdt_{t-1}$			0.2990 (0.000)			0.2354 (0.008)			0.2367 (0.006)			0.2334 (0.005)
$F1\text{-}MST_{t-1}$	0.0025 (0.001)	0.0033 (0.046)	-0.0036 (0.068)									
$F1\text{-}GAUSI_{t-1}$				0.0016 (0.006)	0.0027 (0.013)	-0.002 (0.880)						
$F3\text{-}MST_{t-3}$							0.0003 (0.837)	0.0020 (0.158)	0.0005 (0.794)			
$F3\text{-}GAUSS_{t-3}$										0.0001 (0.815)	0.0000 (0.882)	0.0000 (0.988)
Number of observations	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078
Number of firms	152	152	152	152	152	152	152	152	152	152	152	152
Number of instruments	102	102	98	102	102	98	102	102	98	102	102	98
p-value Hansen J-test	0.4042	0.4463	0.5302	0.4315	0.4984	0.4533	0.3916	0.4694	0.4511	0.4462	0.5375	0.4474

Note: This table provides the results of the GMM-FOD. Heteroscedasticity-consistent standard errors clustered at the firm level are computed and the corresponding *p*-values are reported in parentheses. *p*-values lower the 0.01 and 0.05 mean the coefficient is significant at 1% and 5% respectively. Pe: *Premiums to Total assets*; Li: *Losses incurred to Total assets*; Nibdt: *Net gain from operations to Total assets.*

Table F10.7: Forecasted *Inflation rate* and its effect on *Premiums to Total assets*, *Losses incurred to Total assets*, and *Net gain from operations to Total assets* for small insurers, 1993-2023

Variable	Pe_t	Li_t	$Nibdt_t$	Pe_t	Li_t	$Nibdt_t$	Pe_t	Li_t	$Nibdt_t$	Pe_t	Li_t	$Nibdt_t$
Pe_{t-1}	0.5770			0.5775			0.5738			0.5784		
	(0.000)			(0.000)			(0.000)			(0.000)		
Li_{t-1}		0.4617			0.4578			0.4440			0.4571	
		(0.000)			(0.000)			(0.000)			(0.000)	
$Nibdt_{t-1}$			0.3739			0.3670			0.3538			0.3771
			(0.000)			(0.000)			(0.000)			(0.000)
$F1\text{-}MST_{t-1}$	0.0003	0.0013	0.0000									
	(0.681)	(0.017)	(0.917)									
$F1\text{-}GAUSI_{t-1}$				0.0010	0.0005	0.0011						
				(0.058)	(0.274)	(0.004)						
$F3\text{-}MST_{t-3}$							0.0014	0.0026	-0.0031			
							(0.208)	(0.002)	(0.000)			
$F3\text{-}GAUSS_{t-3}$										-0.0002	-0.0000	0.0001
										(0.114)	(0.984)	(0.359)
Number of observations	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005
Number of firms	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030
Number of instruments	1,950	1,950	1,771	1,950	1,950	1,771	1,950	1,950	1,771	1,950	1,950	1,771
p-value Hansen J-test	0.4260	0.3615	0.6213	0.4184	0.3695	0.5721	0.4195	0.4522	0.5818	0.4408	0.3612	0.6278

Note: This table provides the results of the GMM-FOD. Heteroscedasticity-consistent standard errors clustered at the firm level are computed and the corresponding *p*-values are reported in parentheses. *p*-values lower the 0.01 and 0.05 mean the coefficient is significant at 1% and 5% respectively. Pe: *Premiums to Total assets*; Li: *Losses incurred to Total assets*; Nibdt: *Net gain from operations to Total assets*.

Table F10.8: Forecasted *Inflation rate* and its effect on *Net realized capital gains to Total assets*, *Net investment income to Total assets* and *Capital and surplus to Total assets* for all insurers, 1993-2023

Variable	Rcg_t	Ii_t	$Capital_t$	Rcg_t	Ii_t	$Capital_t$	Rcg_t	Ii_t	$Capital_t$	Rcg_t	Ii_t	$Capital_t$
Rcg_{t-1}	0.1205			0.1003			0.0549			0.0782		
	(0.005)			(0.014)			(0.157)			(0.041)		
Ii_{t-1}		0.6728			0.6703			0.6788			0.6804	
		(0.000)			(0.000)			(0.000)			(0.000)	
$Capital_{t-1}$			0.8019			0.7983			0.8008			0.7969
			(0.000)			(0.000)			(0.000)			(0.000)
$F1\text{-}MST_{t-1}$	-0.0013	0.0014	-0.0023									
	(0.000)	(0.000)	(0.000)									
$F1\text{-}GAUSI_{t-1}$				-0.0007	0.0013	-0.0024						
				(0.000)	(0.000)	(0.000)						
$F3\text{-}MST_{t-3}$							0.0013	0.0005	0.0005			
							(0.000)	(0.000)	(0.171)			
$F3\text{-}GAUSS_{t-3}$										0.0002	-0.0000	0.0007
										(0.000)	(0.931)	(0.000)
Number of observations	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816	46,816
Number of firms	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163	3,163
Number of instruments	2,278	2,100	2,268	2,268	2,100	2,268	2,268	2,100	2,268	2,268	2,100	2,268
p-value Hansen J-test	0.3788	0.3723	0.3605	0.3925	0.4529	0.3480	0.4235	0.3780	0.3572	0.4329	0.3961	0.4077

Note: This table provides the results of the GMM-FOD. Heteroscedasticity-consistent standard errors clustered at the firm level are computed and the corresponding *p*-values are reported in parentheses. *p*-values lower the 0.01 and 0.05 mean the coefficient is significant at 1% and 5% respectively. Rcg: *Net realized capital gains to Total assets*; Ii: *Net investment income to Total assets*; Capital: *Capital and surplus to Total assets*.

Table F10.9: Forecasted *Inflation rate* and its effect on *Net realized capital gains to Total assets*, *Net investment income to Total assets* and *Capital and surplus to Total assets* for large insurers, 1993-2023

Variable	Rcg_t	Ii_t	$Capital_t$	Rcg_t	Ii_t	$Capital_t$	Rcg_t	Ii_t	$Capital_t$	Rcg_t	Ii_t	$Capital_t$
$Rcg_{t\text{-}1}$	0.2463			0.2052			0.1805			0.2168		
	(0.031)			(0.053)			(0.050)			(0.027)		
$Ii_{t\text{-}1}$		0.3487			0.3648			0.3497			0.3577	
		(0.001)			(0.001)			(0.000)			(0.000)	
$Capital_{t\text{-}1}$			0.6841			0.6781			0.6773			0.6803
			(0.000)			(0.000)			(0.000)			(0.000)
$F1\text{-}MST_{t\text{-}1}$	-0.0012	0.0014	-0.0053									
	(0.543)	(0.010)	(0.000)									
$F1\text{-}GAUSI_{t\text{-}1}$				0.0004	0.0012	-0.0048						
				(0.756)	(0.000)	(0.000)						
$F3\text{-}MST_{t\text{-}3}$							0.0027	0.0007	0.0000			
							(0.057)	(0.147)	(0.994)			
$F3\text{-}GAUSS_{t\text{-}3}$										-0.0000	0.0000	0.0006
										(0.962)	(0.581)	(0.096)
Number of observations	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078	2,078
Number of firms	152	152	152	152	152	152	152	152	152	152	152	152
Number of instruments	98	102	98	98	102	98	98	102	98	98	102	98
p-value Hansen J-test	0.4702	0.2721	0.5825	0.3207	0.2430	0.5745	0.5044	0.3112	0.5582	0.3576	0.3085	0.4372

Note: This table provides the results of the GMM-FOD. Heteroscedasticity-consistent standard errors clustered at the firm level are computed and the corresponding *p*-values are reported in parentheses. *p*-values lower the 0.01 and 0.05 mean the coefficient is significant at 1% and 5% respectively.

Table F10.10: Forecasted *Inflation rate* and its effect on *Net realized capital gains to Total assets*, *Net investment income to Total assets* and *Capital and surplus to Total assets* for small insurers, 1993-2023

Variable	Rcg_t	Ii_t	$Capital_t$	Rcg_t	Ii_t	$Capital_t$	Rcg_t	Ii_t	$Capital_t$	Rcg_t	Ii_t	$Capital_t$
Rcg_{t-1}	0.1145 (0.002)			0.0965 (0.006)			0.0456 (0.164)			0.0679 (0.035)		
Ii_{t-1}		0.6300 (0.000)			0.6260 (0.000)			0.6109 (0.000)			0.6093 (0.000)	
$Capital_{t-1}$			0.7602 (0.000)			0.7590 (0.000)			0.7602 (0.000)			0.7608 (0.000)
$F1\text{-}MST_{t-1}$	-0.0015 (0.000)	0.0012 (0.000)	-0.0014 (0.000)									
$F1\text{-}GAUSI_{t-1}$				-0.0010 (0.000)	0.0012 (0.000)	-0.0016 (0.000)						
$F3\text{-}MST_{t-3}$							0.0011 (0.000)	-0.0000 (0.904)	0.0005 (0.073)			
$F3\text{-}GAUSS_{t-3}$										0.0002 (0.002)	-0.0000 (0.274)	0.0001 (0.100)
Number of observations	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005	41,005
Number of firms	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030	3,030
Number of instruments	1,950	1,617	2,325	1,950	1,617	2,325	1,950	1,617	2,325	1,950	1,617	2,325
p-value Hansen J-test	0.3451	0.2585	0.2031	0.5016	0.3418	0.2113	0.4097	0.2477	0.2319	0.4730	0.2587	0.2125

Note: This table provides the results of the GMM-FOD. Heteroscedasticity-consistent standard errors clustered at the firm level are computed and the corresponding *p*-values are reported in parentheses. *p*-values lower the 0.01 and 0.05 mean the coefficient is significant at 1% and 5% respectively. Rcg : *Net realized capital gains to Total assets*; Ii: *Net investment income to Total assets*; *Capital*: *Capital and surplus to Total assets*.

- *Premiums to Total assets*

Table F10.3 indicates a clear and statistically significant positive relationship between *Premiums to Total assets* and inflation for large insurers, whether inflation is measured by the lagged observed rate ($IR_{t\text{-}1}$) or by the lagged one-year-ahead forecast (FI). These findings suggest that large insurers systematically adjust *Premiums* upward in response to inflationary pressures. Such adjustments likely aim to compensate for rising claims costs and inflation-driven increases in administrative and operational expenses, thereby helping to sustain underwriting profitability in real terms. However, when inflation is measured using the lagged three-year-ahead forecast (F3), the relationship becomes statistically insignificant. This implies that pricing decisions are primarily influenced by recent or near-term inflation expectations rather than by forecasts formed several years earlier.

In contrast, the results from Table F10.2 (all insurers) and Table F10.4 (small insurers) point to a weaker and less consistent link between *Premiums* earned and inflation. Across the full sample, significance is limited, emerging only at the 10% level for $F1\text{-}GAUSS_{t\text{-}1}$ and $F3\text{-}MST_{t\text{-}3}$. Among small insurers, only the lagged one-year-ahead GAUSS forecast ($F1\text{-}GAUSS_{t\text{-}1}$) shows a weaker significant relationship at the 10% level. These findings suggest that, while inflation does influence premium-setting across the industry, the degree of responsiveness is considerably stronger among large insurers.

This divergence may reflect structural differences in insurers' operational capabilities and market positioning. Large insurers appear more proactive and efficient in incorporating short-term inflation signals into pricing strategies, likely benefiting from greater pricing power, advanced actuarial modeling, and more adaptable policy frameworks. Their scale and resources may also allow for quicker updates to pricing assumptions in response to changing macroeconomic conditions.

Conversely, small insurers may face a range of constraints that hinder their ability to reprice policies effectively. These may include regulatory oversight, competitive market pressures, slower decision-making processes, or limited research capacity. Additionally, the weaker and more variable inflation-premium relationships for the broader sample and for small insurers may reflect heterogeneity in product offerings, geographic focus, and underwriting strategies. Such factors can influence how inflation is perceived and transmitted into pricing across different segments of the insurance market.

In sum, the results highlight that large insurers are better positioned to respond to inflation through premium adjustments, while smaller insurers demonstrate a more conservative pricing response. This asymmetry underscores the importance of scale, operational agility, and forecasting capacity in adapting to inflationary environments.

- *Losses incurred to Total assets*

For large insurers, *Losses incurred to Total assets* exhibits a positive association with inflation when measured using the lagged value of observed inflation (IR_{t-1}) as well as the lagged one-year-ahead forecasted inflation from both the MST and GAUSS models ($F1\text{-}MST_{t-1}$ and $F1\text{-}GAUSS_{t-1}$). This suggests that claims costs tend to increase in line with recent inflation trends and near-term expectations. However, when inflation is measured using lagged three-year-ahead forecasts (F3-MST_{t-3} and F3-GAUSS_{t-3}), the relationship is no longer statistically significant at conventional levels, indicating that long-term inflation expectations formed three years earlier have little bearing on current loss experience. In short, large insurers' incurred losses appear to respond more directly to realized inflation and near-term expectations than to long-range forecasts.

For the full sample and for small insurers, a similar positive relationship is observed between inflation and incurred losses. Notably, this includes significant associations with both the lagged one-year-ahead ($F1\text{-}MST_{t\text{-}1}$) and three-year-ahead ($F3\text{-}MST_{t\text{-}3}$) inflation forecasts. These findings point to a broader industry sensitivity to inflationary conditions across multiple horizons. Rising claim-related costs—such as medical care, construction materials, and vehicle parts—are all likely contributors to inflation-driven increases in incurred losses. It is interesting to observe that the MST forecasts are more significant.

- *Net gain from operations to Total assets*

The expected relationship between lagged inflation and *Net gain from operations to Total assets* is negative, as inflation tends to elevate operating and claims costs, thereby compressing insurers' profitability. Consistent with this expectation, the results for the full sample reveal a negative association between net operating gains and the lagged three-year-ahead forecasted inflation based on the F3-MST$_{t\text{-}3}$ model. However, surprisingly, a positive relationship is observed when using the same lag from the F3-GAUSS$_{t\text{-}3}$ model. This divergence underscores the influence of the inflation forecasting methodology: different models may capture varying inflationary expectations and macroeconomic contexts, which in turn affect insurers' operational outcomes in distinct ways.

For large insurers, a negative association is found between net operating gains and the lagged one-year-ahead forecasted inflation ($F1\text{-}MST_{t\text{-}1}$), significant at the 10% level. This finding suggests that even relatively recent inflation expectations—when not promptly incorporated into pricing or operational adjustments—can erode profitability. Larger insurers, with more complex structures and longer operational lead times, may face challenges in swiftly adapting to changing inflationary conditions, particularly when cost structures are more rigid or fixed.

Small insurers exhibit a pattern similar to the overall sample: a negative relationship with the $F3\text{-}MST_{t\text{-}3}$ forecast and a positive one with $F3\text{-}GAUSS_{t\text{-}3}$. However, unlike the overall sample, small insurers display a positive relationship with $F1\text{-}GAUSS_{t\text{-}1}$, rather than with $F3\text{-}GAUSS_{t\text{-}3}$. This unexpected, mixed result highlights that small insurers may be more sensitive to the nuances of different inflation signals. Their performance could benefit from inflation dynamics that align with niche markets, more agile decision-making, or localized competitive conditions.

These insights underscore the strategic importance of monitoring and interpreting inflation forecasts—across models and time horizons—as a central component of insurer risk management. Effective pricing and underwriting strategies must account not only for realized inflation but also for the diverse ways in which inflation expectations influence firm behavior and financial outcomes over time.

- *Net realized capital gains to Total assets*

The relationship between lagged inflation and *Net realized capital gains to Total assets* is inherently complex, reflecting the multifaceted interplay between inflation dynamics and asset price movements. Across both the full sample and the subset of small insurers, a consistent pattern emerges: net realized capital gains are negatively associated with both lagged observed inflation and lagged one-year-ahead forecasted inflation, while a positive association is found with the lagged three-year-ahead forecasted inflation.

This pattern suggests that in the short term, inflation—whether realized or expected—tends to exert downward pressure on asset valuations, primarily through rising interest rates that depress bond prices and dampen equity market performance. Consequently, insurers may realize fewer capital gains or even incur losses. Over a longer historical horizon, however, capital markets appear to adjust to inflation expectations, potentially driving price appreciation of nominal assets and thus enhancing capital gains when the assets are eventually sold.

For large insurers, a negative relationship is observed between net realized capital gains and lagged observed inflation, aligning with the notion that near-term inflationary shocks undermine asset values. However, a positive relationship—significant at the 10% level—is identified with the lagged three-year-ahead forecasted inflation ($F3\text{-}MST_{t\text{-}3}$). This result suggests that large insurers, with their longer investment horizons, broader asset diversification, and more sophisticated risk management capabilities, may be better positioned to benefit from inflation-driven nominal gains over the long run.

Despite these directional trends, many of the observed relationships lack statistical significance, especially among large insurers. This points to the dominant role of firm-specific factors—such as investment strategy, asset allocation, risk tolerance, and timing of asset disposals—in determining realized capital gains. Inflation may shape the macroeconomic context in which these gains occur, but it is not the sole determinant.

These findings highlight the importance of incorporating inflation expectations—particularly long-term ones—into investment strategy and asset-liability management. While inflation alone does not dictate capital gains outcomes, its role reinforces the value of forward-looking portfolio design, especially in volatile or inflationary macroeconomic environments.

- *Net investment income to Total assets*

The expected relationship between inflation and *Net investment income to Total assets* is positive, as inflationary environments are typically associated with rising interest rates. Higher rates boost yields on newly acquired fixed-income securities, progressively enhancing insurers’ investment income as maturing assets are reinvested at more favorable terms.

Empirical findings align with this theoretical prediction. A positive and statistically significant association is observed between net investment income and both the lagged value of observed inflation ($IR_{t\text{-}1}$) and the lagged one-year-ahead forecasted inflation ($F1\text{-}MST_{t\text{-}1}$ and $F1\text{-}GAUSS_{t\text{-}1}$). These results suggest that insurers’ investment returns respond relatively quickly to near-term inflationary pressures, leading insurers to invest rapidly in new assets like bonds. The lagged one-year-ahead forecast captures how insurers, at a prior point in time, expected short-term inflation evolve to relative to recent conditions—indicating that firms effectively incorporated these expectations into reinvestment decisions and asset allocation strategies.

By contrast, the relationship between net investment income and the lagged three-year-ahead forecasted inflation ($F3\text{-}MST_{t\text{-}3}$ and $F3\text{-}GAUSS_{t\text{-}3}$) is not statistically significant for large or small insurers. This forecast reflects how, three years earlier, insurers anticipated the medium- to long-term trajectory of inflation. Notably, for the full sample of insurers, a positive and statistically significant relationship emerges between net investment income and the lagged three-year-ahead forecast from the MST model ($F3\text{-}MST_{t\text{-}3}$). This result suggests that, at the industry level, firms may have gradually aligned their investment strategies with earlier long-term inflation expectations.

- *Capital ratio*

The expected relationship between inflation and the *Capital ratio* is negative, reflecting the dual impact of inflationary pressures on insurers' balance sheets. Rising inflation erodes the real value of *Total assets* while simultaneously increasing liabilities through elevated claims costs and operating expenses. This combination compresses surplus and capital relative to Total assets, thereby weakening the *Capital ratio*.

Empirical findings support this theoretical expectation. A consistently negative and statistically significant relationship is observed between the *Capital ratio* and both lagged observed inflation ($IR_{t\text{-}1}$) and lagged one-year-ahead forecasted inflation ($F1\text{-}MST_{t\text{-}1}$ and $F1\text{-}GAUSS_{t\text{-}1}$). These lagged forecasts reflect how, at a point in the past, insurers anticipated short-term inflation trends relative to recent experience. The results indicate that in response to anticipated near-term inflation, insurers—regardless of size—experience capital erosion or adopt more conservative capital policies, likely to preserve solvency under tightening financial conditions.

However, this relationship changes when considering long-term inflation expectations. A positive association emerges between the *Capital ratio* and the lagged three-year-ahead forecasted inflation ($F3\text{-}GAUSS_{t\text{-}3}$), particularly among small insurers. Additionally, the $F3\text{-}MST_{t\text{-}3}$ forecast is positively associated with capital ratios at the 10% significance level for small firms. These forecasts reflect how, three years ago, insurers anticipated inflation would evolve over the medium to long term—suggesting a more strategic and forward-looking capital response.

In summary, the capital ratio's responsiveness to inflation is time-horizon dependent. While short-term inflation expectations are associated with capital strain across all firms, long-term forecasts appear to prompt capital strengthening—especially among small insurers. These findings underscore the importance of incorporating forward-looking inflation expectations into capital planning frameworks to support long-term solvency and operational stability.

11. *COVID-19*, US inflation tail risk, and volatility

11.1 Introduction

Introduced by the pioneering work of Sims (1980). Vector Autoregressions (VARs) are linear multivariate time-series models that capture better the linear interdependencies between macroeconomic variables over time. Although firstly being based on simple formulation. i.e., constant parameter, constant variance, normally distributed error terms, VARs gained widespread recognition and large applications in the macroeconomic analysis by policy makers and forecasters. However, VARs require a lot of parameters to be estimated depending on the number of endogenous variables and the lag structure. VARs are now analyzed using the Bayesian inference to overcome this practical issue related to parameters estimation.

Different from frequentist statistics based on the data generating process and which treat the model's parameters as nonrandom, Bayesian methods treat the VAR parameters as unobserved random variables and provide a framework to fully characterize our knowledge about the probability distributions of these random parameters conditional on the observed data which is assumed to be nonrandom. Thanks to their flexibility, fast computations and improved forecast performance, Bayesian VARs are considered as benchmark models for economic analysis and forecasting as emphasized by, among others, Doan. Litterman and Sims (1984), Litterman (1986), and Sims and Uhlig (1991).

Since then, VARs and Bayesian VARs have been continually extended and improved to consider important features of macroeconomic data, such as time-varying parameters. Sims (1993) stipulates that stationary VAR models appear to be inadequate to model and forecast macroeconomics variables and develops a Bayesian VAR that allows for time-varying variances as well as time-varying autoregressive coefficients and finds that the model produces drastically better forecasts of inflation. Canova (1993) employs a multivariate Bayesian time-varying coefficients approach to improve modeling and forecasting of exchange rates. Cogley and Sargent (2001) develop a Bayesian VAR models with random coefficients to measure parameter drift in US inflation-unemployment-interest-rate dynamics.

Subsequently, many researchers tried to account simultaneously for the time variation in both the coefficients and the volatilities of residuals. Among others, Primiceri (2005), Cogley and Sergent (2005), and Del Negro and Primiceri (2015) propose a Bayesian VAR model in which regression coefficients and variance parameters are allowed to evolve according to random walks to reflect both time variation of the simultaneous relations among the variables of the model and heteroscedasticity of the innovations in studying the impacts of the monetary policy shocks in inflation and unemployment rate. Time variation of the variance covariance matrix of the innovations is modelled using a multivariate stochastic volatility framework which is meant to capture the heteroscedasticity of the shocks and the cyclical variations in macroeconomic uncertainty. Many studies using multivariate stochastic volatility supposed that all the innovations in the model are jointly normally distributed.

However, a large body of macroeconomic research has documented the presence of heavy tails and asymmetries in the empirical distributions of macroeconomic variables. especially during economic downturns. Fagiolo et al (2008) investigate the statistical properties of GDP and industrial production growth rate distributions in OECD countries and find that such distributions appear to be well approximated by an exponential power density, with tails much fatter than the Gaussian ones. Acemoglu et al (2017) assert that the normal distribution does not provide a good approximation to the distribution of aggregate macroeconomic variables at the tails and develop a theoretical model, the macroeconomic tail risks, which is defined as systematic departures in the frequency of large economic downturns from what is predicted by the normal distribution. Adrian et al. (2019) model empirically the full distribution of future real GDP growth as a function of current financial and economic conditions using quantile regressions and find that the estimated distribution is left-skewed during recessions and is closer to being symmetric during expansions. Jensen et al. (2020) document that the US and other G7 economies have been characterized by an increasingly negative business cycle asymmetry over the last three decades due to the increase in the financial leverage of households and firms. Many models were used to capture the asymmetries in the distribution of economics times series. namely the quantile regression methods. Markov switching and more advanced models based on copulas. However. most of these models suppose a Gaussian distribution for residuals and constant volatility.

Moreover. most empirical studies using VAR applications are usually based only on a small number of variables. particularly studies related to the impacts of monetary policy shocks on real GDP and inflation or unemployment. However, Banbura et al. (2010). in their seminal paper. point out that small VAR applications could create an omitted variable bias with adverse consequences both for structural analysis and for forecasting. Hence, Banbura et al. (2010) urged the need for estimating large VAR models to capture complex relationships between macroeconomic variables which entail a risk of over-parametrization. and they propose a novel Bayesian VAR framework based on shrinkage to overcome this issue and to improve structural analysis and the forecasting performance.

In sum, researchers are facing twofold computational challenges in modeling complex interactions between macroeconomic time-series particularly during downturn episodes with higher tail risk and volatility. i) the need for the inclusion of large number time-series creating a risk of parameters proliferation (Banbura et al. 2010), and ii) the need to allow for time-varying coefficients and volatilities (Primiceri. 2005; Cogley and Sargent. 2005). Both challenges are efficiently accommodated with Bayesian VARs, which rely on the Markov Chain Monte Carlo framework to get a posterior distribution that is the product of likelihood and the prior distribution. Prior probability distribution comes from the researcher’s subjective beliefs about the value of the parameters. Bayesian shrinkage is helpful to handle large VARs. Bayesian framework accommodates also non-Gaussian distributions for error terms and stochastic volatility. All these successive developments on BVARs enhanced remarkably the structural analysis based on impulse response functions and improved the accuracy in predicting the real-time density forecasts of macroeconomic variables. particularly during periods with enormous data movements.

Chiu et al (2017) construct a Bayesian VAR model where the orthogonalized shocks feature Student’s *t* distribution as well as time-varying variance. Using US data on industrial production growth, inflation, interest rates and stock returns, they show that their VAR model outperforms alternatives that assume Gaussianity in terms of in-sample fit and out-of-sample forecasting, especially during 2008. Chan (2020) introduces a class of large Bayesian VAR that allows for non-Gaussian, heteroscedastic, and serially dependent innovations. He applies his model to 20 macroeconomic variables and finds that this model outperforms the standard variant with independent, homoscedastic Gaussian innovations and it accommodates better large shocks as seen during the financial crisis 2008-2009.

More recently, the *COVID-19* pandemic created intractable and longer-lasting economic turbulence, specifically, a surge in the *Inflation rate*, distortions in the labor market with spike in the unemployment rate, shortages due to constraints on supply, and an increase in commodity prices. The financial market was also deeply and adversely affected. *COVID-19* created outliers and higher volatility for many key macroeconomic variables and it triggered forces that might alter macroeconomic interactions going forward. Although, the *COVID-19* posed challenges for estimation and forecasting with Bayesian VARs due to outliers, it was an excellent laboratory to enhance theoretically and validate empirically new developments in BVARs which prompted many empirical studies (Hartwig, 2024; Bobeica and Hartwig, 2023; Carriero et al., 2024a, 2024b; and Kiss et al., 2023).

From the methodological perspective, our paper belongs to a rapidly expanding literature on using flexible large BVARs, with heavy tails and stochastic volatility for the innovations (MST-SV hereafter), for macroeconomic forecasting and structural analysis (see Chan (2023) for an exhaustive review of these models). From the perspective of empirical application, our paper is related to the literature that focuses on the effects of large economic downturns on macroeconomics dynamics and transmission channels. Particularly, our paper is most closely connected to and builds on the recent emerging literature that analyses and addresses extreme observations (outliers) of the main U.S macroeconomic variables that are created by *COVID-19* pandemic. These two strands in the literature are briefly discussed previously. Our analysis contributes to literature in distinct ways. First, we apply a novel and flexible BVAR framework, with multivariate skewed t-distribution and time varying volatility for the innovations, to a large and recent dataset of U.S macroeconomic variables ending in 2023:Q4, hence, including longer period after the *COVID-19* pandemic. The MST-SV tackles the problem of unstable estimated parameters when adding the *COVID-19* observations. Second, we provide further evidence on the presence of skewness and fat tails in the distributions of key U.S macroeconomic variables and we investigate how these non-gaussian features evolved during the pandemic period. Third, we analyze the macroeconomic shocks transmission channels during the pandemic era. Particularly, we study the responses of inflation to shocks in real activity, monetary policy and labor market conditions in different points in time during the pandemic era. Fourth, we gauge the performance of the MST-SV model in real time forecasts of the price level and *Inflation rate* during the pandemic using different performance variables and different competing alternatives.

Our results suggest that the *COVID-19* pandemic creates outliers for major U.S macroeconomic variables as witnessed by the simultaneous decrease in the degree of freedom of the t-distribution of residuals, leading to a macroeconomic tail risk. Our findings reveal that the *COVID-19* shock induces a long-lived increase in the stochastic volatility for real GDP, *CPI* and Fed rate but generates transient outliers for the labor market. More importantly, the stochastic volatility of the residuals for major US macroeconomic variables responded differently to the pandemic shock. We also find that the *COVID-19* pandemic altered greatly the manner of how the price level, measured by the *CPI*, responded to shocks in the real GDP, Fed rates, unemployment rate and the cost of employment, compared to the period before the pandemic. We then found evidence that macroeconomic transmission channels and established interconnexions between macro variables were hugely undermined by the pandemic. Finally, we find evidence of added-forecastability in point and density forecasts of the price level and the *Inflation rate* during the pandemic by considering the tail fatness and time varying volatility for innovations compared to standard gaussian BVAR and Professionals' forecasts.

This section is organized as follows. Subsection 11.2 describes the real-time data used. Subsection 11.3 presents the BVAR with stochastic volatility and heavy tails. Subsection 11.4 details our empirical, in-sample and out-of-sample, analysis, and Subsection 11.5 concludes.

11.2 What is the data telling us?

We use quarterly dataset consisting of 12 US macroeconomic variables during the period 1980:Q1–2023:Q4 and sourced from the FRED database of Federal Reserve Bank of St. Louis. When choosing variables, we started with the most relevant ones according to the ranking derived in Jarociński and Maćkowiak (2017) and applied log transformation for some variables. We also follow recent recommendations by Bernanke and Blanchard (2025) and include the Employment Cost Index to capture the effect of the tightness of the labor market on inflation. Our relatively large dataset might mitigate the impact of variables with abnormal dynamics in the context of unstable environments as suggested by Rossi (2021).

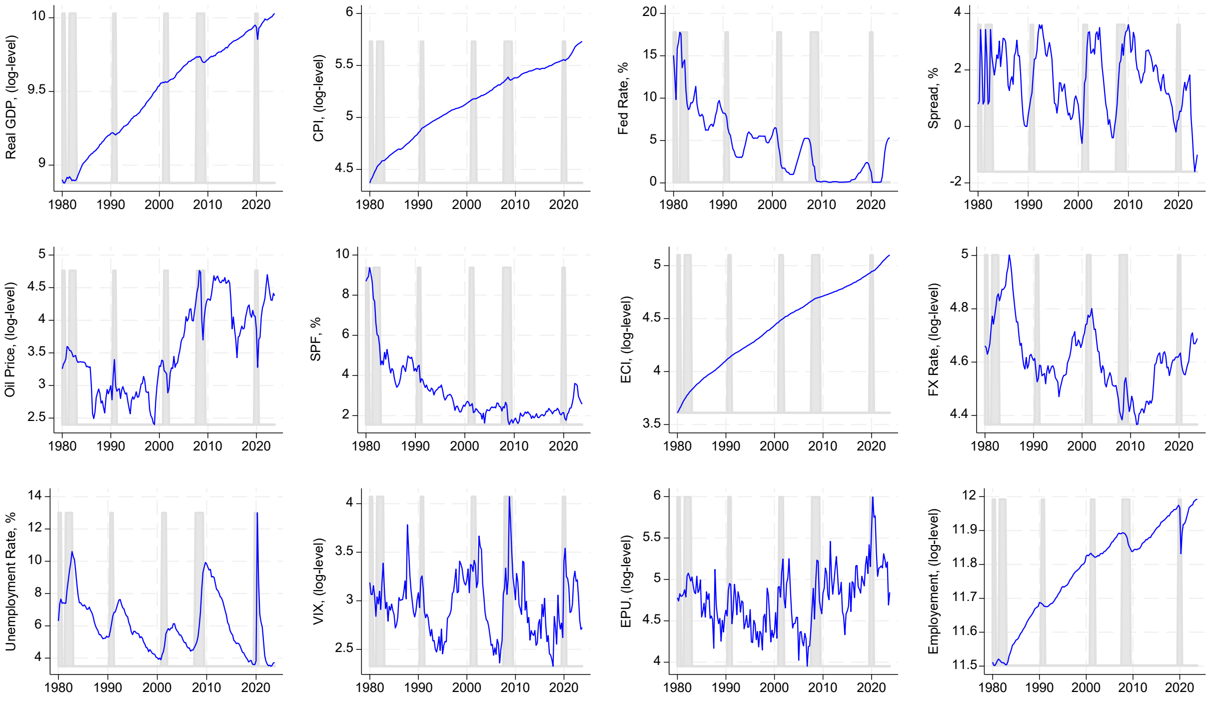
Table 11.1 gives the different macro variables included in the empirical analysis and the estimation of the model.

Table 11.1: Variables

Variable	Transformation
Price index	
Consumer Price Index (*CPI*)	log
Real activity variables	
Real GDP	log
Total Employment	log
Unemployment Rate	none
Employment cost index (ECI)	log
Economic policy uncertainty index (EPU)	log
Survey of Professional forecasters (SPF)	none
Crude oil price	log
Financial market variables	
Federal fund rate	none
Real Exchange rate	log
VIX index	log
Ten-Year Government Bond Spread	none

Figure 11.1 shows the data over the sample period alongside with the NBER recession indicators (dashed area). Except for the real GDP, the *CPI* and the ECI indices that are in a steady increase over time, we observe that most of the others macro variables are evolving with a motion like a random walk. Particularly the 10-year T-Bond spread, the crude oil price, the FX rate, the Fed rate, the VIX and the EPU indices. More importantly, the visual inspection of Figure 11.1 shows drastic changes in the behavior of the time series of the different variables during recession periods which could create outlier observations.

Figure 11.1: Dataset for the estimation of the BVAR



Panel A of Table 11.2 shows up summary statistics for the macroeconomic variables in our study. We find significant skewness and excess kurtosis for most of the variables. We also run a normality test based on skewness and kurtosis which rejects the normality hypothesis for the variables, at conventional confidence levels. However, this does not necessarily imply that the error terms have skewed or heavy tailed distributions. For deeper insight, Panel B of Table 11.2 reports summary statistics for the residuals from an OLS-fit of a homoscedastic VAR (4) model. The values of skewness and kurtosis indicate, interestingly, that residuals are non-Gaussian, which is confirmed by the normality test. Despite many of our variable are log-transformed, these statistics show unconditional skewed as well as fat tailed distribution in the dataset and therefore a need for flexible modelling tools that can capture these features of the data.

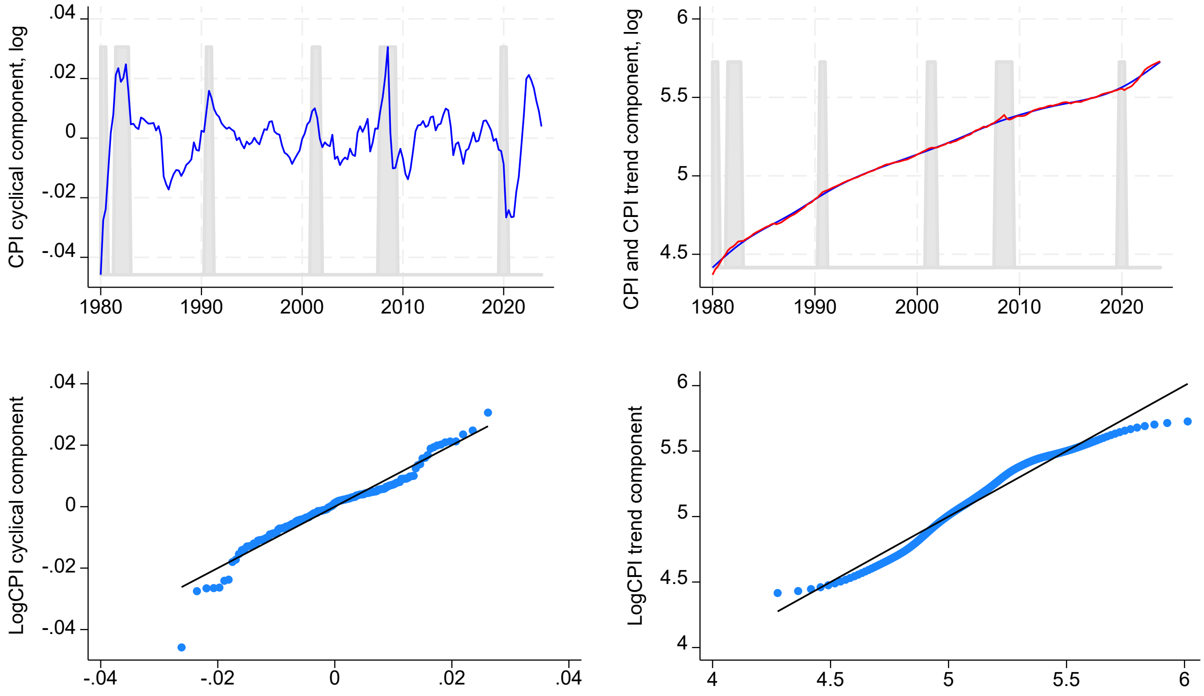
Table 11.2 Summary statistics

Variables	Obs	Mean	STD	Skew	Kurt	Min	Max	Normality Test: *p-value*
Panel A: Summary statistics of macroeconomic variables								
Real GDP (log-level)	176	9.507	0.338	-0.319	1.867	8.879	10.029	0.000
CPI (log-level)	176	5.145	0.343	-0.355	2.099	4.370	5.730	0.000
Fed rate (%)	176	4.408	3.981	1.050	4.035	0.060	17.78	0.000
Spread (%)	176	1.651	1.165	-0.293	2.378	-1.600	3.600	0.028
Oil price (log-level)	176	3.561	0.651	0.195	1.816	2.401	4.762	0.000
SPF (%)	176	3.176	1.579	2.054	7.505	1.555	9.373	0.000
ECI (log-level)	176	4.445	0.389	-0.284	2.004	3.611	5.100	0.000
FX rate (log-level)	176	4.613	0.130	0.592	3.312	4.366	5.002	0.008
Unemployment rate (%)	176	6.102	1.798	0.813	3.430	3.500	13.000	0.000
VIX (log-level)	176	2.957	0.315	0.398	3.122	2.327	4.072	0.079
EPU (log-level)	176	4.764	0.346	0.390	3.447	3.953	5.996	0.048
Employment (log-level)	176	11.782	0.139	-0.534	2.199	11.502	11.992	0.000
Panel B: Summary statistics for the residuals from the OLS-fit of a homoscedastic VAR (4)								
Real GDP (log-level)	172	0.000	0,007	-2,771	24,696	-0,056	0,016	0,000
CPI (log-level)	172	0.000	0,004	-1,134	9,711	-0,022	0,011	0,000
Fed rate (%)	172	0.000	0,374	-0,213	3,772	-1,357	1,080	0,082
Spread (%)	172	0.000	0,417	0,660	5,691	-1,156	1,917	0,000
Oil price (log-level)	172	0.000	0,119	-0,378	4,839	-0,428	0,416	0,002
SPF (%)	172	0.000	0,154	-0,169	4,144	-0,608	0,465	0,039
ECI (log-level)	172	0.000	0,002	-0,457	3,687	-0,006	0,004	0,017
FX rate (log-level)	172	0.000	0,022	-0,138	2,748	-0,060	0,054	0,641
Unemployment rate (%)	172	0.000	0,580	5,716	59,121	-1,229	5,793	0,000
VIX (log-level)	172	0.000	0,165	1,359	6,684	-0,393	0,653	0,000
EPU (log-level)	172	0.000	0,180	0,452	4,465	-0,513	0,683	0,003
Employment (log-level)	172	0.000	0,009	-5,748	59,377	-0,086	0,017	0,000

For further analysis of our main variables, we apply the Hodrick–Prescott filter which breaks down a time series into a short-run (cyclical) and a smooth long-run (trend) component. It produces then a detrended time series. We do this detrending for our main variable, namely the *CPI* (in log). Figure 11.2 presents the trend and cyclical components alongside their quantile-quantile (Q-Q) plots against the standard normal distribution. The Q-Q plots indicate deviations of the quantiles of both long-term trend and short-term fluctuations in inflation from the standard normal. They reveal that the normal distribution significantly underestimates the frequency of large movement in inflation. Importantly, Figure 11.2 reveals also that huge cyclical fluctuations in inflation occur during or subsequently to recession periods (dashed area), as for the second oil price shock in 1979 and the subsequent Volcker monetary policy, the financial crisis of 2008-2009, and more recently the *COVID-19* pandemic.

The presence of skewness and fat tails in the distributions of key macroeconomic variables urges the use of VARs with non-Gaussian error terms to better capture the changing macroeconomic transmission channels during the economics shocks. In fact, Lenza and Primiceri (2022) and Schorfheide and Song (2024) report that forecasts generated since March 2020 from homoskedastic BVARs are often distorted due to *COVID-19* outliers.

Figure 11.2: *CPI* trend and cyclical components (in log) and their Q-Q plots



11.3 VAR models with skewness and heavy tails

In the spirit of Primiceri (2005) and Del Negro and Primiceri (2015), we use a vector autoregressive (VAR) model allowing for time varying variance-covariance matrix of the innovations. In fact, the standard deviations of error terms are assumed to evolve as geometric random walks, namely stochastic volatility.

Let y_t be an $n \times 1$ vector of endogenous variables that is observed over the periods $t = 1, \ldots\ldots, T$.

Consider the following generic VAR (p) model with Gaussian stochastic volatility (Gaussian-SV) as:

$$\mathrm{y}_t = c + \mathrm{B}_1 y_{t-1} + \cdots + \mathrm{B}_p y_{t-p} + u_t \tag{11.1}$$

c is a k-dimensional vector of intercepts; B_j is a $k \times k$ matrix of regression coefficients with $t = 1, \dots, p$. u_t is a k-dimensional vector of heteroskedastic unobservable shocks associated with the VAR equations, with:

$$u_t = A^{-1} H_t^{1/2} \varepsilon_t \tag{11.2}$$

where A^{-1} is a $k \times k$ lower triangular matrix with ones on the diagonal that describes the contemporaneous interaction of the endogenous variables:

$$A = \begin{bmatrix} 1 & 0 & \dots & 0 \\ \alpha_{21} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n1} & \dots & \alpha_{nn} & 1 \end{bmatrix},$$

And H_t is a $k \times k$ diagonal matrix that captures the heteroskedastic volatility:

$$H_t = \begin{bmatrix} h_{1,t} & 0 & \dots & 0 \\ 0 & h_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & h_{k,t} \end{bmatrix}.$$

ε_t is a k-dimensional vector of innovations that follows a multivariate Gaussian distribution with $\varepsilon_t \sim N_k(0, \mathrm{I})$.

The law of motion for each element of $H_t = \mathrm{diag}(h_{1,t}, \dots., h_{k,t})$ is specified as an independent autoregressive process (random walk) with:

$$log(h_{i,t}) = log(h_{i,t-1}) + \sigma_i \eta_{it} \tag{11.3}$$

and

$$i = 1, \dots, k, \qquad \eta_{it} \sim N(0, \mathrm{I}).$$

Following Karlsson (2023), the reduced form shocks u_t are modeled directly as correlated vectors of univariate skew-*t* distributions which allow for skewness and heavy tails u_t. This gives a VAR model with multi-skew-*t* innovations.

$$u_t = (W_t - \bar{W})\gamma + W_t^{1/2} A^{-1} H_t^{1/2} \varepsilon_t, \tag{11.4}$$

with $\gamma = (\gamma_1, \dots, \gamma_k)'$ as a *k*-dimensional vector of skewness parameters. The mixing matrix $W_t =$ diag $(\xi_t) =$ diag $(\xi_{1t}, \dots, \xi_{kt})$ is a $k \times k$ diagonal matrix with $\xi_{it} \sim \mathcal{IG}\left(\frac{\nu_i}{2}, \frac{\nu_i}{2}\right)$. Degree of freedom parameters are collected in the vector $\nu = (\nu_1, \dots, \nu_k)'$. $\bar{W} = \mathrm{E}(W_t) = \frac{\nu}{\nu-2}$ identifies if the innovations have a zero mean.

11.4 Empirical illustration[9]

We now estimate[10] an empirical version of the Bayesian VAR model with stochastic volatility and fat tails introduced above using quarterly US data. We employ a generous lag structure consisting of four quarterly lags to accommodate flexible dynamics between macroeconomic variables as suggested in the relevant literature (Bernanke and Blanchard, 2025; Carriero et al., 2024a). We also estimate the model on the pre- and post-covid period to discover the impact of the pandemic on the behaviors of macro variables and their interconnexions. The analysis is conducted both within- and out-of-sample.

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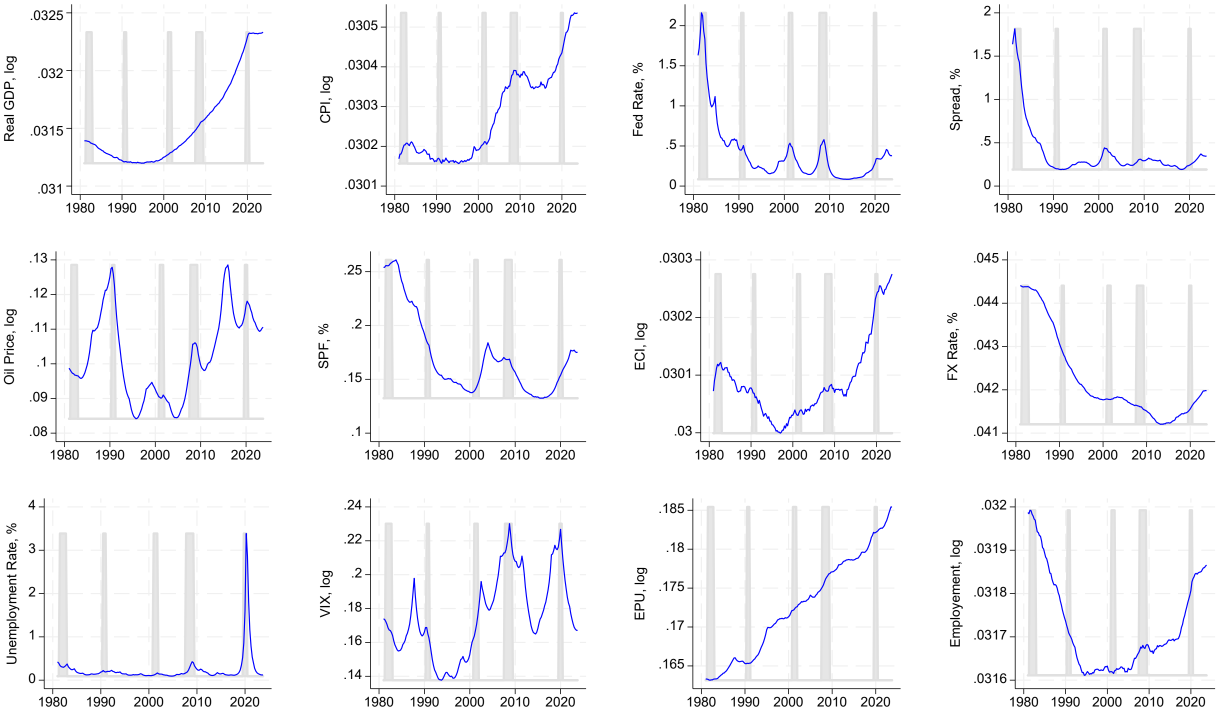
[9] We use the R package developed in Karlsson et al (2023) and available at: https://github.com/hoanguc3m/fatBVARS.

[10] For each estimation at each quarter, the estimation is based on a simulation with 11000 iterations with a burin of 1000 iterations.

11.4.1 Within-sample analysis

The whitin analysis allows us to discover deeply the features of the time series of our macroeconomics data set. Figure 11.3 plots the posterior mean of the estimated time-varying stochastic volatility of the innovations, and presents many interesting features. Figure 11.3 reveals that the standard deviations of residuals vary over time, with broadly low magnitude movements, and they rise around crisis times. The stochastic volatility for the real GDP (in log) decreased during the 80s and 90s and is trending upward afterward. The volatility of both *CPI* and EPU indices (in log) are fluctuating around an upward trend over time. The volatility of the Fed rates dropped drastically during the beginning of the 80s on the eve of the great moderation by Volcker and his unprecedented monetary policy and becomes low and substantially constant afterward before rising again on the onset of the financial crisis 2007-2009. The volatility of the 10-year T-Bond spread evolved in the same way as the Fed rate. The stochastic volatility of residuals in the VIX index equation peaked during the 2007-2009 financial crisis and the *COVID-19*. The stochastic volatility of the employment rate attained historical record during the pandemic. These findings support the use of stochastic volatility as a given feature of the residuals for US macroeconomic variables.

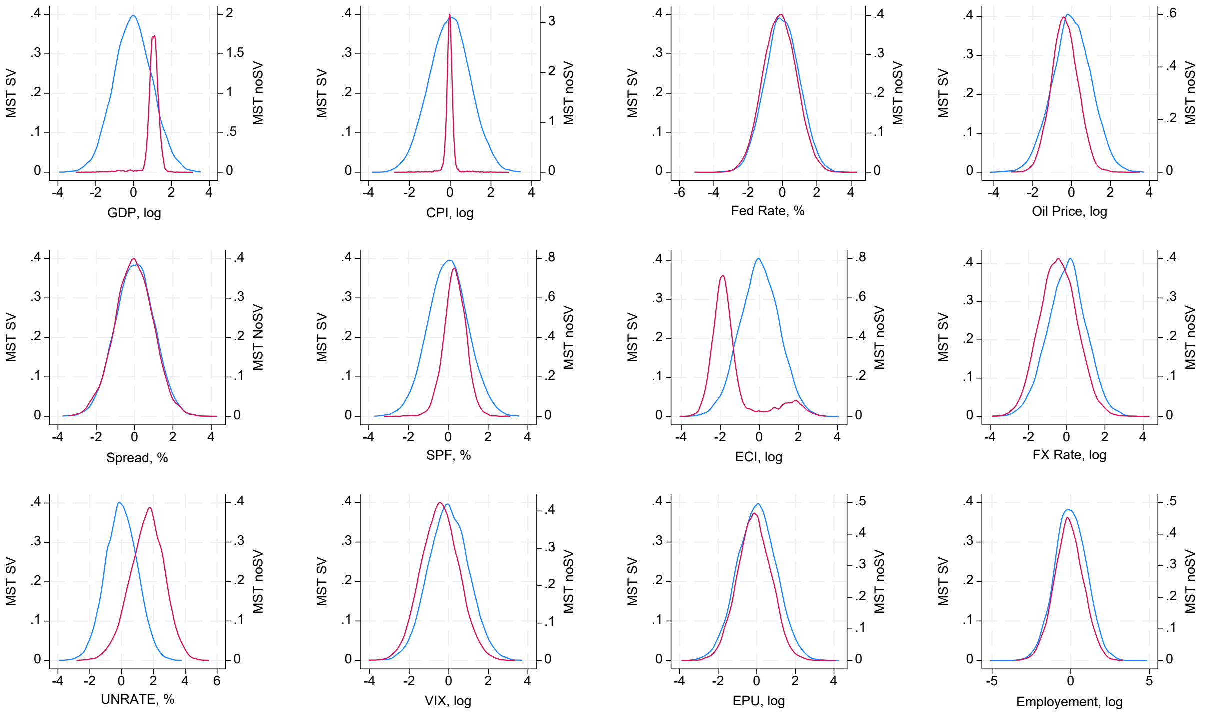
Figure 11.3: Posterior mean of the estimated stochastic volatility



Note: Stochastic volatility $\left(e^{h_t}\right)^{1/2}$ of the residuals in the VAR model with multi-*t* skew distributed innovations and stochastic volatility (MST SV).

Next, we analyze the skewness parameters of the posterior distributions of the residuals in the VAR models with MST with (without) stochastic volatility, namely MST SV (MST noSV). Apart from the Fed rate and the 10-year T-Bond spread, Figure 11.4 exhibits large shifts in the marginal distributions of the skewness parameter coming from both models. Surprisingly, skewness parameters coming from the MST SV are centered around zero, although with some spread out. Conversely, residuals from the MST model appear to have nonzero skewness parameters particularly for the real GDP, oil price, SPF, employment cost index and unemployment rate. In sum, these findings indicate that accounting for time varying volatility may preserve the symmetry of the presumed *t* distribution of residuals. In fact, macroeconomic chocks translate to a higher stochastic volatility without altering the symmetry of the distributions of residuals. We will come back further to this intuition.

Figure 11.4: Posterior densities of the skewness parameters of the VAR models

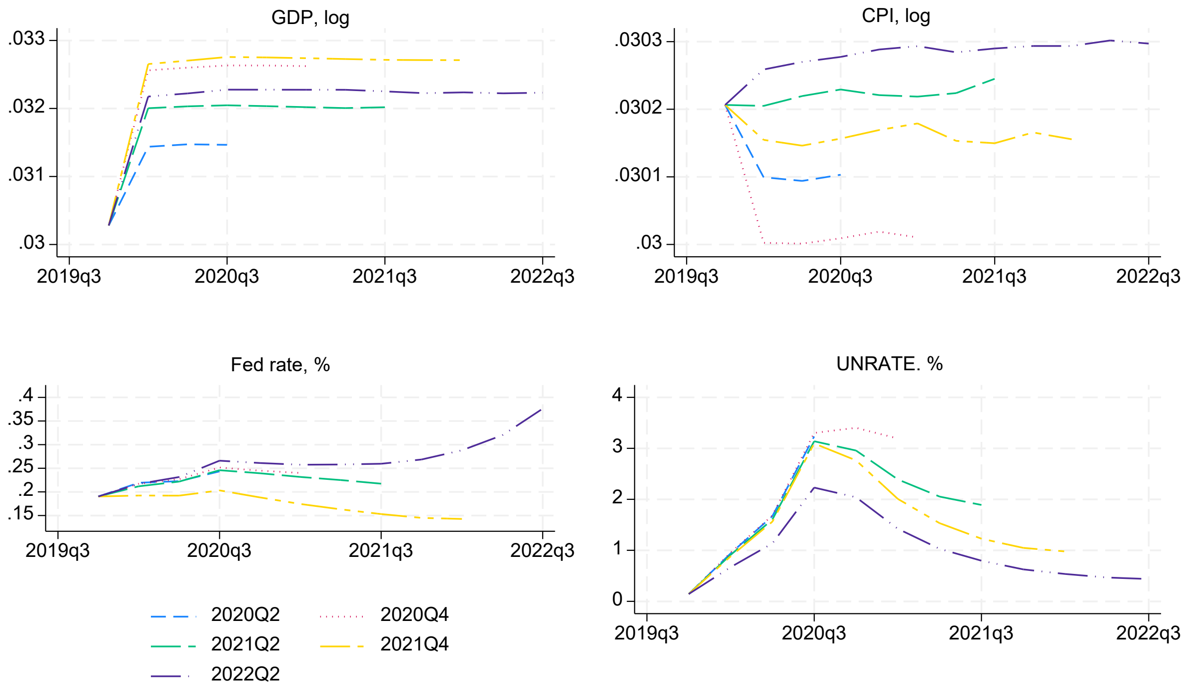


Note: With MST and without stochastic volatility (in red) and MST with stochastic volatility (in blue).

11.4.2 Macroeconomic tail risk and volatility during the pandemic era

In this section, we investigate at which extent major US macroeconomic variables were distorted by the *COVID-19* pandemic. We then re-estimate the MST SV model recursively over an expanding estimation window beginning from 1980:Q1 until 2019:Q4, 2020:Q2, 2020:Q4, 2021:Q2, 2021:Q4 and 2022:Q2, respectively. We uncover how the pandemic observations affect the stochastic volatility of residuals, and the tail fatness and asymmetry of their distributions. For brevity, we limit the analysis in this section to the four major US macro-variables: real GDP (log-level), *CPI* (log-level), Fed rate and unemployment rate, as in Chan (2020). Figure 11.5 depicts the medians of the time varying stochastic volatility of residuals estimated at the different dates at the beginning and during the *COVID-19*. Interestingly, Figure 11.5 exhibits different patterns for the stochastic volatility for different variable/time intersections. On the onset of the *COVID-19* pandemic, the stochastic volatility increases during 2020 compared to its level at 2019:Q4 for the real GDP, Fed rate and unemployment rate (UNRATE) indicating that the pandemic shock translates into an increase in macroeconomic volatility during 2020. Surprisingly, the stochastic volatility for the *CPI* residuals has a completely different pattern by decreasing during 2020, the first year of the pandemic era. This might reveal a delay in the response of the inflation to the *COVID-19* impacts in terms of commodity and goods prices surge due to the pervasive shortages and lockdowns. During 2021 and the first half of 2022, the stochastic volatility for the real GDP and the Fed rate continues to be higher than the pre-pandemic level. The stochastic volatility for the *CPI* reverses and increases during 2021 to attain its pre-pandemic level and exceeds it during the first half of 2022. These findings show, curiously, that the MST SV model treats the pandemic effects on the real GDP, the fed rate and the *CPI* as a persistent increase in uncertainty and not as a rare and transient shock. The stochastic volatility for the unemployment rate decreases during 2021 and the first half of 2022 and comes back to its pre-pandemic level indicating that the pandemic shock in labor market is assumed to be transitory. This latter finding corroborates the results by Carreiro et al., (2024b) who find similar pattern for the stochastic volatility of the payroll growth rate. Remarkably, our findings reveal that the pandemic shock translates to persistent and long-lived increase in the time varying volatility for real GDP, *CPI* and fed rate but creates short-lived outliers for the labor market. It is worthy to mention that our results evidence an important fact that the stochastic volatility of the residuals for major US macroeconomic variables responded differently to the pandemic shock.

Figure 11.5: Posterior medians of the estimated stochastic volatility



Note: Stochastic volatility $\left(e^{h_t}\right)^{1/2}$ of the residuals in the model with multi-*t* skew distributed innovations and stochastic volatility. Medians obtained from different data samples ending at different dates as indicated in the figure. The origin for each panel corresponds to the estimated volatility in 2019:Q4 for comparison.

We turn to the macroeconomic tail risk and investigate how the posterior distributions of the degrees of freedom (DoF) evolved during the pandemic? Recall, the lower the degree of freedom parameter ν, the stronger the *t* distribution departs from Gaussianity and the heavier the tails. Figure 11.6 presents de posterior densities of the DoF obtained over an expanding estimation window from 1980:Q1 until 2019:Q4 (left-hand panel) and until 2022:Q2 (right-hand panel) for the four key macroeconomic variables. Noticeably, there is no evidence of tail fatness in the distribution of residuals before the pandemic as indicated by the high DoF[11]. In 2022:Q2, the densities moved to the left and the DoF decreased significantly, particularly for the unemployment rate. It appears that the pandemic created macroeconomic tail risk comparatively to the pre-pandemic era, but with a

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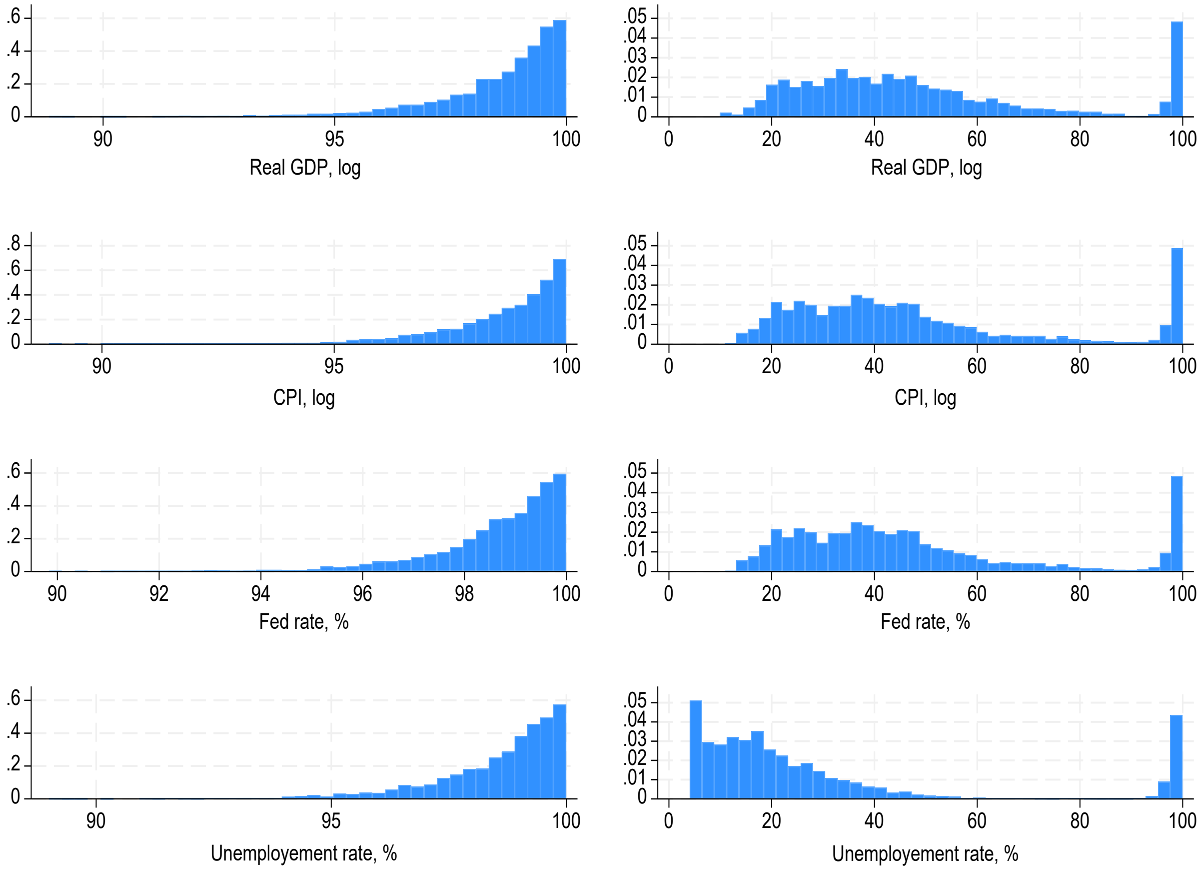
[11] The densities estimated with samples ending in 2020 and in 2021 give qualitatively the same shape as in 2019:Q4.

delay. We observe that tail risk was more pronounced for the labor market, which corroborates the huge spike in the unemployment rate during the pandemic as depicted in Figure 11.1. It is worth mentioning that tail fatness in the distributions of chocks concretized simultaneously during 2022 for the four key variables, however, with different magnitude, generating then tail co-movements. This is the macroeconomic tail risk discussed by Acemoglu et al., (2017).

In unreported results, we do the same estimations with the expanding samples at different time points over the pandemic period, and we investigate the posterior distributions of the skewness parameters for the residuals. Overall, we find qualitatively similar shape in the posterior densities of skewness parameters as depicted in Figure 11.4, with more concentration around zero and less spread out. In conclusion of this section, results evidence that the macroeconomic shock due to the *COVID-19* pandemic materialized firstly in a higher stochastic volatility of the model's residuals which created afterward tail fatness in their distributions, but the symmetry parameters were unaffected on average.

Figure 11.6: Posterior densities of the degrees of freedom (DoF) of the residuals



Note: Residuals from the VAR model with multi-*t* skew distributed innovations and stochastic volatility (MST SV). Left-hand panel exhibits the DoF estimated from an expanded sample ending in 2019:Q4. The right-hand panel is for DoF for a sample ending in 2022:Q2.

11.4.3 *COVID-19* and the transmission of macroeconomic shocks

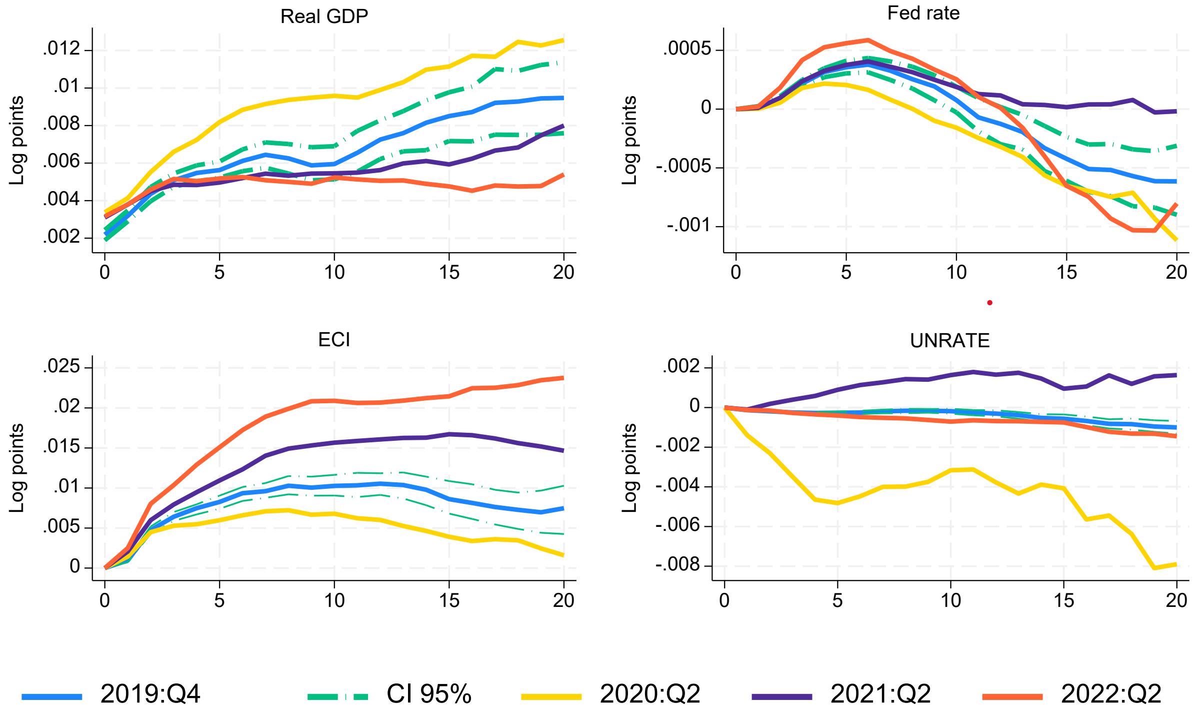
Following the *COVID-19* an exceptional contraction in real activity led to the complete breakdown of established interactions and statistical relationships between key economic variables. Macroeconomic transmission channels were also altered. In this section, we investigate at which extent these interactions and channels were altered by examining the responses of the price level, measured by the *CPI* (in log-level), to shocks in the real output, to monetary policy shocks and labor market shocks as suggested by Bernanke and Blanchard (2025). To be done, we use the impulse response functions (IRF) estimated with our BVAR model with multi-*t* skew distributed innovations and stochastic volatility. The IRF are estimated recursively over an expanding estimation window beginning from 1980:Q1 until 2019:Q4, 2020:Q2, 2021:Q2, and 2022:Q2, respectively, to have a better insight into the responsiveness of the price level to macroeconomic shocks before and during the pandemic era. Figure 11.7 depicts the IRFs of the *CPI* (in log-level) to a one-standard-deviation shock in real GDP, Fed rate, employment cost index, and unemployment rate estimated over the different expanding windows. Figure 11.7 shows that the inclusion of the *COVID-19* observations noticeably affects the IRF estimates as compared to the pre-*COVID-19*. The transmission of the real GDP shock to price level spikes with the inclusion of the 2020:Q2 observation, when the US real GDP slumped deeply due to global lockdowns. Afterward, the reaction of the *CPI* to real GDP shocks gradually weakens and stabilizes at lower levels than the pre-pandemic and flattens in mid-2022. Bobeica and Hartwig (2023) find qualitatively similar reaction of the price level to real GDP shocks for the European context using a Bayesian VAR with multivariate *t*-distributed errors without stochastic volatility.

The impulse responses of the *CPI* to a contractionary monetary shock are significantly positive over the first 10-12 quarters before becoming strongly negative afterward. It appears that the effects of the monetary policy on price levels are not immediate but materialize with some delay. These findings corroborate the results in the relevant literature using the extended narrative measure of Romer and Romer (2004) to identify the monetary policy shocks (see also Miranda-Agrippino and Giovanni, 2021). The inclusion of the *COVID-19* observations gives different shapes for the IRF of the price level to monetary shocks. In the early stage of the pandemic, the positive effect is weaker and shorter, and the negative effect is stronger as compared to the pre-*COVID-19*. In the middle stage of the pandemic, the IRF of the *CPI* flattened and became positive for all the horizons.

In mid-2022, the *CPI* responsiveness to the monetary policy shocks became stronger than during the pre-pandemic era, either positive during the first periods or negative afterward. Recall that during 2022, the Fed fund rate increased gradually after historical low levels and the *CPI* spiked. Very importantly, the transmission of monetary policy shocks depends on the state of the business cycle; namely if the economy is in a recession or expansion cycle as suggested by Tenreyro and Thwaites (2016). In fact, we find evidence that contractionary policy shocks are more powerful than expansionary shocks (compare the IRF in 2020:Q2 versus the IRF in 2022:Q2).

Next, we investigate the impacts of the tightness of the labor market on the price levels and inspect how the Phillips curve, linking the inflation and the unemployment rate, has evolved before and during the pandemic. As in Bernanke and Blanchard (2025), we find that the price level reacts positively to the labor tightness measured by a one-standard deviation shock in the Employment Cost Index (ECI). An increase in nominal wages has twofold impacts on the price level: i) higher demand and ii) higher cost of goods and services.

Figure 11.7: Impulse response functions in a BVAR with multi-*t* skew distributed innovations and stochastic volatility



Note: Medians of the IRF of the *CPI* (in log-level) to a one-standard-deviation shock in real GDP, Fed rate, employment cost index (ECI), and unemployment rate (UNRATE) are plotted. 95% credible interval are for the estimation window until 2019:Q4. IRF are estimated over 20 quarters ahead.

Figure 11.7 shows that the reaction of the *CPI* to a one-standard-deviation shock in the ECI significantly decreased in the early stage of the pandemic compared to its level in the pre-*COVID-19* due to the unprecedented contraction in activity at the beginning of 2020. Afterward, the IRFs gradually strengthened and exceeded their pre-pandemic levels when the economy was recovering, and the labor market was overheated due to monetary and fiscal policies. Turning now to the Phillips curve which links unemployment and inflation and illustrates the trade-off between maintaining price stability and achieving full capacity utilization.

It appears that the Phillips curve was flat during the pre-pandemic era. In fact, IRFs of the *CPI* to the unemployment shocks are flat around zero. The insensitivity of inflation to changes in unemployment during the last two decades led many economists to suggest that the Phillips curve had disappeared—or was "hibernating." that is, its slope approached zero (Blanchard, 2016; Stock and Watson, 2020; Hazell et al., 2022). The *COVID-19* waked the Phillips curve. The reaction of the price level is strongly negative at the beginning of the pandemic, indicating a steepening of the Phillips curve, namely higher unemployment reduces inflation. Recall that at that time, 2020:Q2, the unemployment rate reached historical records. Later, the Phillips curve surprisingly reverses in mid-2021 when the unemployment rate remained at high levels and the inflation was surging. Rossi et al (2024) finds qualitatively similar evidence that the Phillips curve is becoming again alive using estimation data up to the end of 2021. In the late stage of the pandemic, the Phillips curve hibernated again in mid-2022 when the IRF hovered close to zero. The changing behavior of the Phillips curve was evidenced early on by Stock and Watson (1999) who argued that the coefficients of the Phillips curve are time varying.

In sum, our findings indicate how transmission channels of macroeconomic shocks were altered by the *COVID-19* pandemic. Moreover, these transmissions channels are not constant during the pandemic era, but they are changing from one period to another to reflect the moving macroeconomic dynamics and labor market conditions during that period.

11.4.4 Real-time forecast evaluation

To assess the out-of-sample predictive accuracy of the BVAR with multi-*t* skew distributed innovations and stochastic volatility (MST-SV), we conduct a recursive out-of-sample forecasting exercise using expanding time windows. Starting from 1989:Q4 to 2023:Q4, the MST-SV model was re-estimated quarterly using all available data from 1980:Q1. The goal was to forecast the *CPI* (in log-level) for 12 quarters ahead (*t*+1 to *t*+12), where *t* represents the current quarter. To evaluate the MST-SV model's performance, we conducted a parallel analysis using a rival standard Gaussian Bayesian VAR as a benchmark model. This simpler model assumes a Gaussian error distribution and excludes stochastic volatility. The metric used to evaluate the point forecasts is the loss functions of mean squared and absolute forecast errors, denoted by MSFE and MAFE, respectively, and calculated as follows for a variable *i* at h steps ahead, for $h = 1, \dots, 12$:

$$MSFE_{i,h} = \frac{1}{T_1 - T_0 - h + 1} \sum_{t=T_0}^{T_1 - h} \left(\bar{y}_{i,t+h|t} - y_{i,t+h} \right)^2 \tag{11.5}$$

and

$$MAFE_{i,h} = \frac{1}{T_1 - T_0 - h + 1} \sum_{t=T_0}^{T_1 - h} \left| \bar{y}_{i,t+h|t} - y_{i,t+h} \right| \tag{11.6}$$

where T_0 is the last observation in the first estimation sample, namely 1989:Q4, and T_1 the last observation on variable *i*, namely 2024:Q4. $\bar{y}_{i,t+h|t}$ is the median of the posterior predictive sample for the step h using the expanding windows up to time t. $y_{i,t+h}$ is the actual realization of variable i at h steps ahead. The loss function is then calculated as the ratio of the MSFE (MAFE) for the MST-SV model divided by the MSFE (MAFE) of the Gaussian BVAR, namely the benchmark model. Hence, if the ratio is less than 1, it means that the loss of the MST-SV forecasts is smaller than that of the benchmark forecasts, and vice versa if the ratio is greater than 1.

Table 11.3 reports the point forecast results for the three horizons 4, 8 and 12 quarters ahead, alternatively, 1-year, 2-years, and 3-years ahead. Table 11.3 shows evidence of added-forecastability by the MST-SV model over the standard Gaussian BVAR in forecasting the price levels at the different forecasting horizons. The longer the forecasting horizon, the bigger the improvement in point forecasts by the MST-SV relative to the Gaussian BVAR. Il appears then that considering heavy tails and skewness in the distribution of residuals and allowing for time varying variances improves substantially the point forecasts of the inflation.

Table 11.3: Relative improvements in MSFE and MAFE relative
to the standard Gaussian BVAR model

	Relative MSFE			Relative MAFE		
	$h = 4$	$h = 8$	$h = 12$	$h = 4$	$h = 8$	$h = 12$
Loss function	0.471	0.147	0.039	0.594	0.373	0.258

Note: Results for the forecasting of the *CPI* (in log-level). Forecasting horizons are 4. 8 and 12 quarters ahead.

It’s worth mentioning that the MSFE and MAFE loss functions evaluate forecast performance averaged over the sample period. However, it is well known that macroeconomic time series are prone to instabilities particularly during turmoil periods when several macroeconomic relationships changed drastically and transmission channels were deeply altered as during the great recession 2008-2009 or the *COVID-19*. In such a context, variations in unstable environments are observed where structural breaks are often found in macroeconomic variables over a relatively long-time span. In such a context, Giacomini and Rossi (2010) have suggested that selecting a model with the best average forecasting performance could lead to incorrect selection decisions. In fact, traditional tests of forecast evaluation are not reliable in the presence of instabilities because they assume stationarity which is violated in the presence of instabilities. Rossi (2021) raises an important question: *How can one assess models’ ability to accurately predict the target variable when the predictive ability changes over time*?

We then use the fluctuation test developed by Giacomini and Rossi (2010) to compare the relative forecasting performance of our competing models over the entire time path in the presence of possible instabilities. The fluctuation test measures the relative local forecasting performance of the model over time and provides useful information that is lost when one is using averaged performance measures. The null hypothesis of the fluctuation test is an equal predictive ability at each point in time for the competing models, and it is rejected when the test statistic is higher than a critical value. The alternative is inequal predictive ability. Our competing models are the MST-SV against a benchmark Gaussian BVAR. We run the fluctuation test to compare the forecasting performance of the MST-SV and the Gaussian BVAR models for the three forecasting horizons, namely 4, 8 and 12 quarters ahead.

As an illustration, Figure 11.8 plots the fluctuation test statistics of Giacomini and Rossi (2010) for the forecasts of *CPI* (in log-level), respectively, for the three horizons[12]. The test statistics are 6.70, 9.54 and 7.30, respectively, for the horizons 4, 8 and 12 quarters ahead. Overall, these test statistics are higher than the critical value of 3.179. We then reject the null hypothesis of equal forecasting ability and give evidence to the alternative about the dominance of the Bayesian VAR, with skew-*t*-distributed residuals and stochastic volatility, over a rival Gaussian BVAR with constant volatility. However, the visual inspection of Figure 11.8 reveals that the fluctuation test shows that the MST-SV has varying forecasting efficiency over the time path. In fact, the MST-SV model could perform better in certain time points and might have similar forecasting accuracy as the Gaussian BVAR in other subperiods. More importantly, Figure 11.8 reveals twofold remarks. The forecasting performance of the MST-SV appears to be strongly better: i) around turmoil periods as for financial crisis 2007-2009 and *COVID-19*, and ii) for longer forecasting horizons. As expected,

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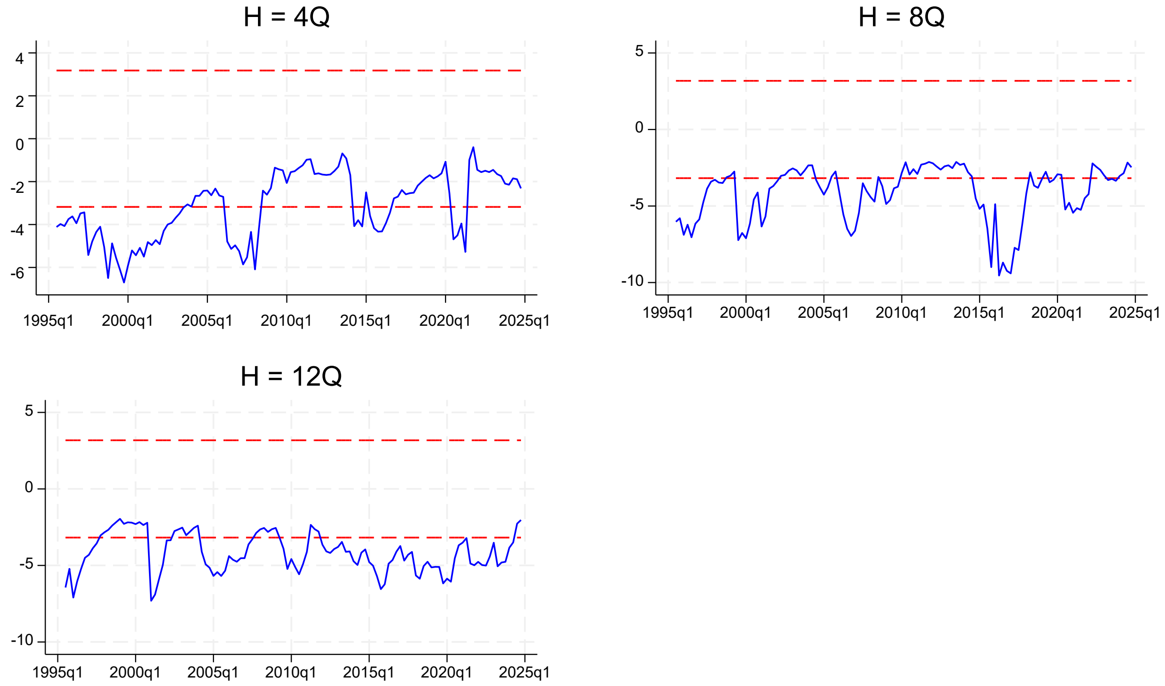
[12] We use a two-sided test with a confidence level of 95% and a rolling window of 20 quarters (5 years). Using others rolling windows gives qualitatively the same results. Giacomini and Rossi's (2010) test rejects the null hypothesis of equal predictive ability when the test statistic is outside the band lines (2-sided alternative). When the test statistic is below the lowest band line, the first model forecasts significantly better. Our first model is the MST-SV.

this is essentially due to the ability of BVAR models, with the multi-skew *t*-distributed innovations and stochastic volatility, to capture better outliers and the higher volatility in macroeconomic variables created by turmoil episodes.

Figure 11.8: Fluctuation tests of Giacomini and Rossi (2010)



Note: For forecasts of quarterly *CPI* (in log-level) from the MST-SV model using a recursive window (our first model). The forecasts start from 1989:Q4 to 2023:Q4 using all available dataset from 1980:Q1. The rival model is a Gaussian BVAR (our second model). Dashed lines are critical values at the 95% confidence level. If a test statistic (solid lines) is inside the band lines at a time point, then the null hypothesis of equal predictive ability holds. When test statistic (solid lines) is below the lowest band line, the MST-SV forecasts are significantly better than the standard Gaussian BVAR forecasts.

11.4.5 How does *COVID-19* impact the forecasting of inflation

The fluctuation test of Giacomini and Rossi (2010) revealed that the MST-SV model has time varying forecasting efficiency, and it outperforms the standard gaussian BVAR, particularly, on the onset of the great financial crisis and *COVID-19* pandemic in forecasting the *CPI* (in log-level). To have a deeper insight of the magnitude of the impact of *COVID-19* in the forecasting ability of our two competing models, we rerun the recursive forecasting exercises of the log *CPI* at six time points before, during and at the end of the pandemic, namely 2019:Q4, 2020:Q2, 2020:Q4, 2021:Q2, 2021:Q4 and 2022:Q2. We predict the log *CPI* for 4 and 8 quarters ahead. Because we have only six estimation points, we rely more on forecast variables based on density forecast measures, namely: i) the average log predictive likelihood (ALPL), ii) the average continuous rank probability score (ACRPS). CRPS is obtained as the quadratic difference between the predictive cumulative distribution function and the empirical distribution of the variable. CRPS is less sensitive to outliers than the log predictive likelihood (Clark and Ravazzolo (2015)). iii) the average continuous rank probability score with quantile weighting (qwACRPS). The ALPL can be written as follows:

$$ALPL_{i,h} = \frac{1}{T_1 - T_0 - h + 1} \sum_{t=T_0}^{T_1 - h} \log p\left(y_{i,t+h}^{o} | y_{1:t}\right), \tag{11.7}$$

where $p\left(y_{i,t+h}^{o} | y_{1:t}\right)$ is the h-step ahead posterior predictive density function evaluated at the realization of the variable i. Higher values indicate that actual observations are more likely under the predictive density and hence a better density forecasting performance of the model. The ACRPS is equal to:

$$ACRSP_{i,h} = \frac{1}{T_1 - T_0 - h + 1} \sum_{t=T_0}^{T_1 - h} \left[-\mathrm{E}_f \left| y_{i,t+h|t} - y_{i,t+h}^{o} \right| + 0.5\mathrm{E}_f \left| y_{i,t+h|t} - y_{i,t+h}' \right| \right] \tag{11.8}$$

where f is the predictive density of the variable $y_{i,t+h|t}$. $y_{i,t+h|t}$ and $y_{i,t+h}'$ are independent random draws form f. We generated randomly 10,000 draws from f using Monte Carlo simulations. Lower values indicate that actual observations are more likely under the predictive distribution, and hence a better density forecasting performance of the model. It worthies to mention these scoring rules could give different answers regarding the best performing model in the event of extreme observations.

Gneiting and Ranjan (2011) developed the qwCRPS as a proper scoring function of the entire predictive density to measure the density forecast accuracy. qwCRPS is derived from a weighted sum of quantile scores for a range of quantiles and it allows higher weighting for specified tails to emphasize selected portions of the density. The qwCRPS is given by:

$$qwCRSP_{i,h} = \frac{1}{T_1-T_0-h+1}\sum_{t=T_0}^{T_1-h}\left[\frac{2}{J-1}\sum_{j=1}^{J-1}\upsilon(\tau_j)QS_{\tau_j,i,t+h}\right] \tag{11.9}$$

with $J = 20$ and $\tau_j = \frac{j}{J} = 0.5, 0.10, 0.15, \ldots, 0.90, 0.95$. We considered both a left-tail and right-tail-weighting. The weighting function for the left-tail weighted version (qwCRPS-left) is set to $\upsilon(\tau_j) = \left(1-\tau_j\right)^2$ and set to $\upsilon(\tau_j) = \tau_j^2$ for the right-tail weighted version (qwCRPS-right).

Tables 11.3 and 11.4 report performance valuation for the density forecasts of the log *CPI* by the MST-SV model relative to a benchmark standard gaussian BVAR for four and eight-quarters ahead, respectively. For the different variables retained, the relative improvement in the density forecast is computed as the difference between the MST-V and the benchmark model. Entries greater than 0 indicate that the MST-SV model has a better performance in forecasting price level (log *CPI*)[13]. Overall, the results indicate the outperformance of the MST-SV model over the standard gaussian BVAR in forecasting the inflation during the pandemic era for both horizons, 4 and 8 quarters ahead. However, the relative performance of the MST-SV model is stronger in predicting inflation for 8 quarters ahead. It is then evident that forecasters are better of using models

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[13] For the CRPS, qwCRPS-right and qwCRPS-left, the relative performance could be computed as the ratio of the metric of the MST-SV model over the benchmark. Entries less than 1 indicate that the MST-SV is better. We do that and find ratios largely below 1.

permitting flexible modelling of innovations in terms of both fat tails and – potentially – asymmetry. It might be worthy noticing that the relative outperformance of the MST-SV model becomes slightly lower when *COVID-19* observations are added and this till 2021:Q2. Afterward, the MST-SV model gains in relative performance when the macroeconomic chocks due to the *COVID-19* are well established and crystallized in the parameters' estimation. This corroborates our findings in the previous sections related to the delay in the response of the tail fatness and asymmetry parameters to the *COVID-19* chock.

Table 11.4: Relative improvements in density forecasts for *CPI* (in log-level)

	2019:Q4	2020:Q2	2020:Q4	2021:Q2	2021:Q4	2022:Q2	Average
			Log Predictive Likelihood (LPL)				
Gauss BVAR	-0.752	-0.663	-0.620	-0.616	-0.625	-0.606	-0.647
MST-SV	1.264	1.116	1.156	1.097	1.120	1.934	1.281
			CRSP				
Gauss BVAR	-0.212	-0.191	-0.182	-0.185	-0.181	-0.180	-0.189
MST-SV	0.174	0.120	0.118	0.116	0.117	0.154	0.129
			qwCRSP-right				
Gauss BVAR	-0.074	-0.062	-0.060	-0.060	-0.061	-0.062	-0.063
MST-SV	0.050	0.043	0.041	0.041	0.041	0.052	0.045
			qwCRSP-left				
Gauss BVAR	-0.072	-0.074	-0.069	-0.068	-0.068	-0.062	-0.069
MST-SV	0.050	0.044	0.042	0.039	0.041	0.053	0.045

Note: For four-quarters ahead by the MST-SV model relative to the benchmark model, namely a standard BVAR model with Gaussian innovations and without stochastic volatility. Forecasts start at the mentioned dates and use all available data from 1980:Q1. The density forecast variables are log predictive likelihood (LPL), CRPS, qwCRSP-right, and the qwCRSP-left. The first line in each panel reports the density forecast metric of the benchmark model. The figures for the MST-SV model are the relative improvements calculated as the differences of the different variables of the MST-SV model minus the ones of the benchmark models.Entries greater than 0 indicate that the MST-SV model is better.

Table 11.5: Relative improvements in density forecasts for *CPI* (in log-level)

	2019:Q4	2020:Q2	2020:Q4	2021:Q2	2021:Q4	Average
Log Predictive Likelihood (LPL)						
Gauss BVAR	-1.568	-1.547	-1.412	-1.371	-1.404	-1.460
MST-SV	1.336	1.236	1.207	1.268	1.263	1.261
CRSP						
Gauss BVAR	-0.619	-0.574	-0.511	-0.491	-0.482	-0.535
MST-SV	0.476	0.410	0.380	0.353	0.351	0.394
qwCRSP-right						
Gauss BVAR	-0.210	-0.184	-0.163	-0.157	-0.166	-0.176
MST-SV	0.164	0.141	0.123	0.117	0.123	0.136
qwCRSP-left						
Gauss BVAR	-0.217	-0.218	-0.185	-0.176	-0.176	-0.194
MST-SV	0.162	0.153	0.128	0.124	0.123	0.138

Note: For eight-quarters ahead by the MST-SV model relative to the benchmark model, namely a standard BVAR model with Gaussian innovations and without stochastic volatility. Forecasts start at the mentioned dates and use all available data from 1980:Q1. The density forecast variables are log predictive likelihood (LPL), CRPS, qwCRSP-right, and the qwCRSP-left. The first line in each panel reports the density forecast metric of the benchmark model (Gauss BVAR). The figures for the MST-SV model are the relative improvements calculated as the differences of the different variables of the MST-SV model minus the ones of the benchmark models. Entries greater than 0 indicate that the MST-SV model is better. Remark: the forecasting exercise for 8 quarters ahead ended in 2021:Q4 because our data ended in 2023:Q4.

11.4.6 Using other benchmarks for inflation expectations

In the previous section, we gauged the forecast performance of the MST-SV model against a competing standard gaussian BVAR. We now put the MST-SV model in competition with more elaborated forecasts made by practitioners, namely the Survey of Professional Forecasters (SPF) and the Federal Reserve of Cleveland. Professional forecasters do not uniquely rely on models, but they use extensively their judgement when forming their beliefs about the future. Hence, they are more able to readjust and update their predictions during challenging times with quick and drastic changes. For example, inflation had a puzzling behavior during the pandemic. It declines at the beginning of the pandemic and surges quickly and drastically afterward driven by the global lockdowns and disrupted supply chains. Personal judgements and beliefs allow professional forecasters to have much more flexibility in their prediction scheme by distinguishing between the behavior of inflation in the short run and the long run. This is very challenging to do even by more advanced quantitative models based on rationality and backward looking interconnexions between macroeconomic variables to extrapolate future movements. For its own part, The Federal Reserve Bank of Cleveland estimates the expected rate of inflation over the next 30 years along with the inflation risk premium, the real risk premium, and the real interest rate. Their estimates are model-based and use Treasury yields, inflation data, inflation swaps, and survey-based measures of inflation expectations[14].

To be done, we extrapolate the predicted inflation time series from the already forecasted price levels (in log), namely the log *CPI*. In keeping with Federal Reserve practices, we construct time

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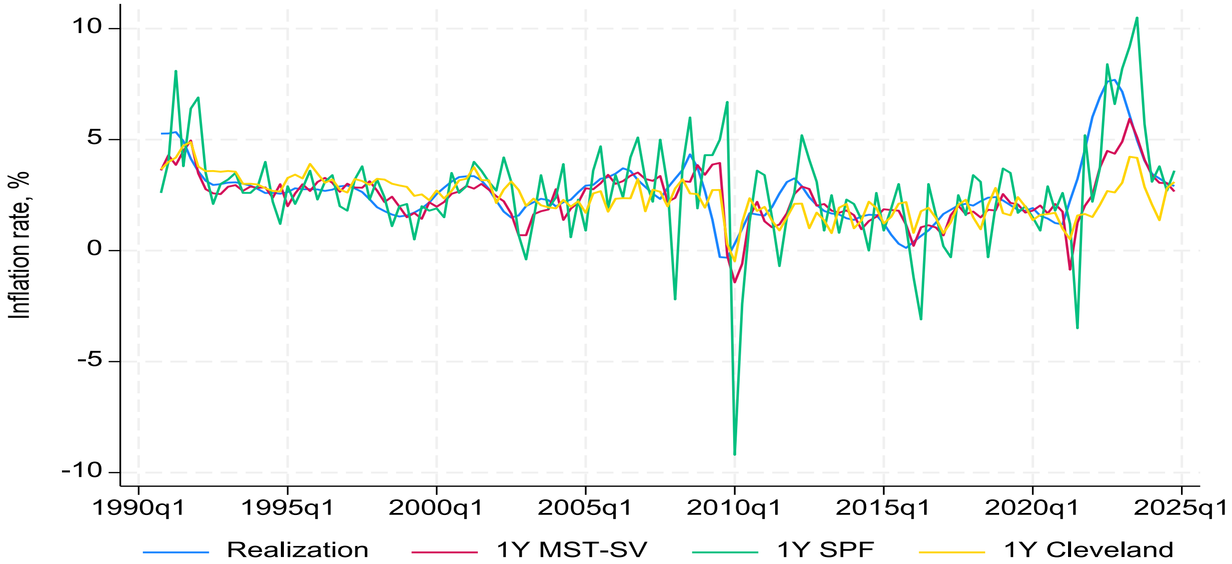
[14] The model is based on the work by Joseph Haubrich, George Pennacchi, Peter Ritchken, Inflation Expectations, Real Rates, and Risk Premia: Evidence from Inflation Swaps, *The Review of Financial Studies*, Volume 25, Issue 5, May 2012, Pages 1588–1629, https://doi.org/10.1093/rfs/hhs003

series of inflation predictions at different horizons—1-year, 2-years, and 3-years ahead—based on the median of the predicted log *CPI*. The 1-Year ahead inflation forecasts are calculated as the average of predicted log *CPI* for *t*+1 to *t*+4, minus the average of realized log *CPI* over the previous four quarters. 2-Years head inflation forecasts are constructed as the difference between the average log *CPI* for *t*+5 to *t*+8 and *t*+1 to *t*+4. Finally, 3-Years ahead inflation forecasts are derived as the difference between the average log *CPI* for *t*+9 to *t*+12 and *t*+5 to *t*+8.

Figure 11.9: One-year-ahead forecasts of the *Inflation rate*



Note: The figure plots One-year-ahead forecasts of the *Inflation rate* made by the Survey of Professional Forecasters (the green line, labelled "1Y SPF"), by the MST-SV model (the red line, labelled "1Y MST-SV"), and by the Fed of Cleveland (the orange line, labelled "1Y Cleveland"), together with the actual realization of the annual *Inflation rate* (the blue line, labelled "Realization"). The period is from 1990:Q4 to 2024:Q4.

Figure 11.9 plots the realized annual *Inflation rate* over the period 1990:Q4 to 2024:Q4, alongside the matched 1-Year ahead inflation forecasts coming from the Survey of Professional Forecasters (SPF)[15], the MST-SV model and the Fed of Cleveland. The visual inspection of Figure 11.9 reveals

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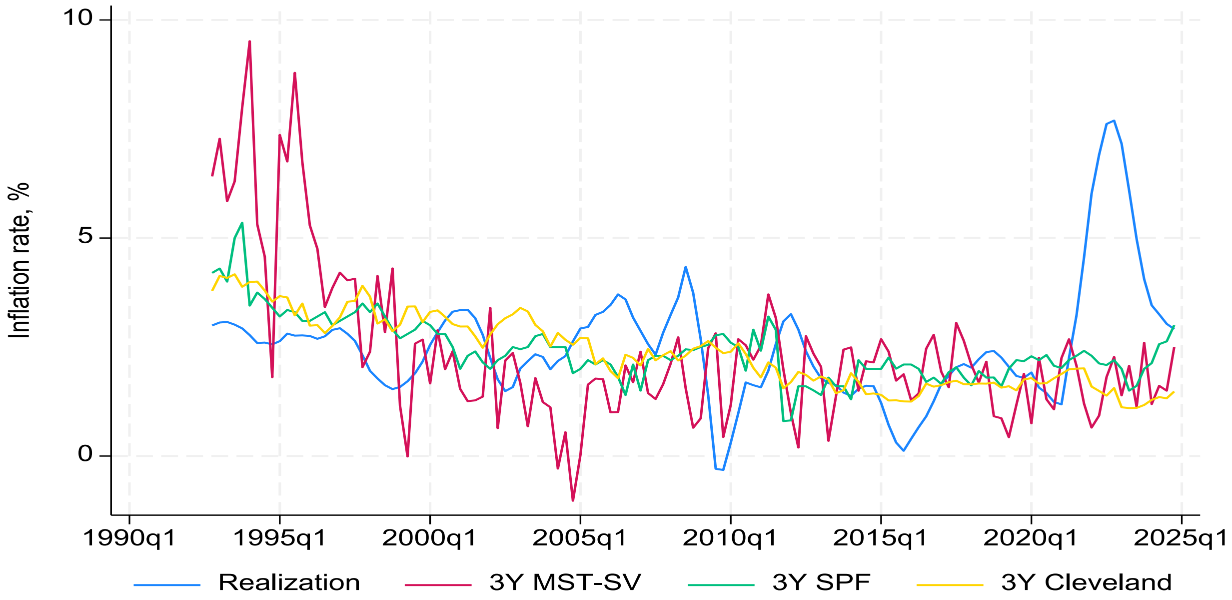
[15] We use the median responses coming from individual forecasts.

that the realized inflation is time varying and these variations might be sudden and drastic particularly during downturn episodes (the global financial crisis and *COVID-19*). The forecasted inflation by SPF appears to be very volatile in time. Particularly, SPF forecasts have dramatic shifts on the onset of the financial crisis and the *COVID-19* indicating that professional forecasters could adjust quickly and radically their beliefs about future patterns of inflation based on new information and circumstances. The predictions by MST-SV model and by the Fed of Cleveland seem to be less volatile and are adjusted smoothly. In addition, Figure 11.9 highlights interesting time-varying patterns in the forecasting performance of the three concurrent alternatives. The three prediction models under-predicted the disinflation during the great recession in 2008-2009 and greatly under-predicted the inflation during the pandemic era. Figure 11.10 plots the realized annual *Inflation rate* over the period 1992:Q4 to 2024:Q4, alongside the matched 3-Year ahead inflation forecasts coming from our three competing alternatives. Surprisingly, the forecasts from our MST-SV model appear to be very volatile compared to the two other models, that lead to more stable forecasting of the inflation for 3-year ahead. It appears that the mean-reversion behavior of the inflation at medium horizons, due to monetary and fiscal policies, is better forecasted by SPF and the Fed of Cleveland model than by the MST-SV model.

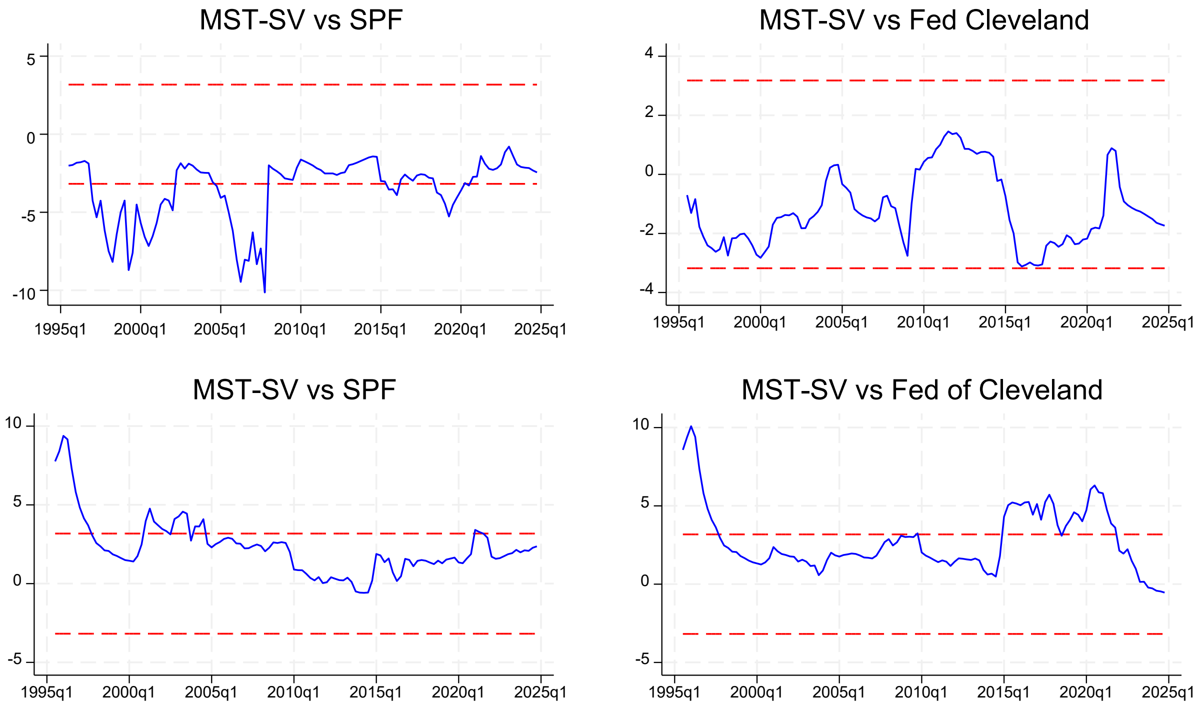
Figure 11.10: Three-years ahead of the *Inflation rate*



Note: The figure plots 12-quarters-ahead forecasts (3 years) of the *Inflation rate* made by the Survey of Professional Forecasters (the green line, labelled “3Y SPF”), by the MST-SV model (the red line, labelled “3Y MST-SV”), and by the Fed of Cleveland (the orange line, labelled “3Y Cleveland”), together with the actual realization of the annual *Inflation rate* (the blue line, labelled “Realization”). The period is from 1992:Q4 to 2024:Q4.

To have a deeper understanding of the forecasting performances of the three rival models, we use the fluctuation test developed by Giacomini and Rossi (2010). Surprisingly, the fluctuation test indicate that our MST-SV model outperforms the SPF in forecasting 1-year ahead inflation for a long period of time ending on the onset of the financial crisis. Afterward, the two models, SPF and MST-SV, have similar forecasting ability for the 1-year ahead inflation. In addition, the test indicates that the MST-SV and the Fed of Cleveland model have similar forecasting ability for the 1-year ahead inflation during all the periods. For the 3-years ahead forecasts, the MST-SV model has similar forecasting ability than the SPF parting from 2000s. Compared with the Fed of Cleveland model, our MST-SV was outperformed from 2015 to the end of the *COVID-19* pandemic. The time-varying forecasting performance of the competing models suggests that combining these models could improve the overall forecasting ability in the context of unstable economic environments.

Figure 11.11 Fluctuation tests of Giacomini and Rossi (2010)
for forecasts of quarterly *CPI* (in log-level) from the MST-SV model


MST-SV vs SPF

MST-SV vs Fed Cleveland

MST-SV vs SPF

MST-SV vs Fed of Cleveland

Note: Test made using a recursive window. The forecasts start from 1989:Q4 to 2023:Q4 using all available dataset from 1980:Q1. The Top Panel is for 1-year ahead forecasts and the Down Panel is for the 3-years forecasts. The rival models are SPF forecasting and the Fed of Cleveland (our competing models). Dashed lines are critical values at the 95% confidence level. If a test statistic (solid lines) is inside the band lines at a time point, then the null hypothesis of equal predictive ability holds. When test statistic (solid lines) is below the lowest band line, the MST-SV forecasts are significantly better than the competing forecasts.

11.5 Conclusion

The *COVID-19* pandemic is an unprecedented shock to the global economy in recent history. It triggered enormous data movements and created outliers in the distribution of main macroeconomic variables. These outliers could Well-established macroeconomic dynamics and interconnexions are deeply undermined. The Pandemic then posed several challenges for the estimation and analysis of multivariate macroeconomic time-series. Particularly, estimated models may become unstable and generate unlikely forecasts with the inclusion of the pandemic extreme observations. We tackle these methodological challenges using a flexible Bayesian VAR framework allowing for heavy tails and stochastic volatility for innovations to appropriately treat these extreme observations as suggested, among others, by Lenza and Primiceri (2022) and Schorfheide and Song (2021). We apply this novel model for a large U.S dataset starting from 1980:Q1 to 2023:Q4. We hence include in our estimations all the pandemic period to have a better understanding of its macroeconomic effects. We find empirical evidence that *COVID-19* pandemic created outliers for main U.S macroeconomic variables as the degrees of freedom of the student t-distributions of residuals became lower with the inclusion of post-pandemic observations. The simultaneous shifts in the tail fatness of macro-variables could create macroeconomic tail risk as suggested by Acemoglu et al (2017). The *COVID-19* shock generated a long-lasting increase in the stochastic volatility for the real GDP, the price level (measured by the log *CPI*) and the Fed rate. However, the increase in volatility for the labor market was transient. Notably, the magnitude of the effects of the *COVID-19* on macroeconomic volatility vary from one period to another and they vary cross-sectionally. Specifically for the inflation, the impulse response functions reveal that the *CPI* (in log-level) responded differently to shocks in the real output, the monetary policy and tightness in the labor market during the pandemic era as compared to pre-COVID periods. Hence, our analysis shows that macroeconomic transmission channels were highly altered by the pandemic shock. More importantly, forecasts accuracy variables and Fluctuation tests of Giacomini and Rossi (2010) confirm the added-forecastability in point and density forecasts of the price level and the *Inflation rate* during the pandemic period for multi-periods ahead by considering the tail fatness and time varying volatility in macroeconomic disturbances compared to standard gaussian BVARs and other more elaborated competing forecasts.

12 Social inflation in the US property and casualty insurance industry

12.1 Introduction

Over the past decades, the United States (US) property and casualty (P&C) insurance landscape has escalated in complexity as a result of unprecedented litigation activity. According to the Swiss Re Institute (2024), the cost of P&C claims has outpaced economic *Inflation rate* in the US, peaking at 7 percent in 2023. Another study by the US Chamber of Commerce Institute for Legal Reform (McKnight & Hinton, 2024) revealed that total tort[16] costs grew at an average annual rate of 7.1 percent between 2016 and 2022, outpacing both *Inflation rate* and national GDP growth which averaged 3.4 percent and 5.4 percent, respectively. The same upward trend can be seen in commercial and personal liability, which experienced average annual growth rates of 8.7 and 3.9 percent, respectively, throughout that period.

This phenomenon challenged established theories on risk exposure factors within the insurance sector. Per the analysis of industry experts, this "superimposed inflation" stems from the convergence of evolving social patterns and standards, jurisdiction-specific legal infrastructure and proceedings, and litigation trends (Oh, 2020). They gradually embraced the notion of social inflation (Kelley et al., 2018; Pain, 2020; Oh, 2020; Wellington, 2023; Dixon, 2024) to frame and capture these underlying factors contributing to rising claim costs. As the debate continues, there is not full consensus on such a phenomenon; a few analysts challenging this perspective argue that social inflation is a concept backed by little to no compelling evidence and formulated by industry professionals in insurance in order to rationalize the hike in *Premiums* (Hunter et al., 2020;

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[16] Tort law provides compensation for individuals who have been injured or whose property has been damaged by the wrongdoing of others.

Doroshow et al., 2023; Klein et al., 2023). Yet, when turning to the supportive research regarding this issue, we encounter evidence that changes in social and legal standards drive deviations in the expected loss distribution, which significantly influence operations and pricing dynamics within the insurance industry (Oh, 2020).

In this section, we intend to address the definition, drivers, scope, and costs of social inflation in the US P&C insurance market, by examining empirical data and scholarly evidence that capture the breadth and repercussions of this phenomenon.

The remainder of this section is structured as follows. Subsection 12.2 extends the definition of social inflation. Subsection 12.3 traces back to the origin of social inflation from the 1970s leading up to its resurgence from 2010 until today. Subsection 12.4 explains the motivations behind social inflation, specifically, the underlying factors that drive this phenomenon. Subsection 12.5 illustrates the growth of social inflation, providing insights into the magnitude of its underlying causes, according to readily available historical data. Subsection 12.6 discusses the importance of social inflation in 2025, with an emphasis on the implications and current relevance of this phenomenon. Subsection 12.7 discusses how to manage social inflation from both the insurers and reinsurers standpoint, and how governments could intervene to address the phenomenon. Subsection 12,8 provides a conclusion consolidating the implications of social inflation and explores potential mitigating measures that could be undertaken to counter the adverse effects of this phenomenon within the US property and casualty insurance industry. Table A12.1 presents the definitions of different abbreviations.

Overall, this section endeavors to shed light on the phenomenon of social inflation and suggests mitigating measures to restrict the underlying risks. These insights will be relevant to insurers and reinsurers in their risk assessment processes and pricing formulation, and to legislators.

12.2 Definition

The term *social inflation* entails several dimensions. Fundamentally, it refers to the sustained increase in insurance claims costs, in conjunction with incurred losses, exceeding standard projections based on general economic inflation trends. This superimposed inflation explicitly encompasses the inflationary pressures anchored in non-economic factors such as the evolving societal attitudes towards litigation, illustrated by higher propensity to file claims, and changes in general stance on corporate social responsibility driven by demographic and political transitions. In other words, this phenomenon is mainly related to shifts in legal and social conventions dictating which party should bear the costs associated with legal claims arising from unexpected events (Pain, 2020).

At a more granular level, additional influences, such as insurance contractual clauses, along with procedural and litigation funding industry practices, have played a role in both the emergence and escalation of this trend. Specifically, Assignment of Benefits[17] (AOB) agreements represent a key feature of insurance policy structure that particularly motivates abuse from predatory third parties such as contactors, third-party adjusters and attorneys (Klein et al., 2023), especially in property insurance, by allowing them to interfere with claims processes. A study conducted by the Florida Office of Insurance Regulation (FLOIR) revealed that the number of AOB-related cases increased

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[17] Assignment of Benefits (AOB) is an insurance provision allowing a policyholder to “assign a claim payment from the insurer directly to a third party, such as [...] a direct payment to a contractor in the case of a homeowner policy” (US Property Treaty Reinsurance, XL Catlin, 2016).

from 408 in 2000 to more than 28,200 in 2016 (Poll, 2018; Florida Office of Insurance Regulation, n.d). For claims processed with AOB agreements, the study estimated the average severity to be approximately 85 percent than claims handled direct by policyholders, without third-party benefit assignment. In complement to the FLOIR's study, the Insurance Information Institute (III) has more recently documented a 94-percent increase in claims filed through AOB agreements between 2013 and 2018, growing from 79,000 to 153,000.

Besides, state-specific statutory rules governing damages give rise to discrepancies in legal outcomes, often impacting the predictability and volatility of damage awards. Across the US, the existence and extent of caps on personal injury cases vary depending on the state law. As of February 2024, a few states such as Arizona, Arkansas and California had constitutional provisions that banned caps on compensatory and punitive damages in such cases (Thomson Law Injury Lawyers, 2024). Overall, these legislative frameworks on damage awards in comparable jurisdictions, coupled with the growing inclination to favor plaintiffs, further foster social inflation by creating case law and setting precedents that supports higher compensation for claimants. This observable upward trend in damage awards, especially in personal injury cases (Swiss Re Institute, 2024a), while not directly linked to insured losses, increases the likelihood of extreme judgments[18].

Though generally confined to cost escalations driven by litigation dynamics (Kelley et al., 2018), more comprehensively, social inflation also includes costs related to emerging societal hazards and scientific advancements (Figure 12.1). Namely, claims severity tends to rise in the presence of significant public health and safety concerns — such as due to chemical, environmental and

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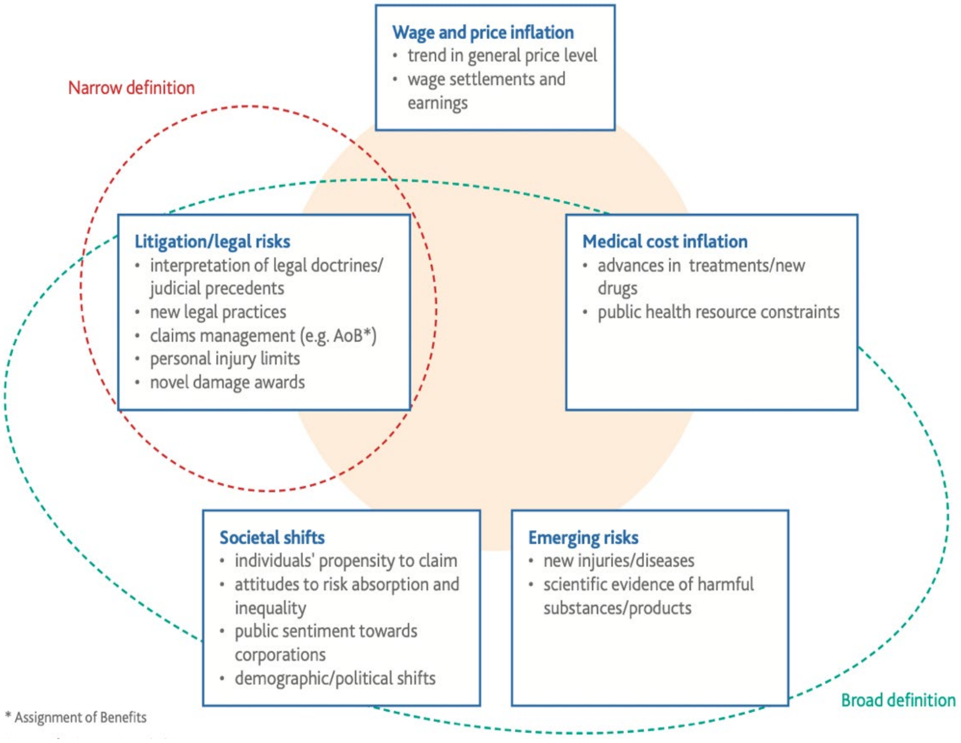
[18] Although the terms "award", "verdict" and "judgment" might seem interchangeable, each marks a separate stage in the progression of a case. An award is an amount of damages a jury decides should be paid after a trial. A decision that has the status of an award (or a verdict) can be challenged or appealed to a national court (Clark, 2019). A judgment is a formal, irrevocable and final court decision that makes the award legally binding and enforceable.

consumer goods hazards, pandemics, accidents, and infrastructure failures — as the extent of damages and losses suffered by policyholders or by affected third parties increase. In addition, as new treatment and medications are developed, (Pain, 2020; Heim, 2021), and as healthcare capacity become limited, medical cost increases, and inflates the value of personal injury and liability claims, through higher compensatory damages, thereby contributing to amplifying the effects of social inflation.

Figure 12.1: Elements of social inflation



Source: The Geneva Association.

12.3 Origin of social inflation

The social inflation theory is not a recent development, as highlighted in some studies (Heim, 2021) but is embedded in historical precedents. The concept was explicitly documented by Warren Buffett in 1977, in his chairman's letter addressed to the stockholders of Berkshire Hathaway. In this correspondence, he forecasted a monthly 1-percent rise in costs within the insurance sector. Buffet attributed this to economic and "social inflation" — that he defined as "a broadening definition by society and juries of what is covered by insurance policies" (Warren Buffett, 1978).

This terminology was initially formulated to highlight transforming social viewpoints and behaviors influencing legislative and judicial environment at the time in the US, fueling a growing wave of lawsuits related to asbestos exposure, with direct consequences for insurers. A first wave of social inflation concretely materialized in the US during the mid-1980s liability crisis, when shifts in legislation and case law drove an expansion of the scope of tort liability. Near the end of the 1990s, the insurance sector faced a second wave of social inflation as legal precedent has made mass tort claims more accessible, and medical malpractice lawsuits have risen, accompanied by substantial jury awards against physicians. As mitigating measures, tort reforms such as cap noneconomic and punitive damages were enacted, at both federal and state levels, to constrain class actions, intangible awards, and attorney fee structures.

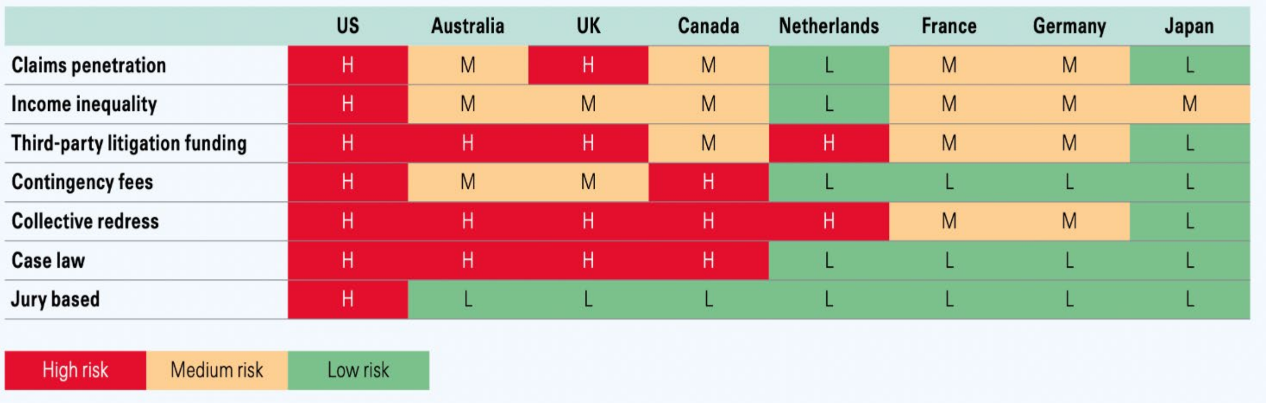
In 2010, PartnerRe (2010) revisited and offered a broader interpretation of social inflation, in a research-based report, suggesting that it was an outcome of several contributing factors. According to the international reinsurer, the primary causes behind this occurrence include the growing influence of social media on legal proceedings, the greater leniency in the treatment of claims by workplace compensation panels, the rising attorney participation in claims litigation, the social developments that influence jury members and lead to exceptionally high jury awards, the escalating public skepticism toward large corporations, and the growing income inequalities.

Four decades after its introduction, the concept of social inflation has regained prominence in discussions among insurance executives. Notably, leading European providers of reinsurance such as Swiss Re, Munich Re and Hanover Re, started discussing social inflation, over the recent years, as a significant risk to their profitability and pricing models. In a US white paper issued in 2020, Munich Re (2020) acknowledges the risks emerging from social inflation and articulates their proactive approach to managing its portfolio through pricing adjustments, limits handling and re-underwriting, in response to modernizing ethical standards. More recently, Hanover Re (2024) further highlights that, in the US particularly, social inflation is gaining momentum and will compel insurers and reinsurers to rethink their pricing approaches and contractual terms. Several insurance institutes including the Insurance Information Institute (2022) mentioned that commercial general, commercial and personal automobile and umbrella insurance were further exposed to this type of inflation due to costlier legal proceedings. For these products, unforeseen rising costs threaten coverage affordability and, in the long run, availability. Yet, despite being widely recognized and referenced internationally, some are still disputing the existence of social inflation, a stance that could lead to persistent mispricing and inadequate reserve allocations (Pain, 2020).

12.4 Motivations behind social inflation

By definition, social inflation points to the evolving societal dynamics that are amplifying insurance costs. Among these patterns, the growing expectations of corporate accountability stand out, paired with a heightened culture of litigation and higher monetary settlements. The inflationary impact of the factors driving social inflation exhibits significant cross-jurisdictional variation; its extent is contingent upon cultural norms, geopolitical and socioeconomic conditions, and legal frameworks. Although, this phenomenon is more likely to manifest with greater persistence and intensity in the United States, as identified by the Swiss Re Institute (2024), it is also becoming prominent in other Anglo-Saxon countries sharing similar legal systems such as the United Kingdom (UK), Canada and Australia (see Figure 12.2).

Figure 12.2: International comparison of drivers of future social inflation



	US	Australia	UK	Canada	Netherlands	France	Germany	Japan
Claims penetration	H	M	H	M	L	M	M	L
Income inequality	H	M	M	M	L	M	M	M
Third-party litigation funding	H	H	H	M	H	M	M	L
Contingency fees	H	M	M	H	L	L	L	L
Collective redress	H	H	H	H	H	M	M	L
Case law	H	H	H	H	L	L	L	L
Jury based	H	L	L	L	L	L	L	L

High risk · Medium risk · Low risk

Source: Swiss Re Institute

Note: *Claims penetration* refers to the ratio of liability claims to GDP; *income inequality* is measured with standardized Gini coefficients based on the Standardized World Income Inequality Database.

Through various channels, the rise in socio-economic disparities fosters a legal setting in which social inflation takes root. As the share of national income accruing to large corporations has grown, particularly since the 1980s, individuals falling within the lower and middle tiers of the income distribution have experienced stagnating wages and reduced economic mobility. During this period, in the United States, where income disparities were more pronounced than peer countries, anti-corporate narratives have gained traction across the political spectrum. These disparities have been exacerbated during the Great Recession, after which one-quarter of all income was captured by the top 1-percent of income earners (Stiglitz, 2011). This fueled changes in corporate responsibility perception, illustrated by a growing skepticism within the general public and the civil justice system that cast insurers and large corporations as lucrative entities, making them prime targets for liability. This shift is evident in the increasing polarization within the jury pool (Orrick, 2023), the growing body of case law, the expansion of the concept of liability, the higher claims penetration, and the introduction of plaintiff-oriented legislation aimed at putting more pressure on corporate accountability over the last two decades.

In particular, in the US civil justice system, several institutional, procedural frameworks aimed at addressing the disproportionate access to legal resources arose.

One of the most consequential developments is the rise of litigation finance, which enables third-party investors to fund lawsuits in exchange for a portion of the potential settlement or award. Moreover, the growing prevalence of contingency-based legal services enhanced legal inclusivity for low-income litigants unable to afford legal costs upfront. Collective redress and the emergence of statutes supporting claimants have also emerged as critical components of the US civil justice system, aiming to balance power asymmetries and to strengthen consumer and individual protections by broadening liability standards, particularly in cases involving corporate or institutional defendants. These initiatives reflect an ongoing effort to mitigate the barriers that income inequality poses to justice, ensuring that individuals, regardless of their income status, have a chance to seek legal redress.

However, despite their role in lowering legal barriers for underprivileged groups, these mechanisms tend to trigger higher compensatory and punitive damages — trends that are magnified by social media advertising, further reinforcing anti-corporate sentiment and compounding the cycle of social inflation. On the other hand, rising premium levels imposed by insurers, as a defensive reaction, amplify derogatory narratives portraying them as excessively profit-oriented and inadvertently sustain a recursive dynamic of social inflation.

The third-party litigation funding (TPLF) industry exerts a transformative influence on the civil justice system and concentrates approximately 52 percent of the global litigation funding market in the US. In a climate characterized by economic disparities, such mechanism claims to offer relief by providing alternative funding sources to bridge the gap in legal affordability (Locatelli, 2024) and sustain lengthy litigation. This multi-billion-dollar industry serves as a platform through which third-party investors and hedge funds can finance lawsuits in expectation of a fixed interest or a percentage of the litigation proceeds upon trial success. TPLF caters to a broad spectrum of stakeholders ranging from attorney firms, individual claims, collective plaintiffs, to commercial entities. However, despite its appeal, an emerging narrative portrays TPLF as a predatory practice, where investors capitalize on the evolving patterns of public behavior and exert undue influence over litigation outcomes, often through non-transparent arrangements (US Chamber of Commerce, 2024).

The industry's potential to thrive is fueled by the high success rates and returns it delivers to investors, combined with the lack of transparency surrounding these practices.

Indeed, uncorrelated to underlying economic cycles, this industry delivers lucrative returns, with a nearly 25 percent return on investment (AM Best, 2024) and success rates ranging between 85 and 98 percent (Swiss Re Institute, 2021; US Chamber Institute for Legal Reform, 2022). Over five-year investment horizons, patent TPLF funds usually offer an approximate 20-percent internal rate of return (IRR) annually, which corresponds to approximately doubling or more their initial investment (Stroud, 2023).

Moreover, the industry has evolved under minimal regulatory oversight from its early stages in the US. Consequently, in the absence of nationwide disclosure requirement (Swiss Re Institute, 2021; see Table A12.2), such financial agreements frequently bypass detection during the course of litigation, giving rise to an underlying conflict of interest between the plaintiffs, law firms and third-party funders. The case involving Sysco Corporation and Burford Capital (US Chamber of Commerce Institute for Legal Reform, 2023), one of the biggest actors in the industry (see Table

A12.1), exposes the limitations of TPLF, where the involvement of the funding firm conflicted with the interests of the litigant, fueling concerns over both procedural transparency and a diminished plaintiff autonomy.

The repercussions of such conflicts also extend to defendants and their insurers as TPLF brings new dynamics into the legal process that diverge from conventional legal standards. Indeed, this controversial practice operates as more than a procedural tool, it exacerbates the occurrence and the cost of legal disputes. The involvement of a third-party investor, and its share in the potential compensation granted to the litigant, are inherently correlated with larger legal fees, payouts, awards, and extended durations of litigation. Hence, TPLF adds complexity and undermines fair claim resolution by introducing an undisclosed stakeholder's financial interest in the proceedings.

A report written by Westfleet Advisors (2022), indicates that the US litigation funding market grew by 16 percent in 2022, with the demand for financing continuing to rise and expected to remain strong. In parallel to the US, similar trends in social inflation risks related to the TPLF industry are observed in other jurisdictions such as Australia and the UK — where its modern form initially emerged (The Practice, 2019; Locatelli, 2024) — and the Netherlands. Overall, the combination of the regulatory void, the rapid growth of TPLF, and its incentive for claimants to undertake lengthy and speculative mass tort positions legal actions, positions TPLF as a high-risk contributor to social inflation in the US.

At a fundamental level, comparable to TPLF, contingency fee arrangements[19] are intended to democratize access to the legal system and lower the economic barrier to litigation for plaintiffs

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[19] Contingency fee arrangements involve a contract stipulating the conditions according to which attorneys should be compensated, specifically, as a percentage of the settlement awarded to the plaintiff.

who may not afford upfront legal fees. They are particularly common in personal injury, medical malpractice and corporate collections litigations, in which legal representatives are entitled to a share varying from 20 percent to 50 percent of the recovered amount upon success. However, while turning legal representation compensation into a variable cost contingent on performance rather than a fixed remuneration, these agreements exert a strong influence on litigation practices and, by extension, on the cost dynamics driving social inflation in the property and casualty insurance industry. In fact, they incentivize the initiation of a wider variety of legal actions, including those typically perceived as carrying a high degree of uncertainty or yielding limited monetary value. The aggregate effect is an inflationary pressure on claims frequency and severity, particularly in lines of business such as general liability, commercial automobiles, more specifically personal/bodily injuries (Dixon et al., 2024), and medical malpractice.

Moreover, by enabling the transfer of the plaintiffs' risk of losing the case to the lawyer, the structure of contingency fee arrangements provides an incentive for attorneys to seek claim success vigorously and aim for the highest possible recoverable amount. This motive ultimately alters the behavior of attorneys in ways that exacerbate adversarialism. In commercial cases, the plaintiffs' bar is increasingly relying on the use of litigation strategies, such as reptile theory (Abraham, 2022), that reframe the narrative from the facts of the case to emotionally compelling, community-centered safety concerns. This litigation approach eventually increases the potential for greater punitive damages as a measure to defend public interests and cultivates a reinforced sense of corporate accountability.

Amidst structures that encourage legal participation in the United States, collective redress mechanisms constitute a strategic approach for individuals and organizations pursuing identical concerns to collectively sue a defendant and address widespread claims (Bacharis, 2024).

By nature, these initiatives result in a higher volume of claims being filed and promotes larger legal costs and settlements for the insurer, particularly when punitive damages are involved. By way of those channels, this factor plays an additional role in fueling the phenomenon of social inflation in the US (DAC Beachcroft, 2024).

Collective redress takes several forms, with class actions and mass torts being the most common. General historical data related to class actions reveal that, in the US, approximately forty percent of the companies integrated class action waivers in their procedures (ClassAction.com, 2017). Growing reliance on arbitration agreements for risk mitigation signals the heightened relevance and legal exposure stemming from class actions. On the flip side, other firms are restricted from applying this provision due to regulatory barriers enforced in their respective jurisdictions.

Beyond the US, similar trends in social inflation risks related to the legal landscape are similarly expanding in other Anglo-Saxon jurisdictions such as the UK, Canada, Australia and the Netherlands that share common law systems. Tort law in Europe differs significantly from the US, primarily due to the absence of juries and the influence of civil law traditions. In most European countries, tort cases are adjudicated by professional judges rather than juries, however, class actions are growing rapidly in Europe.

For the past decade, the US civil justice system has been plagued by inflated compensatory and punitive damages, particularly in personal injury cases. The growing anti-corporate bias, that had redefined the law, and plaintiff-oriented judicial developments, created conditions unfavorable to defendants and promoted the proliferation of these “nuclear verdicts”[20] (Orrick, 2023).

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[20] Nuclear jury verdicts refer to jury verdicts reaching or exceeding $10 million.

This trend unfolds unevenly and is reflected by state-by-state divergence in procedural rules, thresholds for damages, availability of class actions, statutes of limitations, and in the regulatory acceptance of third-party litigation funding. Some jurisdictions referred to as judicial hellholes[21] (American Tort Reform Association, 2022), such as California, Florida, New York, introduce new bases for liability, especially in the context of corporate conduct. To illustrate this point, the example of Lemon Laws (Standley, 2024) highlights that regulatory scope of the laws enforced highly varies across US states in terms of vehicle eligibility, legal presumptions, warranty period and consumer protections. These statutes not only facilitate access to legal remedies in some states but also set precedents that may elevate compensation standards in similar litigation contexts. Some states such as New York and New Jersey extended Lemon Law protection — a clause protecting consumers from defective vehicles — to certain used vehicles. By contrast, states such as Texas restrict its scope to new vehicles exclusively. The case of Lemon Laws, among a few others, exemplifies how the divergent legislative frameworks recalibrate the dynamics of civil litigations and redefine the contours of liability and the resulting compensations. This variability across states not only complicates nationwide legal predictability but also incentivizes forum shopping and unequally affects civil justice outcomes throughout the country (Dodson, 2024). Empirical evidence further suggests that social inflation does not manifest at the same rate in every state and that trial awards were specifically high in states characterized as judicial hellholes, such as New York, New Jersey and California (Dixon et al., 2024).

The stochastic nature of jury awards—often disconnected from economic damages—introduces model risk, especially in the context of protracted legal proceedings. As a result, insurers are forced

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[21] A judicial hellholes represents "a jurisdiction where judges in civil cases systematically apply laws and procedures in an unfair and unbalanced manner, generally to the disadvantage of defendants" (American Tort Reform Association, 2022).

to adopt more conservative reserving practices and seek higher reinsurance limits, thereby escalating costs throughout the insurance value chain. As a matter of facts, we observe notably a number of reinsurers initiating a rigorous assessment and strengthening of their reserves to mitigate the legal and financial risks associated with increasingly common nuclear and thermonuclear[22] verdicts. Notably, Swiss Re (2024) allocated an additional $2.4 billion to its US casualty reserves during the third quarter of 2024.

The United States, operating under a common law system similar to jurisdictions such as Canada, Australia and the UK, relies heavily on case law, which shapes future court decisions and further contributes to the phenomenon of social inflation. In this common law framework, the role of juries in tort cases complicates efforts to regulate this phenomenon, in contrast to European countries and Japan which legal systems rely on civil law (Figure 12.2, Gallagher, 2025).

Taken together, these factors—the increasing societal willingness to punish corporate defendants, the innovative and incisive litigation strategies, common law systems and the expansion of tort law—have created fertile ground for social inflation to take root. In the following section, we assess how these drivers of social inflation have translated into measurable changes within the insurance landscape over time.

12.5 Growth of social inflation

The past decade has been characterized by a pronounced escalation in social inflation within the US property and casualty insurance market, in particular. Comprehensive quantitative evidence is not readily available to accurately measure the behavioral tendencies underlying the notion of

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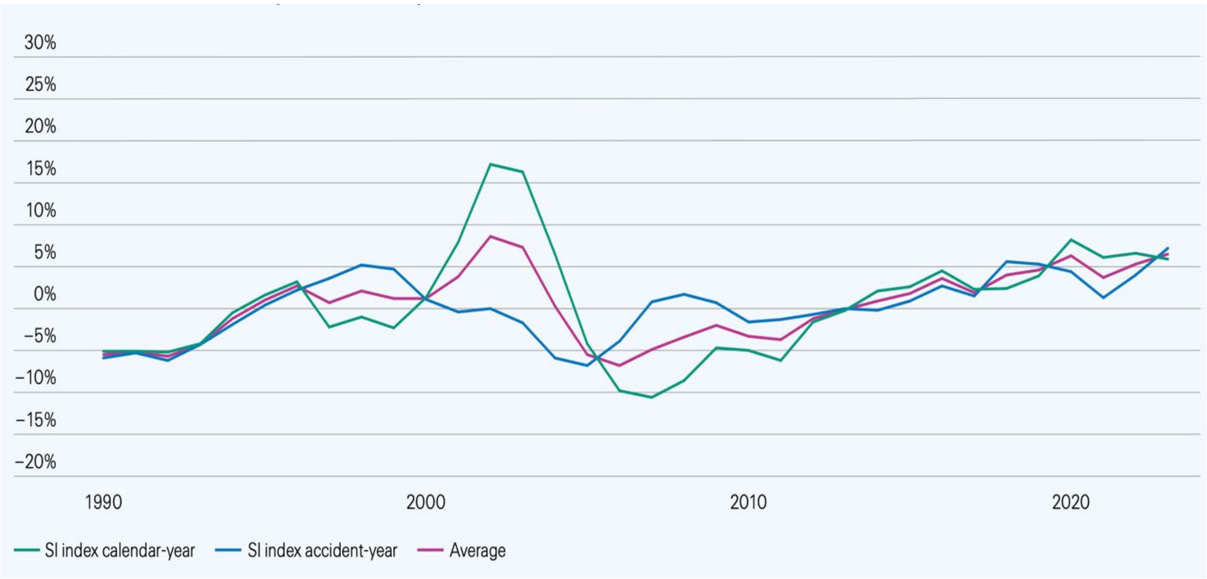
[22] “Thermonuclear verdicts” is a term coined to characterize verdicts exceeding $100 million.

social inflation. However, its growth can be captured by a newly established index, the noticeable prominence of anti-corporate bias, the surge of tort filings in state court and the prevalence of nuclear alongside changes in claims severity.

12.5.1 Social inflation index

Figure 12.3: US social inflation index, accident-year, calendar-year and average, 1990-2023



Source: Swiss Re Institute (2024a)

Given the abstract nature of the underlying dynamics of social inflation, a standardized and widely recognized index has yet to be developed. In the absence of any prior efforts to provide a measurable framework for these evolving patterns reshaping the insurance landscape, the Swiss Re Institute (2024a) pioneered the construction of a social inflation index[23]. They derived its calculation from the working definition that describes social inflation as claims severity growth,

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[23] Social inflation = claims severity growth – economic inflation.

difference from economic inflation. To approximate claims severity[24], they subtracted exposure growth and changes in claims frequency from claims growth.

Overall, the Swiss Re Institute (SRI) depicted a relatively concerning outlook of this phenomenon, estimating that, on average, social inflation rose by 5.4 percent annually between 2017 and 2022, in the US, while economic inflation increased by 3.7 percent (Swiss Re Institute, 2024). Consistent with assertions by industry stakeholders who have identified such inflationary pressures since the late 1990s, we observe, in Figure 12.3, a positive index and a peak around 2003. Thereafter, the index turned negative and continued to trend below zero for nearly a decade. From 2014 to 2023, the social inflation index gradually rebounded, transitioning from zero to consistently positive values, and reaching 7 percent on average (Figure 12.3). This observation reflects how broader social factors have been driving up claim costs beyond traditional economic inflation over the last ten-year span.

Beyond the index used by SRI to model social inflation, there is further evidence that indirectly chart the ways in which this phenomenon evolved over the past two decades. In particular, the trend in tort verdicts and the frequency of awarded damages arising from them, provide further insights.

12.5.2 Growing verdicts and plaintiff win rate

Without considering the context of the damages, the size of a verdict, in isolation, does not inherently imply deviation from the norm. However, it provides a useful signal of extreme or

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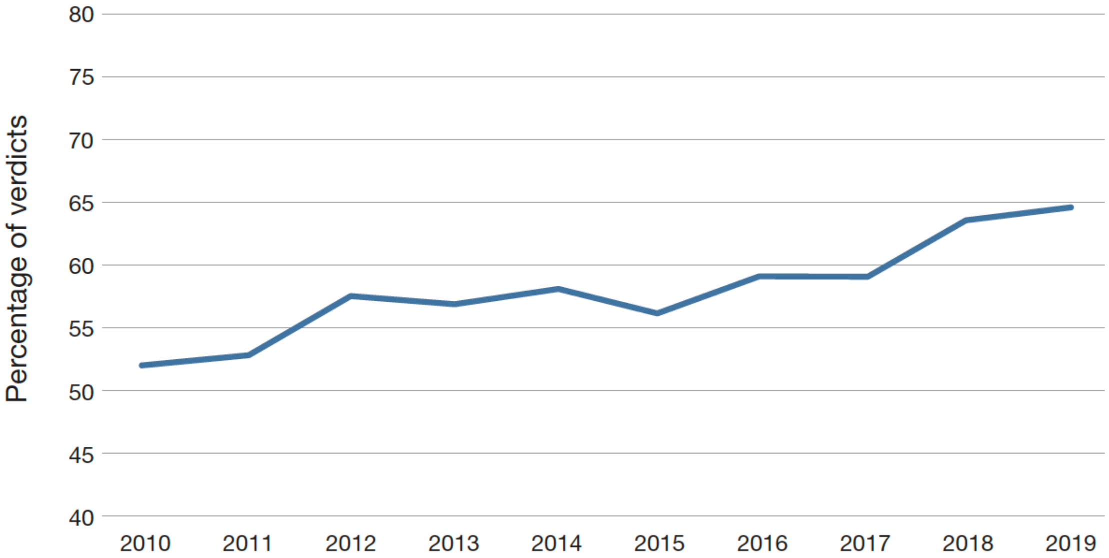
[24] *Claims* severity = claims growth – exposure growth – frequency changes.

inflated awards. Specifically, the conjunction of plaintiff success rate, paired with awards amounts could serve as a potential proxy for social inflation.

Trends in trial awards and plaintiff success rate were analyzed to find evidence of social inflation in a study conducted by Dixon et al. (2024). They collected 26,114 personal injury and wrongful death (PI/WD) tort verdicts, ranging from 2010 to 2019, from Law.com VerdictSearch, a leading platform featuring verdict and settlements data.

They examined the share of tort verdicts won by plaintiff across this period in order to provide context for interpreting award amounts. The plaintiff win rate for all PI/WD verdicts saw a moderate increase of 5 percent between 2011 to 2012, from an initial 52.5 percent, followed by a more recent rise from 2015 to 2019, reaching a nine-year high of approximately 65 percent (Figure 12.4). The plaintiff win rates are notably higher for cases involving private automobiles, commercial trucking and other commercial vehicles, spanning from 64 percent to 69.1 percent, distinctly above the 57.5-percent observed across all verdicts (Table A12.3). The observed increase in win rates could reflect actual social inflation, but could also be partly attributable to factors such as changes in verdict reporting practices over time.

Figure 12.4: Plaintiff Win Rate for All PI/WD Tort Verdicts in Dataset, 2010-2019

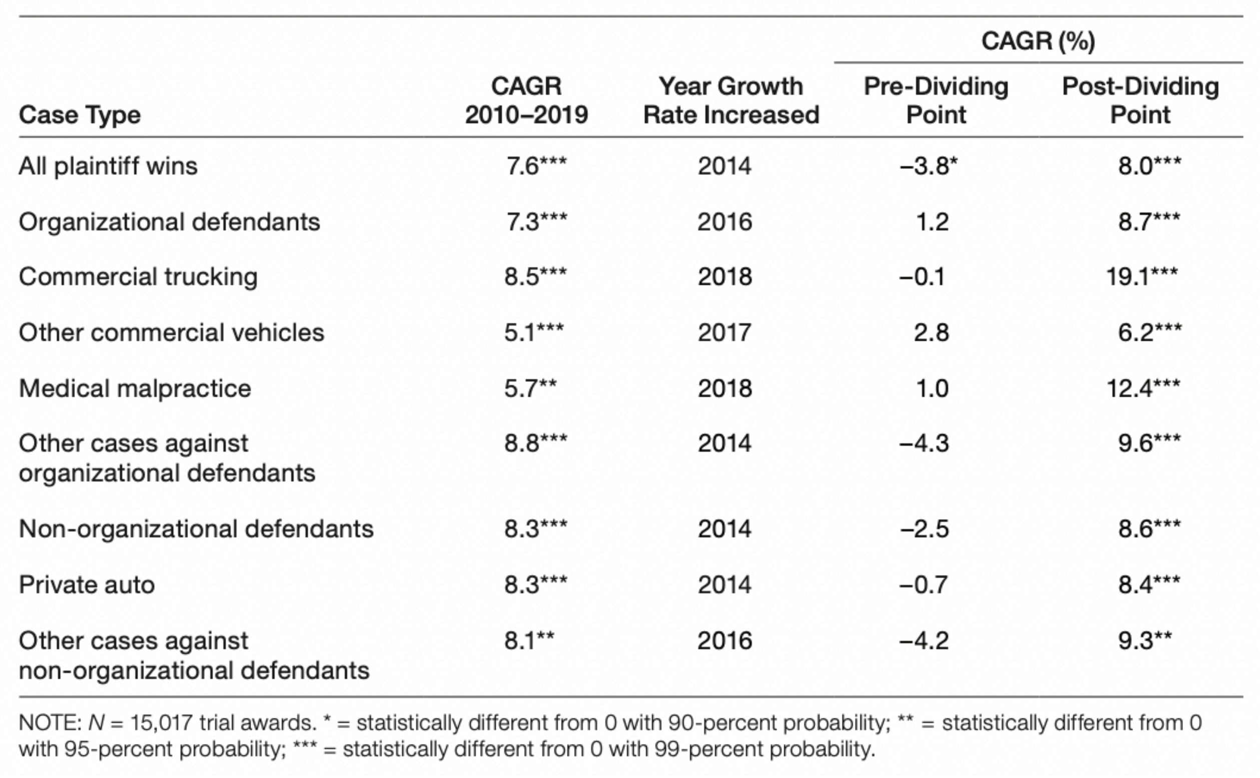


Source: VerdictSearch, Dixon et al. (2024).
Note: $N = 26{,}114$ verdicts.

With respect to trial awards, their findings suggest that, across all cases categories, there is statistically significant evidence that they expand annually at a compounded rate ranging from 5.1 to 8.8 percent between 2010 and 2019. For instance, for organizational defendants cases, trials awards rise at a compounded annual growth rate (CAGR) of 7.3 percent, from 2010 to 2019 while for cases involving private automobiles, the compound annual growth rate stands at 8.3 percent for the same period. Holding cases attributes constant, the CAGR is 7.6 percent. The growth rate began to rise at some point between 2014 to 2018, across the different case categories, further demonstrating that trials awards has been on an upward trajectory within the last decade. This regression analysis (Table 12.1) indicates that, over the study period, both the commercial trucking and private automobile segments, along with organizational and non-organizational defendants, faced the greatest exposure to the increase in trial awards. The post-2014 increase in plaintiff success rates combined with the rise in damages awarded points to three plausible interpretations; the first of which involves judicial shifts favoring plaintiffs. An alternative explanation may lie in the possibility that stronger cases are more likely to be brought to court. A final possible interpretation could be that there is increased access to external litigation funding, potentially resulting in more robust case presentation.

Taken together, these findings strongly imply the presence of factors promoting social inflation, notably within the area of commercial auto liability, as similarly reported by insurance and reinsurance experts (Insurance Research Council, 2020; Lynch and Moore, 2022; Araullo, 2024).

Table 12.1: CAGRs for PI/WD inflation-adjusted trial awards per Plaintiff, 2010-2019



			CAGR (%)	
Case Type	CAGR 2010–2019	Year Growth Rate Increased	Pre-Dividing Point	Post-Dividing Point
All plaintiff wins	7.6***	2014	–3.8*	8.0***
Organizational defendants	7.3***	2016	1.2	8.7***
Commercial trucking	8.5***	2018	–0.1	19.1***
Other commercial vehicles	5.1***	2017	2.8	6.2***
Medical malpractice	5.7**	2018	1.0	12.4***
Other cases against organizational defendants	8.8***	2014	–4.3	9.6***
Non-organizational defendants	8.3***	2014	–2.5	8.6***
Private auto	8.3***	2014	–0.7	8.4***
Other cases against non-organizational defendants	8.1**	2016	–4.2	9.3**

NOTE: *N* = 15,017 trial awards. * = statistically different from 0 with 90-percent probability; ** = statistically different from 0 with 95-percent probability; *** = statistically different from 0 with 99-percent probability.

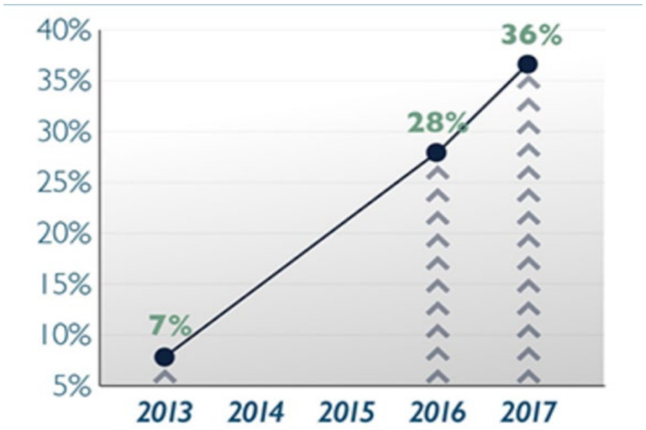
Source: Dixon et al. (2024)

12.5.3 Third-party litigation funding

Third-party litigation financing has gained traction and radically revolutionized the dynamics of the legal industry throughout the past decade in the United States. Frequently referenced and criticized for contributing to rising litigation costs (Swiss Re Institute, 2024b), this industry's development since its inception can serve as an additional indicator of the expansion of social inflation.

According to Evans and Klevens (2017), 36 percent of law firms in the US adopted this practice in 2017, up by 8 percent relative to the prior year, and by 29 percent since 2013 (Figure 12.5).

Figure 12.5: Litigation funding use in US law firms, 2013-2017



Source: Daily Report Law.com (2017), Esquire Deposition Solutions (2017)

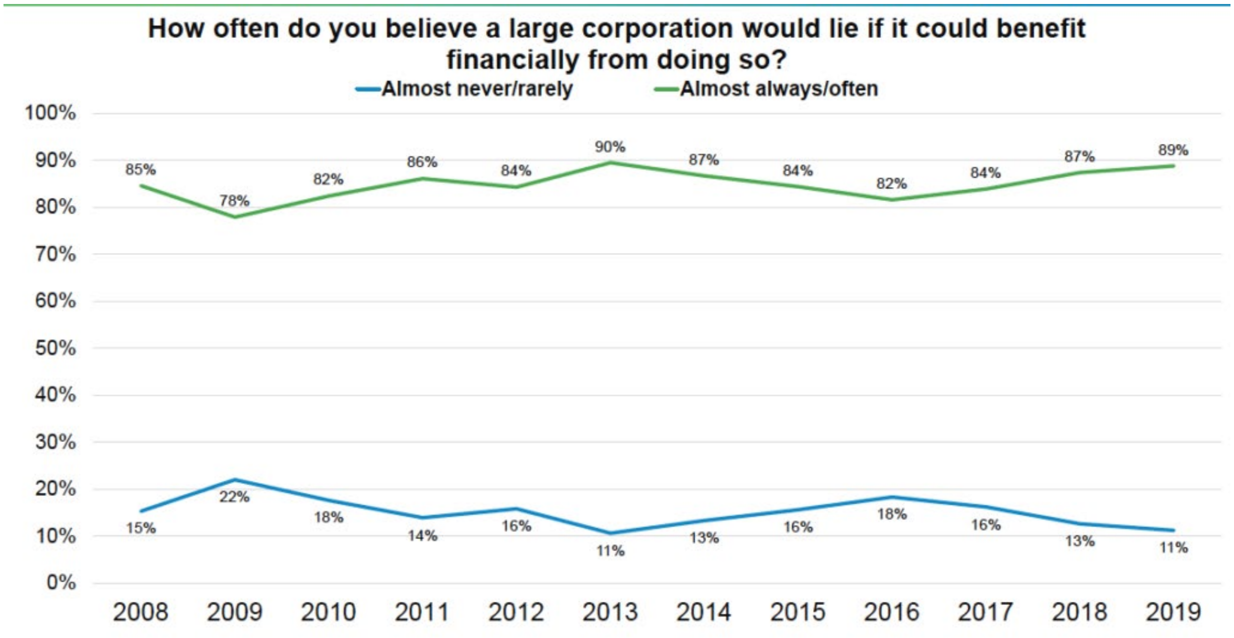
The reliance on TPLF by law firms in 2020 was primarily driven by financial constraints. However, according to a survey conducted by Lake Whillans and Above the Law (2020), an estimated 6 percent of the motivations behind the use of TPLF could be attributable to other factors, some of which could be considered potentially unjustified. Analysis of data from 2016 and 2020 suggest that the involvement of TPLF in tort lawsuits is associated with a decline in the compensation share granted to the plaintiffs by at least 12 percent (Figure A12.2). The costs borne by individual plaintiffs and corporate litigants rise in the presence of TPLF and according to the Swiss Re Institute (2021), it would require a 27-percent increase in awards to compensate them for the costs incurred by the use of TPLF.

12.5.4 Anticorporate bias

A national Juror Survey conducted from 2008 to 2019 (Broda-Bahm, 2020) reveals that the percentage of juror who believe that large corporations would often lie if it could benefit them financially from doing so has been steadily increasing during the study period reaching 89 percent of the surveys, the highest percentage recorded since 2013 (Figure 12.6).

In parallel, the percentage of jurors believing that large corporate would rarely lie if it could benefit financially has been steadily dropping since 2016, reaching 11 percent of the surveys, also the lowest percentage experienced since 2013. These figures reflect the constant anticorporate climate that reigns among jurors in the US over the past decade.

Figure 12.6: Anticorporate stability over time, 2008-2019



Source: Persuasion Strategies, JD Supra (2020).
Note: National Juror Survey 2008-2019, N=5,672.

In a related study on juror attitudes, Orrick (2023) surveyed over a thousand jury-eligible individuals from regions[25] prone to nuclear verdicts. After adjusting for demographic factors such as age, race, education level, profession and political orientation, the results indicate that, from the pre-COVID era to today, negative perceptions of corporations have doubled from 27 to 45 percent. Moreover, 41 percent of the participants revealed a diminishing faith in science compared to the period before the pandemic. Additional insights show that the percentage of prospective jurors inclined to side with single plaintiff over large corporations nearly doubled, reaching 59 percent compared to 33 percent during the pre-pandemic period (Figure A12.3).

This erosion of institutional credibility compels jurors to take greater responsibility in legal proceedings and administer their own form of justice. This dynamic, particularly exacerbated in

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[25] California, Florida, Kansas, Illinois, Indiana, Louisiana, Minnesota, Missouri, Texas, New Jersey, and New York.

the post-pandemic context, thereby amplifies liabilities for defendants and contributes to rising insurance costs related to litigation.

12.6 Importance of social inflation in 2025

The costs and severity of claims have been on the rise for several years, however, with the current and expected expansion of the TPLF market, the technological advancements, and the growth of other forms of inflation, this year is set to be a defining period for insurers as it marks a critical threshold for the intensification of social inflation.

Industry experts affirm that the development of the main catalysts of social inflation, such as TPF, is set to persist in the foreseeable future. According to recent market research conducted by various consulting firms, the US litigation funding market is expected to reach a CAGR ranging between 8.9 percent and 11.1 percent within the next ten years (Research Nester, 2025; Credence Research, 2025). This significant growth reflects increasing investor interest and availability of external capital to finance legal claims. As a result, this expansion is driving greater litigation activity, which, in turn, shifts the risk landscape. This observation underscores the critical need for insurers to better capture influx of third-party funding to adequately manage social inflation and its impacts on reserve and pricing adequacy.

The challenge is considerable, particularly within the casualty insurance industry.

The inherently long-tail characteristic of casualty claims implies that losses can emerge or escalate several years after policies are written, making the ability to accurately predict liabilities more complex for insurers (Pain, 2020; Moorcraft, 2020; Munich Re, 2024).

While the sector is beginning to experience signs of stabilization, the financial impact of historical under-reserving, particularly for excess liability lines over the last five years, continues to weigh on balance sheets (Moorcraft, 2020). This results in a complex environment where insurers are responsible for managing both prior claim costs and emerging social inflation dynamics.

The expanding use of Artificial Intelligence (AI) solutions is expected to significantly reshape the litigation landscape by introducing new and complex risks such as data breaches, fraudulent activities and other forms of cybersecurity challenges. As organizations increasingly rely on automated systems, the potential for misuse or accidental exposure of sensitive information grows, introducing new regulatory and legal implications.

Furthermore, the large-scale integration of AI could result in notable employment disruption across several industries, undermining economic stability across the labor force. This shift can contribute to the cycle of social inflation (Kelley, 2018), as rising unemployment often leads to increased claims.

The "dangerous double barrel" of social and economic inflationary pressures, as described by industry experts (Seaman, 2023), further threatens the P&C insurance market.

Economic inflation is likely to fuel further social inflation through several means.

First, it contributes to an increase of the overall cost of claims and prompts insurers to adjust their operational proactivity, across different insurance segments, accordingly. For instance, P&C insurers would be required to assess the accuracy of declared values, as there might be a substantial discrepancy between them and actual replacement costs driven by economic inflation. It also leads to increase in legal defense costs and the attorneys' rates set by law firms as the market experiences upward price pressure.

Furthermore, economic inflation impacts other aspects of insurer operations such as investments. There is a risk of a detrimental effect on investment earnings along with the availability of capital.

Besides, beyond macroeconomic influences, factors such as escalating costs related to the transition toward a green economy and carbon neutrality, commonly referred as "greenflation", must be factored into general inflation analysis (Seaman, 2023). Considering this additional component, which is gaining momentum as multiple firms strive to reduce their carbon emissions, highlights the presence of a triple threat of inflation for the insurance industry.

Marked by a higher probability of tail-risk events, as well as a diminished capacity to forecast and underwrite risks, the ramifications of social inflation are now unprecedented.

As TPLF continues to evolve, its trajectory reflects an increasing role in the US litigation ecosystem, and its implications for litigation outcomes, insurance costs, and the integrity of the legal system. Collectively, these points reinforce its position as a critical focus in current policy conversations.

On top of that, navigating the dual challenges of economic and social inflation poses further challenges and requires a multifaceted approach.

A few actions are taken within the casualty insurance industry to address losses, however, the impact of these changes may take several years to materialize.

12.7 How to manage social inflation

Navigating the complex landscape of social inflation would involve actions taken on two levels.

This risk being out of the control of (re)insurers, they can take preventive actions to assess and mitigate its impact. The government, on the other hand, should intervene to regulate the legal environment by enforcing transparency standards and implementing reforms that curb excessive litigation and fraudulent claims.

12.7.1 Private management by insurers

From the insurers' perspective, addressing the realities of social inflation could imply a combination of advanced and data-driven risk assessment, underwriting and actuarial practices, proactive claims management, transparent risk communication with policyholders, fraud detection investment and advocacy for state-level legal reforms.

There is an increasing need for insurance carriers and reinsurers to anticipate and prepare reserves in front of the growing number of long-tail claims from social inflation factors. Investing in predictive analytics (Deloitte, 2024) and trained human capital can help in the diagnostic of trends in social inflation and outlier claims at an early stage to prevent escalation. It not only would contribute to enhancing risk forecasting but also support sound underwriting and premium pricing.

Leveraging statistical tools such as Monte Carlo simulations could assist P&C insurers in modeling the uncertainty in future claims by generating a wide range of possible outcomes based on varying social and legal assumptions By simulating thousands of scenarios with different input variables such as the probability of extreme loss events, the share of claims going to court, or attorney involvement rate, we can capture a range of possible claim outcomes and assess the tail risk that might lead to significant cost increases.

Additionally, using text mining tools such as natural language processing (NLP), sentiment analysis based on media, news, or social media data can be integrated into risk models. By tracking societal shifts —public sentiment toward corporate accountability or changes in legal interpretations,— this can serve as a leading indicator of future litigation trends.

These methods would create a robust and dynamic risk model, that can better account for social inflation and improve claims forecasting and reserve management.

Professionals with the P&C insurance and reinsurance industry could retool traditional actuarial approach to assess risks and include social inflation in their risk inventory and strategic plan, using a segment-specific approach. This can be done by tailoring the methodology to recent societal trends and integrating more dynamic models that can simulate different stress scenarios that reflect emerging trends. For example, in order to monitor, measure and report social inflation impact, actuaries could incorporate legal risk indices such as ESG, public sentiment, and real-time litigation data to their models.

Insurers can effectively respond to the challenge of social inflation by addressing the root causes driving the rising costs of claims. A critical step involves strengthening their claims management teams, ensuring that claim adjusters are not only sufficiently staffed but also properly trained and equipped with the necessary resources and technology. By doing so, insurers can expedite the claims handling process, reducing delays that often lead to increased legal fees, prolonged negotiations, and higher settlement amounts. Prompt and efficient claims resolution helps prevent unnecessary escalation, ultimately controlling costs and mitigating the financial impact of social inflation on the insurance industry. Furthermore, proactive claims management allows insurers to identify patterns or emerging risks early, enabling them to implement targeted strategies that limit exposure to costly claims in the future.

Additionally, insurers should consider implementing lower policy limits for policyholders who choose not to utilize the services of the insurer's trusted network of contractors and service providers. This approach incentivizes the use of vetted professionals who can deliver quality repairs or services efficiently, helping to control costs and reduce the risk of inflated claims. By encouraging policyholders to work with a reliable network, insurers can better manage claim expenses, maintain consistent service standards, and minimize opportunities for unnecessary or excessive repairs that contribute to social inflation.

Insurers could leverage AI to proactively identify fraudulent claims and target policyholders that would be potentially inclined to sign AOB agreements. They should provide them with clear, accessible education on the potential drawbacks of such arrangements. By informing these policyholders about the risks—such as loss of control over the claim process, increased likelihood of disputes, and potential for inflated costs—insurers can effectively dissuade them from signing AOB agreements. This targeted outreach not only helps protect both parties from unnecessary litigation and inflated claims but also promotes more transparent and efficient claims management. Insurers can also mitigate social inflation by offering policy options with coverage limits and exclusions tailored to emerging social inflation risks can help manage exposure.

Insurers need to continue to engage actively in the public policy debate to promote changes in the legislative framework in order to ensure fairness in settlement awards. Along with organizations such as the US Chamber of Commerce, American Tort Reform Association (ATRA), and state-level tort reform coalitions, insurance and reinsurance companies could initiate and pursue lobbying efforts by discussing how TPLF fuels social inflation and advocating for stricter regulations within this growing industry. The advocacy approach could encompass issuing articles and reports about the drivers of social inflation, as well as organizing conferences and symposiums to encourage conversation and engage stakeholders.

Along similar lines, to further mitigate excessive jury awards and promote more lenient interpretations of liability, insurers should lobby for additional legal reforms, such as reasonable caps on non-economic damages and limitations on collective redress —class actions and mass tort. Reinsurers may join efforts with primary insurers to campaign for those regulatory changes.

Although insurance companies, can help to limit the growth of social inflation at their own level by implementing this set of recommendations, they are unable to lead the effort. Policymakers should intervene to regulate litigation dynamics and prevent unfair practices.

12.7.2 Social management by government

The involvement of a third-party through litigation funding prompts ethical scrutiny regarding the ultimate decision-makers involved in the litigation process. Initiatives aimed at restructuring TPLF operations should address those regulatory blind spots and their contribution to social inflation by improving transparency and preserving the integrity of legal proceedings. Their implementation could play a crucial role in curbing rising litigation costs and sanctioning abuse in the legal system, as well as fraudulent litigation.

In states where third-party litigation funding remains unregulated, lawmakers should push for legislation around transparency and mandatory disclosure of litigation financing; courts and all parties involved in civil litigation should be informed of any agreement in which a third party finances legal costs in exchange for a portion of potential proceeds. Several states including Indiana, Louisiana, and Montana have enacted laws imposing strict regulations on TPLF, paving the way for other states to adopt similar measures. Montana's new law, specifically, requires TPLF agreements disclosure, litigation funders registration with the state's secretary, holds investors jointly liable for costs, and imposes a 25-percent cap on the investors' share of potential compensation arising from legal actions (US Chamber Institute for Legal Reform, 2023a, 2023b).

Attorneys' clients must also be notified if their legal counsel has a TPLF arrangements. The latter should systematically be subject to discovery to foster transparency and accountability.

Third party funders should be prohibited from exerting any influence over litigation or settlement decisions, to uphold ethical standards and guarantee that procedural and strategic decisions remain within the control of attorneys and their clients.

Finally, in an effort to reduce the incidence of meritless legal claims and abusive litigation practices, both third-party investors and their partnered law firms should be jointly held liable for any sanctions imposed by the court (Behrens, 2025).

Policymakers should also consider passing legal reforms that aim to promote more impartial legal decisions, protect consumers, businesses and insurers from exploitative trial lawyer tactics by regulating and sanctioning misleading legal advertising. These costly promotional strategies are often structured to drive up participation in mass tort litigation and compel companies to enter into comprehensive settlements, even when the underlying claims lack direct causative evidence (Silverman, 2017; Insurance Information Institute, 2022).

As an added measure, in light of the abuse related to AOB agreements, the regulatory provisions of the relevant states ought to be subject to reforms.

The aforementioned series of targeted initiatives and interventions— including the regulation and enforcement of compulsory disclosure of third-party litigation funding practices, disciplinary measures for predatory legal advertising, and the improvement of claims management and data-driven underwriting practices— could contribute to mitigating the issue of social inflation.

12.8 Conclusion

This report poses the question of whether the US property and casualty insurance industry is subject to social inflation and to what extent. Social inflation, characterized by the increasing costs of insurance claims due to societal and legal shifts, constitutes a major issue for policyholders, insurers and re-insurers. This phenomenon, which originated in the 1970s and has resurfaced over the past five years, is particularly driven by the growing use of third-party ligation funding and contingency-fees, higher jury awards and punitive damages, increasingly assertive legal strategies by plaintiff lawyers, plaintiff-friendly legislation and the expansion of liability through new legal doctrines.

Evidence exhibits heterogeneity across different lines of business, with commercial trucking and private auto being the most affected. Empirical studies and data also point to social inflation as a cross-jurisdictional concern, placing upward pressure on insurers' loss ratios.

Considering the unpredictable nature and the growing importance of social inflation in the present era, the necessity to find mitigating measures to control the risks implied by this phenomenon becomes crucial to ensure the long-term profitability and stability of insurance operations.

As a first step, it is important that P&C insurance industry professionals adopt a segmented approach, as certain regions and line of business are particularly prone to social inflation and merit close monitoring. A standardized risk modeling framework would fail to account for cross-jurisdictional and line-specific differences.

Insurers and reinsurers could integrate scenario-based models in their reserving approaches to better capture the impact of litigation trends and societal expectations. Investment in advanced litigation analytics and claim pattern forecasting based on historical and real-time data can also improve underwriting discipline.

Given the rise in mass tort cases and those supported by third-party litigation funding, policy terms should be reassessed to reduce ambiguity and clarify exposure boundaries. Insurers should strategically embed AI tools into their risk management and claims handling models to optimize pricing and improve customer satisfaction, while maintain the integrity of their information.

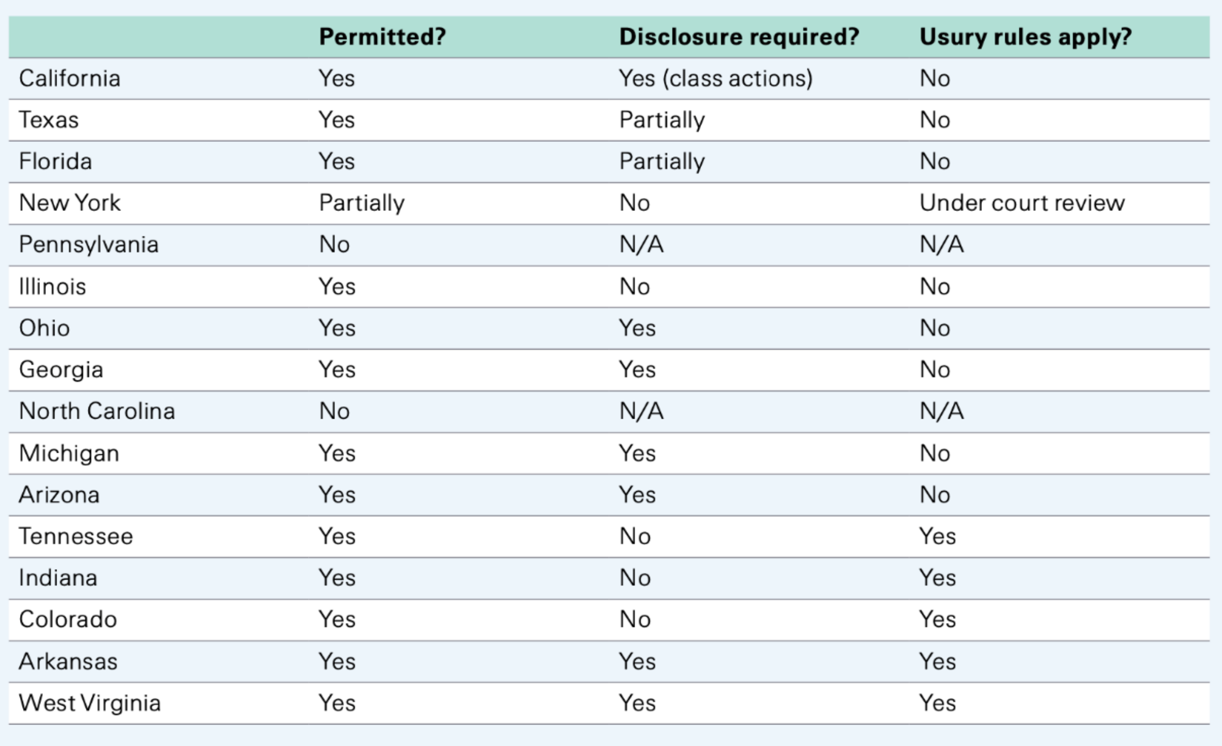
On the policy front, regulatory and legislative bodies should implement mandatory disclosure of third-party litigation funding agreements to improve transparency in the civil justice system. Ultimately, regulatory frameworks tailored to law firms can mitigate abusive practices of attorneys and help rebalance fairness and efficiency in the legal process. Together, these measures can support a more resilient insurance environment and safeguard access to justice without compromising the sustainability of the insurance sector.

Appendix A12: Additional information

Table A12.1: Abbreviations

Abbreviation	Definition
AI	Artificial intelligence
AOB	Assignment of benefits
ATRA	American Tort Reform Association
CAGR	Compound annual growth rate
COVID	Coronavirus disease
DID	Difference-in-differences
FLOIR	Florida Office of Insurance Regulation
III	Insurance Information Institute
IRR	Internal rate of return
LAE	Loss adjustment expense
LFC	Litigation finance company
NLP	Natural language processing
P&C	Property and casualty
PI/WD	Personal injury and wrongful death
SRI	Swiss Re Institute
TPLF	Third-party litigation funding
UK	United Kingdom
US	United States

Table A12.2: Summary of TPLF rules for a selection of US states, as of October 2021



	Permitted?	**Disclosure required?**	**Usury rules apply?**
California	Yes	Yes (class actions)	No
Texas	Yes	Partially	No
Florida	Yes	Partially	No
New York	Partially	No	Under court review
Pennsylvania	No	N/A	N/A
Illinois	Yes	No	No
Ohio	Yes	Yes	No
Georgia	Yes	Yes	No
North Carolina	No	N/A	N/A
Michigan	Yes	Yes	No
Arizona	Yes	Yes	No
Tennessee	Yes	No	Yes
Indiana	Yes	No	Yes
Colorado	Yes	No	Yes
Arkansas	Yes	Yes	Yes
West Virginia	Yes	Yes	Yes

Source: Swiss Re Institute (2021)

Figure A12.1: Largest dedicated LFCs, 2020 assets under management (USD millions)

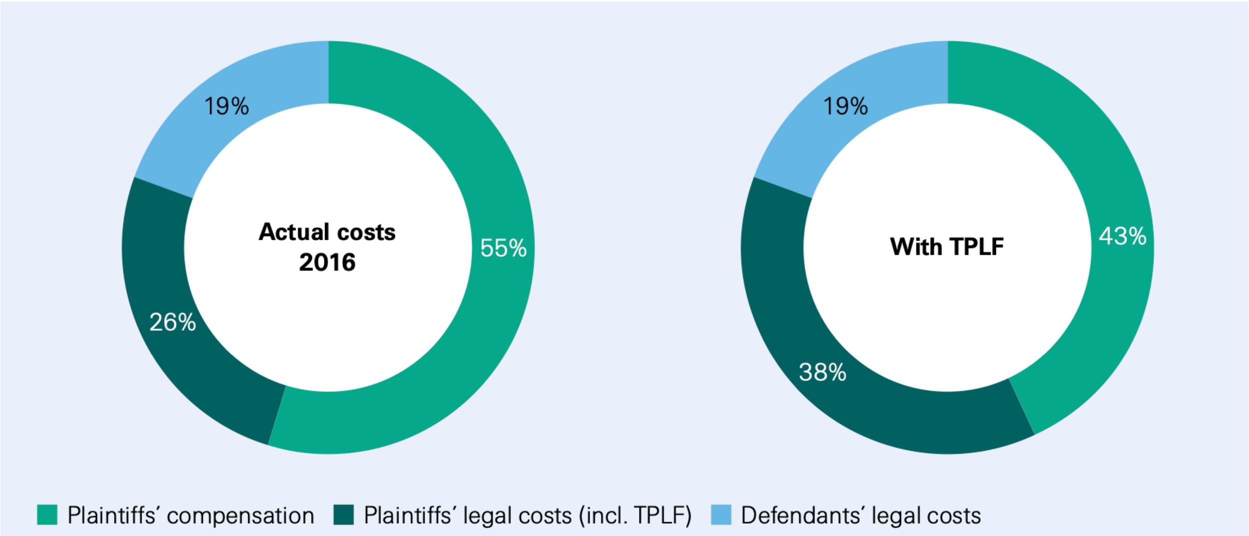
Source: Swiss Re Institute (2021)

Table A12.3: Plaintiff Win Rates in PI/WD Tort Verdicts by Category, 2010-2019

Verdict Category	Number of Verdicts	Plaintiff Win Rate (%)
All verdicts	26,114	57.5
Case type		
Medical malpractice	2,553	34.8
Commercial trucking	1,068	64.0
Other commercial vehicles	3,234	69.1
Private auto	9,913	64.6
Other cases against organizational defendants	8,071	51.6
Other cases against non-organizational defendants	1,275	50.3

Source: VerdictSearch, Dixon et al. (2024)

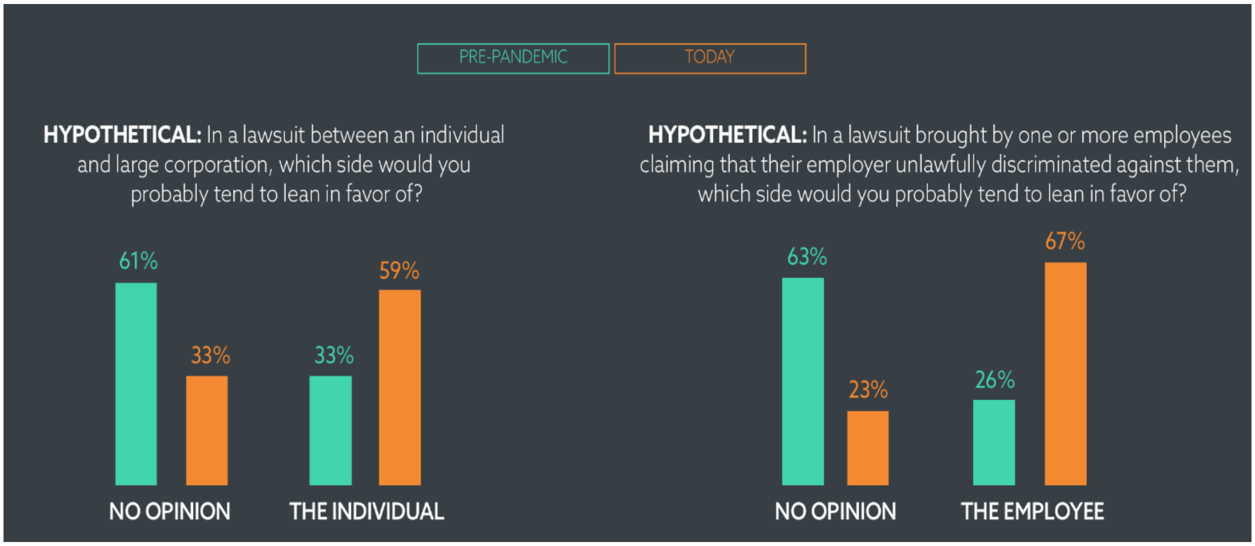
Figure A12.2: Estimated distribution of commercial liability tort system costs without and with TPLF contribution



Note: for modelling assumptions, we use 2016 data from the Institute for Legal Reform for legal system costs and 2020 data from Research Nester for realised returns on litigation funding investments. We triangulate these two datasets by holding the award amount fixed.

Source: Swiss Re Institute (2021), Institute for Legal Reform, Nester

Figure A12.3: Anti-corporate bias, pre- and post-pandemic



Source: Orrick (2023)

Conclusion of the report

The aim of this study is to analyze the impact that inflation risk could have on the financial performance of insurers in each of the two main sectors of the US insurance industry: P&C and Life. Very few contributions have analyzed the effect of inflation on the insurance industry. During the 1951-1976 period, inflation had a negative correlation with underwriting profits and investment returns in the P&C insurance industry (D'Arcy, 1982). No significant correlation between the levels of underwriting profits and inflation was observed during the 1977-2006 period. A negative and significant correlation was observed between inflation and investment returns during this period (Krivo, 2009). Other contributions to the literature are reviewed in Section 1 of the report.

Section 2 describes the evolution of inflation measured by the *Inflation rate*, with a special attention on our period of analysis, 1973 to 2023. The United States has experienced three inflationary shocks since 1973. The first shock started in 1974. It was linked to an oil shock as for the second shock, the biggest in this period of analysis, that started in 1979. A third shock started in 2020 and was linked to the *COVID-19* pandemic. The *Inflation rate* exhibited an overall downward trend from 1990 to 2020. It oscillated at below 6 % throughout this period.

Three other observations can be made from this time period. The first is that the *Inflation rate* reached a historically negative low point in 2009. The second observation stems from the specific nature of the post-1990 period. The *Inflation rate* became more volatile than before 1990. Protecting against volatility associated with fluctuating inflation became a new necessity. Finally, the *Inflation rate* and the nominal rate of LT government bonds (10-year maturity) moved in the same direction over the entire period. We can clearly see in Figure 2.2 that the steady slide in

Inflation rate observed since the early 1990s has led to a reduction in the interest rates on LT government bonds in which insurers invest significantly.

The US more recent inflation period following the *COVID-19* pandemic was mainly explained by strong increases in the prices of food and energy (Bernanke and Blanchard, 2025). Supply disruptions in key sectors of the economy is also a cause. Labor supply became tight and then contributed to wage inflation.

Section 3 analyses in more detail the properties of the US *Inflation rate* series during the 1973-2023 period. Our analysis of the impulse response of inflation to 1970s oil shocks, the 1979 monetary policy reform shock and the *COVID-19* shock yielded a number of observations. First, all three shocks had an instantaneous impact on inflation, as shown in figures 3.3, 3.4, and 3.5. The instantaneous magnitude of the shock was greater with the oil shocks. Second, we observed that the oil shocks and the 1979 monetary policy reform shock had permanent consequences (lasting effect) on inflation, whereas the *COVID-19* shock had short-term consequences on inflation. Third, according to our forecast based on the *COVID-19* shock, we expected the decline in inflation observed in 2022 to continue in 2023 and 2024. The main difference of the *COVID-19* shock on inflation with respect to the oil shocks is probably explained by the early intervention of the Fed in 2020.

Section 4 presents the main insurance business indicators studied that include the *Combined ratio*, the *Operating ratio*, and the Return on assets (*ROA*). Section 5 adds more structural analysis of inflation in the 1973-2023 period with the Autoregressive Distributed Lag (ARDL) model and the Error Correction Model (ECM) for long-term effect and short-term effect of inflation on financial variables in the P&C and Life sectors. We have modeled the links between the *Inflation rate* and the variables *Premiums, Total expenses, Combined ratio, Net investment income*, *Operating ratio, Pretax operating income* and *ROA* in each of the two insurance sectors, using the ARDL (c,q) model and the ECM. The advantage of ARDL model is that it can be applied to both nonstationary and stationary data. However, we worked with stationary variables exclusively. We differentiated our variables that turned out to be nonstationary to make them stationary. This approach enables us to use usual tests of coefficient significance (Fisher or Student tests), which assume white noise in stationary residuals. As the series are stationary, they can also be modeled using a VAR process.

Our results indicate that *Premiums*, *Total expenses*, and *Net investment income* variables are positively affected by inflation, which is a quite natural result. These effects seem to compensate each other since profitability variables such as *Combined ratio*, *Operating ratio*, *Pretax operating income*, and *ROA* are not affected by inflation according to the results summarized in Table 5.57. These preliminary results may be explained by the implicit assumption of linearity in the stochastic inflation processes in the above models.

Section 6 studies impulse response of inflation on insurers' financial variables in the two insurance sectors using the VAR process. We show that the shock of the *COVID-19* pandemic, by comparison to previous oil shocks, had a significant positive but short-term impact on inflation.

Robustness checks of VAR model are analyzed in Section 7. In this section, we revisit the impulse responses derived from the VAR estimations to investigate whether our conclusions about insurance variables' responses to inflation shocks are robust to an alternative econometric methodology, namely the Local Projection (LP) estimation. We estimate the same VAR specifications discussed previously, and we draw the impulse response functions generated by the LP estimations alongside the VAR estimations. Overall, we can say that both methodologies give similar impulse responses function for near forecasting horizons as predicated by the theory and as conjectured by simulation-based literature comparing LP and VAR estimations. However, for more distant forecasting, discrepancies between the two approaches become more apparent. Particularly, the VAR estimation depicts smoother response pattern than the ones estimated by local projection (LP), which may also explain the results in Section 5.

Section 8 analyses the nonlinear stochastic processes of inflation during the 1973-2023 period. We observe that the US *Inflation rate* series is characterized by a random trend and nonlinear dynamics (asymmetry). These results led us to select the two-regime Markov model for analyzing the effect of inflation on different performance indicators of the insurance industry.

In Section 9, we confirm that the US *Inflation rate* series is characterized by a random trend and nonlinear dynamics. These characteristics led us to select the two-regime Markov model over the MS-GARCH model to study the impact of inflation on various fundamental indicators of insurance industry performance. We show that performance indicators are differently affected by inflation in the Life and P&C insurance sectors according to the inflation regime considered.

Table 9.15 summarizes the impact of inflation on various fundamental determinants of insurance company performance in the US. The table shows that both Life and P&C insurers were significantly exposed to inflation fluctuations, especially in periods of high inflation (State 2). Inflation in State 1 (low inflation) did not affect significantly the P&C underwriting variables and had a positive effect on investment income at only 5%. It was surprising to observe that the net effect on both the *Operating ratio* and *ROA* generated negative results on profitability. Results in State 2 are more coherent since the negative result on *Premiums* generated a negative performance overall. The positive result on investment did not create a significant hedging effect in this sector.

The table indicates that the impact of inflation on *ROA* in the Life sector was not significant, in State 2. Other factors than the *Operating ratio* seem to have affected the *ROA*. The impact of inflation on Life insurers performance indicators in State 1 was negative for the underwriting activities, but the good performance of investment created a net positive effect on profitability.

The P&C sector seems to have been more affected by inflation during our period of analysis. The negative effect on *Premiums* in State 2, probably explained by a reduction in purchasing power of clients, affected insurance demand and the higher interest rates did not compensate for the negative underwriting results. In the Life sector, the hedging effect of investment was efficient in State 1 and neutral in State 2.

Section 10 evaluates the impact of inflation—both observed and expected—on *Reinsurance demand*, *Liquidity creation ratio*, and *ROA* for P&C US insurers from 1993 to 2023, with particular attention to differences across firm size. The analysis distinguishes between lagged observed *Inflation rate* and inflation forecasts made one and three years prior ($F1_{t-1}$ and $F3_{t-3}$), capturing how insurers react to realized inflation and how prior expectations shape current outcomes.

For *Reinsurance demand*, the findings reveal a clear positive relationship with lagged observed inflation, suggesting that insurers react to actual inflation through reinsurance protection. In contrast, long-term inflation expectations formed three years earlier are negatively associated with current *Reinsurance demand*. This implies that when insurers anticipated prolonged inflation in the past, they likely adopted more conservative strategies which manifest in more stable financial positions. Short-term forecasts ($F1_{t-1}$), however, show no significant impact on *Reinsurance demand* across the full sample, indicating that recent expectations may have had a limited influence on current decisions. Short-term forecasts may be too volatile, particularly those following the *COVID-19* pandemic.

Liquidity creation ratio demonstrates a time-sensitive dynamic. Insurers increase liquidity creation in response to realized inflation and short-term forecasts, likely as a response to manage near-term uncertainty in bond values. Conversely, long-term inflation forecasts are associated with decreasing liquidity creation in the economy and investing more in liquid assets. These patterns are more pronounced among small insurers, who are more exposed to inflationary risks and show clearer adjustments.

Large insurers, by contrast, do exhibit less significant changes in *Liquidity creation ratio*, likely due to their greater diversification, stronger asset-liability matching, and broader access to financial instruments. Regarding profitability, *ROA* improves with prior inflation expectations, a surprising result obtained, particularly with lagged one- and three-year-ahead forecasts, suggesting that insurers who planned for inflation were better positioned to adjust pricing, reallocate investments, or take advantage of higher interest rates. In contrast, realized inflation does not significantly affect *ROA* at the industry level. Firm-level differences are notable. Overall, the findings indicate that insurers are responsive to long-term inflation expectations as well to realized inflation. Proactive strategies—particularly those based on long-term forecasts—appear to enhance profitability and stabilize operations, while reactions to realized inflation are more defensive.

We also examined the direct effects of inflation on six key financial indicators: *Premiums to Total assets*, *Losses incurred to Total assets*, *Net gain from operations to Total assets*, *Net investment income to Total assets*, *Net realized capital gains to Total assets*, and *Capital ratio*. Findings indicate that large insurers adapt more quickly and systematically to inflation. They tend to raise

Premiums in response to current inflation and short-term expectations, likely to protect underwriting margins against rising claims and operational costs. In contrast, small insurers exhibit weaker and less consistent premium adjustments, possibly due to regulatory constraints, limited pricing power, or slower internal decision-making processes.

In summary, both observed inflation and lagged inflation expectations significantly influence insurer financial performance, but effects vary by firm size and inflation horizon.

Large insurers seem to respond more immediately to recent inflation pressures, while small insurers are more affected by past expectations, reflecting differing operational agility and strategic planning horizons. These findings highlight the importance of robust inflation risk management incorporating forward-looking pricing, disciplined underwriting, proactive capital planning, and dynamic investment strategies tailored to evolving macroeconomic conditions.

According to the Geneva Association (2023), there is a wide range of management actions insurers can take to respond to inflation. In terms of product design, insurers could offer more low-cost products with an increased focus on risk and loss prevention. With tight labor markets and increasing wage pressure, insurers can also improve operational cost efficiency and overall productivity. One underwriting response to inflation is to reset the insurance price of risks that exhibit high claims costs. This activity depends on the competitive environment in insurance markets, insurers' anticipation about central banks' ability to reduce inflation and the degree of public policy and regulatory constraints. In investment management, inflation protection on asset allocation can be achieved by moving the investment portfolio away from bonds toward commodities, equities and real estate. For many insurers, however, such potential activity is constrained by their very high solvency capital requirements. In general, effective insurer responses to inflation would have to occur ex-ante, rather than ex-post. This is why inflation anticipation remains a key issue. Once inflation occurs, the value of inflation-linked securities and the level of interest rates reflect capital markets' inflation expectations, which drive up the cost of any hedging strategy. More research is still needed to match aggregate information on inflation and insurer behavior.

The *COVID-19* pandemic posed several challenges for the estimation and analysis of multivariate macroeconomic time-series. Particularly, estimated models may become unstable and generate unlikely forecasts with the inclusion of the pandemic extreme observations. We tackle these methodological challenges in Section 11 by using a flexible Bayesian VAR (BVAR) framework allowing for heavy tails and stochastic volatility for innovations to appropriately treat these extreme observations as suggested in the literature. We find empirical evidence that *COVID-19* pandemic created outliers for main US macroeconomic variables as the degrees of freedom of the Student-*t* distributions of residuals became lower with the inclusion of post-pandemic observations. The simultaneous shifts in the tail fatness of macro-variables could create macroeconomic tail risk. The *COVID-19* shock generated a long-lasting increase in the stochastic volatility for the real GDP, the price level (measured by the log *CPI*) and the Fed rate. Specifically, for inflation, the impulse response functions reveal that the *CPI* (in log-level) responded differently to shocks in the real output, the monetary policy and the tightness in the labor market during the pandemic period as compared to pre-COVID periods. Hence, our analysis shows that macroeconomic transmission channels were highly altered by the pandemic shock. More importantly, forecasts accuracy variables and fluctuation tests confirm the added-forecastability in point and density forecasts of the price level and the *Inflation rate* during the pandemic period for multi-periods ahead by considering the tail fatness and time varying volatility in macroeconomic disturbances compared to standard Gaussian BVARs. These results indicate that the nature of inflation shocks may affect significantly the methodology to be used in studying the effect of inflation in a particular industry.

In Section 12 we pose the question of whether the US property and casualty insurance industry is subject to social inflation and to what extent. Social inflation, characterized by the increasing costs of insurance claims due to societal and legal shifts, constitutes a major issue for policyholders, insurers and reinsurers. This phenomenon, which originated in the 1970s and has resurfaced over the past five years, is particularly driven by the growing use of third-party ligation funding and contingency-fees, higher jury awards and punitive damages, increasingly assertive legal strategies by plaintiff lawyers, plaintiff-friendly legislation and the expansion of liability through new legal doctrines.

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Considering the unpredictable nature and the growing importance of social inflation in the present era, the necessity to find mitigating measures to control the risks implied by this phenomenon becomes crucial to ensure the long-term profitability and stability of insurance operations.

As a first step, it is important that P&C insurance industry professionals adopt a segmented approach, as certain regions and line of business are particularly prone to social inflation and merit close monitoring. A standardized risk modeling framework would fail to account for cross-jurisdictional and line-specific differences.

Insurers and reinsurers could integrate scenario-based models in their reserving approaches to better capture the impact of litigation trends and societal expectations. Investment in advanced litigation analytics and claim pattern forecasting based on historical and real-time data can also improve underwriting discipline. Given the rise in mass tort cases and those supported by third-party litigation funding, policy terms should be reassessed to reduce ambiguity and clarify exposure boundaries.

On the policy front, regulatory and legislative bodies should implement mandatory disclosure of third-party litigation funding agreements to improve transparency in the civil justice system. Ultimately, regulatory frameworks tailored to law firms can mitigate abusive practices of attorneys and help rebalance fairness and efficiency in the legal process. Together, these measures can support a more resilient insurance and reinsurance environment and safeguard access to justice without compromising the sustainability of the insurance and reinsurance sectors.

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