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FEATURE ARTICLE

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A re-examination of the US insurance market's capacity to pay catastrophe losses

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Abstract

Cummins, Doherty, and Lo (2002) present a theoretical and empirical analysis of the capacity of the property liability insurance industry in the US to finance catastrophic losses. In their theoretical analysis, they show that a sufficient condition for capacity maximization is for all insurers to hold a net of reinsurance underwriting portfolio that is perfectly correlated with aggregate industry losses. Estimating capacity from insurers' financial statement data, they find that the US insurance industry could adequately fund a $100 billion event in 1997. As a matter of comparison, Hurricane Katrina in 2005 cost the insurance industry $40 to $65 billion (2005 dollars). Our main objective is to update the study of Cummins et al. (2002) with new data available up to the end of 2020. We verify how the insurance market's capacity has evolved over recent years. We show that the US insurance industry's capacity to pay catastrophe losses is higher in 2020 than it was in 1997. Insurers could pay 98% of a $200 billion loss in 2020, compared to 81% in 1997.

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1 | INTRODUCTION

Cummins et al. (2002) present a theoretical and empirical analysis of the capacity of the property and liability insurance industry in the US to finance catastrophic losses. In their theoretical analysis, they show that a sufficient condition for capacity maximization is for all insurers to hold a net of reinsurance underwriting portfolio that is perfectly correlated with aggregate industry losses. Estimating capacity from insurers' financial statement data, they find that the US insurance industry could adequately fund a $100 billion event in 1997. As a matter of comparison, Hurricane Katrina in 2005 cost the insurance industry $40 to $65 billion (2005 dollars), representing about 10% of total insurers' capital (Swiss Re, 2020).[1] The hurricane's total cost was about $125 billion, indicating how low insurance coverage is for these losses. Moreover, at least 1800 fatalities were reported with Katrina. Such events may also cause numerous insolvencies and severely destabilize the insurance markets. According to the authors, the prospect of a mega-catastrophe also brings with it a real threat of insurer failures and unpaid claims. Surviving insurers may have to reduce future sales of property liability insurance, causing price increases and availability problems. Some insurers may even leave the market (Born & Klimaszewski-Blettner, 2013).

Our main objective is to update this important study published in 2002 with new data that is available up to the end of 2020. We want to verify how the insurance market's capacity has changed over recent years. The article of Cummins et al. (2002) covers all catastrophe losses managed by insurers. In recent years, new risks have become important, including cybersecurity, terrorism, liability (social inflation), pandemic, and climate risks. Although our data includes all these new risks, our discussion will focus on the emergence of climate risk, because of its relative importance, at least in the United States, where the data come from.

The rest of the paper is organized as follows. The next section presents recent developments on climate finance in the finance literature, while Section 3 discusses the importance of climate risk for the property and liability insurance industry. Section 4 reviews the main contributions in the insurance literature on catastrophic risk, including the contribution of Cummins et al. (2002). Section 5 presents the theoretical model proposed for estimating the insurance industry's capacity to compensate catastrophic losses, and Section 6 presents our empirical estimates. We show that the US insurance industry's capacity to pay catastrophe losses is higher in 2020 than it was in 1997. Insurers could pay 98% of a $200 billion loss in 2020, compared to 81% in 1997. We also document in detail the data and methodology used to carry out our research. Section 7 analyzes different causes of the relative capital increases over the study period. Section 8 concludes and proposes different avenues for future research. The online appendix contains additional data used for the robustness of the estimations.

2 | CLIMATE FINANCE

Climate finance is defined by the United Nations Framework Convention on Climate Change as "local, national, or transnational financing—drawn from public, private, and alternative sources of financing—that seeks to support mitigation and adaptation actions that will address

[1]The $40 billion estimate does not include the flood cost to the National Flood Insurance Program while the $65 billion does.

climate change" (reported in Hong et al., 2020). Such financing is intended to change the world economy and build resilience to climate change.

Many financial sectors, ranging from banking and insurance to real estate, are directly impacted by the risks from tornadoes, wildfires, and floods. This raises difficult questions, which were recently discussed in a special issue of the *Review of Financial Studies,* edited by Hong et al. (2020): How can financial market prices mitigate risks from global warming? How can capital markets raise sufficient financing? How should the distribution of damages from catastrophic events be managed? Despite this type of reflection, however, no studies in finance or insurance have looked at the causal effects of climate change on the insurance industry, though various correlations have been documented.

Here is a typical question in the recent financial literature: Given the potential impact of climate change, are asset prices or firm values sensitive to exposure to climate risks? Three recent contributions address this important question on market efficiency in pricing these risks. Murfin and Spiegel (2020) use information on recent residential real estate transactions to determine whether house prices reflect the differential risks of sea levels rising. They obtain limited house pricing effects with their methodology. By contrast, Baldauf et al. (2020) use transaction data to measure the effect on house prices of flooding projections for individual homes and local measures of *beliefs* about climate change. They demonstrate that houses projected to be underwater are sold at a discount. Issler et al. (2020) study wildfires in California between 2000 and 2018 with a comprehensive data set that merges information on fires, mortgages, property characteristics, and weather zones. Using the difference-in-differences approach, the authors find a significant causal increase in mortgage delinquency and foreclosure after fire events.

A crucial input in the analysis of climate change risks is the causal impact of climate events on economic activity, which is known as the distribution of damages. It raises an important question about the modeling and sharing of extreme weather risks.[2] Do extreme weather risks, such as the impact of Hurricane Sandy in 2012 or of the 2018 California wildfires, have long-run causal effects on insurance markets? These distributions of damages depend on location-based decisions by households and firms, and technological (self-protection and self-insurance) decisions on preventing and mitigating disaster damages. They also depend on market insurance coverage (including moral-hazard and adverse-selection effects). By modeling these loss distributions suitably, the insurance industry should be able to play a critical role in facilitating risk-sharing and extending insurance coverage for extreme weather events. These research results should also improve public authorities' role in improving social resilience against climate risk (GAO Government Accountability Office, 2007; Hallegate, 2012, 2014; Postal, 2008).

3 | CLIMATE RISK AND THE INSURANCE INDUSTRY

The potential causal impacts of new climate patterns on damages from catastrophe risks must be better estimated by the insurance industry and public authorities. These potential impacts may have been underestimated in risk management for many years.

[2]Many references consider weather and climate risks to be synonymous. In this study, we use the NASA (2005) definitions of climate and weather. The main difference between the two definitions is time. Weather is atmospheric conditions over a short period of time, while climate covers a long period of time. Climate change is related to changes on average daily weather. We thank a referee for pointing out this importance of the difference.

Here are some worldwide statistics obtained from the Munich Re reports of 2014, 2019, and 2021:[3]

- Climate change was rated number one among the top 10 risks facing the insurance sector (Ernst & Young, 2008).
- Eighty-eight percent of all natural catastrophic events worldwide were weather-related between 1980 and 2014 (83% in 2019); and 40% of the overall losses from 1980 to 2014 occurred in Asia (43% in 2019).
- Sixty-four percent of insured losses were incurred in North America (incl. Central America and the Caribbean) during this period (35% in 2019), which represents about 30% of overall losses in this region, which is similar to the proportion of overall losses in the rest of the world. Insurance penetration is low, even in developed countries.
- Natural disasters accounted for $280 billion in economic losses around the world in 2021 ($120 billion insured). The record year was 2011, with losses of $355 billion. About 10,000 deaths were attributed to natural disasters in 2021. In the United States, $145 billion in losses were observed in 2021, with $85 billion insured.

The average economic losses related to natural catastrophes over the last 10 years are $187 billion ($340 billion in 2017 only). The year 2019 was below the last 10-year average, with a total loss of $150 billion, while, in 2020, the total loss was $210 billion (Munich Re). However, event frequency has increased. In 2019, there were 33 events of over $1 billion in total losses each. Nine events cost the insurance industry over $1 billion that year, and all of them were weather risk events (cyclones, storms with flooding, and tornadoes). Moreover, in April 2020, severe weather events in the US cost insurers billions of dollars, with 14 tornadoes occurring that month—the fifth-highest monthly number on record since 1950, according to AON (2021).

In 2021, 22 weather disasters of $1 billion or more were observed in the United States, for a total of $145 billion in damages. Since 1980, 310 events of $1 billion or more have accounted for $2.5 trillion, with an average of $148 billion per year over 2016–2021 (www.climate.gov/disasters2020).

Modeling firm AIR Worldwide now estimates that the losses to insured industry from Hurricane Ida in 2021 will be between $20 billion and $30 billion (possibly 35 billion with 67 billion economic losses, according to Munich Re). The estimate includes wind and storm surge losses of $17 to $25 billion, and private-market insured losses from inland flooding of $2.5 billion to $5 billion. These estimates include insured physical damage to residential and commercial property and autos, but do not include National Flood Insurance Program losses. Most insured losses are in the homeowner and commercial property lines of business in Louisiana and in the Northeast, including New York and New Jersey. With an estimated $30 billion in insurance losses, Ida is in the range of Hurricanes Andrew, Maria, Irma, and Harvey. State officials have reported more than 80 deaths due to Ida.[4] Irma caused economic losses of 67 billion in 2007, with 30 billion to the insurance industry, according to Swiss Re.

The escalating frequency and severity of extreme weather-related events highlights a dangerous link between insurance risk and climate change, even though less than 40% of the total losses are covered. According to a Price Waterhouse Coopers survey conducted in 2017,

[3]See also the Sigma (Swiss Re) reports (2009, 2015, 2022), the AON reports, as well as Carillo et al. (2022) and Guo et al. (2022).
[4]According to the recent estimates, Hurricane Ian could cost insurers more than 50 billion.

natural catastrophes are now the second-highest risk that insurance companies face, while global warming is ranked fourth. A more recent survey by Deloitte (2020) found that most US state insurance regulators expect all types of climate change risks to insurance companies to increase over the medium to long term. More than half the state regulators surveyed also indicated that climate change is likely to have a high impact on coverage availability and underwriting assumptions. US state regulators and lawmakers are concerned about the insurance industry's response to climate change. Two traditional mechanisms are usually used to reduce financial fragility: insurers can increase premiums in the states or counties most affected, or increase reinsurance coverage (Grenier, 2019). However, these two alternatives may not be sufficient to ensure the long-run stability of the industry.

We can summarize the major issues related to climate risks as follows (Dionne, 2015):

- For many years the population has concentrated in high-risk areas. This increases insurers' exposure to major catastrophes related to natural hazards (low frequency and high severity) (Goussebaïle, 2016; Grislain-Letrémy & Villeneuve, 2019).
- The demand for insurance coverage for weather risk among individuals is low (Arrow, 1982; Dixon et al., 2006; Robinson & Botzen, 2022) because the potential insured underestimate the risk and are biased in estimating their potential net loss due to anticipated government intervention. For example, although flood insurance has been subsidized by the US federal government since 1968, demand remains low (Kousky, 2018; Landry & Jahan-Parvar, 2011; Wagner, 2022).
- On the supply side, a survey funded by the National Association of Insurance Commissioners (NAIC) mentions that insurers reported increased engagement in climate-related activities over recent years, while they were not really prepared to cover weather risk in 2014 (NAIC, 2020). See also the study of Gatzert and Reichel (2022).
- Natural hazard losses fluctuate radically. This is a long-run issue. Insurers cannot restrict themselves to recent loss history to calculate premiums and capital. They must compute, for example, the estimated maximum loss or the expected shortfall (or CVaR), obtained from data over many years, and perform appropriate dynamic stress testing.
- Prevention is a long-run investment activity, yet insurance coverage is annual. This creates a problem of the insurance industry having a long-run commitment to potential investors, leading to underinvestment in prevention.
- Insurers can spread their liabilities through reinsurance. In principle, the effects of catastrophes can be diversified through the worldwide reinsurance market. Historically, the capacity available to reinsurers was limited, but it has increased significantly since Hurricane Andrew (Cummins & Weiss, 2000, 2004).[5] Even though insurers and investors around the world are now more convinced that lack of action to combat climate change is becoming costly in the long run, no real structural changes have been made. The current actions intended to reduce the social costs of climate risk may not be the most efficient. In fact, some reinsurers have limited their exposure to such losses, and rating agencies seem to encourage such a move to maintain the current ratings of (re)insurance companies. Some reinsurers are more positive but argue that this new environment is very complex and that the reinsurance industry is learning how to improve its participation in these new environmental and economic realities (Drexler & Rosen, 2022; Kessler, 2015).

[5]On reinsurance, see Bernard (2013), Cummins et al. (1997, 2001, 2021), Chen et al. (2020), Desjardins et al. (2022), and Powell and Sommer (2007).

- Insurance-linked securities (ILS) are becoming important in the reinsurance market for catastrophe losses related to climate risk and earthquakes (Carayannopoulos et al., 2022; Götze & Gürtler, 2022; Lakdawalla & Zanjani, 2012). They are not very prevalent in the insurance market. ILSs can lower the cost of risk transfer in harsh (re)insurance market conditions. They help maintain (re)insurance capacity and offer multi-year protection. They limit credit risk by collateralizing losses. For investors, ILSs are noncorrelated with other market, liquidity, and credit risks, so they represent an important diversification asset. Moreover, the capitalization of financial markets is much higher than that of (re)insurance markets. ILS penetration can reduce the price of insurance in the long run and increase the demand for insurance. However, the participation of financial markets in weather risk after a major disaster is a long-run commitment issue: will they stay in such a risky market after suffering a very big loss?
- Securitization and market consolidation are other market mechanisms that can improve market capacity (Akhigbe & Madura, 2001; Berger et al., 2000; Boubakri et al., 2008; Cummins & Trainar, 2009; Cummins & Weiss, 2009; Cummins & Xie, 2006; Cummins, Tennyson, et al., 1999; Weiss & Chung, 2004; Weston et al., 2004).

Although estimates vary, it seems clear that a substantial gap exists between the existing reinsurance coverage and a catastrophic loss exceeding the $15–20 billion range. For example, Swiss Re (1998) estimated that reinsurers would pay 39% of a once-in-a-century catastrophe loss in the United States, such as a $56 billion hurricane or a $65 billion earthquake in California. The Swiss Re study estimated there was a worldwide total of $53 billion in catastrophe excess-of-loss reinsurance in place in 1997. Cummins and Weiss (2000) showed that the reinsurance industry could have funded $60 billion of a $100 billion above-expected loss.

According to 2014 data, the total reinsurance capital is about $575 billion ($660 billion, 2021), including $62 billion in ILS capacity other than traditional reinsurance. Alternative capacity (ILS) includes collateral reinsurance, sidecar, industry loss warranty (ILW), and CAT bonds. As complements to reinsurance, they represented about 10% of the global catastrophe reinsurance capital in 2014 (250-year occurrence). We may think there is sufficient capacity because annual average long-run catastrophe losses are around $150 billion, but there have been significant recent exceptions: in 2011 ($375 billion), 2017 ($340 billion), and 2021 ($343 billion) (AON, 2022)[6].

4 | ACADEMIC RESEARCH ON CATASTROPHIC RISK AND THE INSURANCE MARKET[7]

The early academic contributions agree that natural catastrophes affect the insurance market and that this effect was increasing over time because of population migration to coastal areas and the increased valuation of properties in these high-risk areas. Shelor et al. (1992) and Lamb (1995) obtain contradictory results, however, on what effect natural disasters have on the insurance industry's profitability. Berz (1997) was one of the first to hypothesize the impact of

[6]Exact statistics vary from one source to another, but the ranges are comparable.

[7]See the special issue on climate risk and insurance published in 2022 by *The Geneva Papers on Risk and Insurance—Issues and Practice* for additional topics not discussed here, including applications in France (Charpentier et al., 2022) and in Japan (Shao, 2022).

the greenhouse effect on the insurance industry, concluding that the future of the insurance industry could be jeopardized if insurers do not adapt to the new climate conditions. He did not document the effect with data, however. Cummins et al. (2002) show that unanticipated natural events may create liquidity problems for insurance companies in the short run, and solvency problems in the long run.

In their theoretical analysis, Cummins et al. (2002) propose a sufficient condition for capacity maximization: all insurers must hold a net of reinsurance underwriting portfolio that is perfectly correlated with aggregate industry losses. Estimating capacity using insurers' financial statement data for 1983–1997, they find that the industry could adequately fund a $100 billion insured loss event, whereas US insurers' equity capital was approximately equal to $370 billion (see Table 2). To provide an idea of the potential losses at that time, Hurricane Andrew (1992) represented a loss of $19 billion, while the Northridge earthquake (1994) cost more than $13 billion. Moreover, scenarios constructed in 1997 by catastrophe modeling firms suggest the feasibility of a $76 billion hurricane in Florida, a $21 billion hurricane in the Northeast, a $72 billion California earthquake, and a $101 billion New Madrid earthquake.

Cummins et al. (2002) also show that the industry would be able to pay very high percentages of industry losses. For example, for a $20 billion catastrophe, they estimate that the industry could have paid at least 98.6% of the insured loss in 1997. The estimated percentages paid for larger losses declines, however. For example, according to their parameter estimates, the industry would have been able to pay, in 1997, about 96.4% of a $100 billion loss based on the group sample, and 92.8% based on the company sample. For a $200 billion loss, the industry could have paid 84.0% based on the group sample, and 78.6% based on the company sample.

Moreover, such events may cause numerous insolvencies and severely destabilize insurance markets. For instance, a $100 billion catastrophe is projected to cause 30 insolvencies for the group sample and 136 insolvencies for the company sample. The number of insolvencies at 1991 capitalization levels would have been 108 groups and 216 companies. This means that many insurers were not ready for such potential catastrophes and may have become good targets for acquisition. Their data are taken from the regulatory annual statements filed by insurers with the NAIC.

They are able to estimate insurers' responses for different scenarios, such as a Category-5 hurricane hitting Miami or a magnitude-8.2 earthquake in San Francisco. Their measure of capacity is based on how much equity or surplus is available, and how effectively the riskiness of insurance losses is spread though the insurance market. The traditional instrument for spreading risk among insurers is reinsurance. By buying and selling options on their portfolios with each other or with specialized reinsurers, insurers can change the risk characteristics of their portfolios.

However, there is a very large number of potential catastrophe scenarios, and the data requirements to conduct such an analysis for the entire insurance industry are enormous. Moreover, while such scenarios are valuable for planning at the firm level, they do not provide enough detail to assess the risk-spreading efficiency of the total insurance market. Rather, they seek a more general response function. Cummins et al. (2002) estimate the distributional characteristics of catastrophic losses and allocate such losses to individual insurers, using correlations between losses and financial data. The result is an option-like function that defines the estimated deliverable insurance payments conditional on any given size of aggregate catastrophic loss and that projects the number of insurer insolvencies that would result.

When capital and surplus levels are high, most insurers plan to use capital to make deals. According to a recent survey by KPMG (2018), about three-quarters of insurers expect to conduct an acquisition, and two-thirds plan to seek partnership opportunities over the next 3 years. Eighty-one percent say they will conclude up to three acquisitions or partnerships in the same period. As a top priority, 37% hope to transform their business model, 24% want to transform their operating model, and 10% are looking to acquire new innovative capabilities and emerging technologies through their acquisitions. The key goal is to obtain a deal that generates a contribution over the next 10–15 years.

A. M. best manages a database of more than 1000 property- and casualty-insurance companies that have failed in the United States since 1969 (Kelly, 2015). The most common reasons for insolvency are deficient loss reserves, inadequate pricing, and rapid growth. Natural disasters are the seventh-most common reason, accounting for 7% of insolvencies. The Financial Services Authority (FSA) in the United Kingdom has assessed 270 property and casualty insurance companies that failed in the European Union since 1969. Many factors are identified as primary or contributing factors, with natural hazards found to have made a small contribution. Yet, in both these studies, the data cover a very long period, and it is not clear that they are representative of the last 20 years.

Regarding other pertinent contributions, Anderson and Gardiner (2008) provide a guideline to help insurance companies manage climate risk. Availability and affordability are the major problems. Insurers alone cannot effectively reduce the social cost of climate risk. More coordination with governments is necessary for prevention. Another failure is the lack of a link between sustainability and disaster resilience. Insurers must be more active in unifying green and disaster-resilience efforts in sectors such as construction, agriculture, and land use (see also Hallegate, 2014).

Mills (2009) analyzes different mechanisms that aim to improve the insurance industry's capacity to cover insurable losses: new coverage products; a better understanding of climate change; and the financing of activities intended to reduce climate risk, including government participation when necessary. Gollier (2005) discusses in detail the necessary role played by government to reduce the fragility of the insurance industry when extreme events occur. He argues that the government should act as a reinsurer to reduce the number of bankruptcies. The government should be the reinsurer of last resort, as in the Terrorism Risk Insurance Act (TRIA) or the Price-Anderson Act. Others favor stronger private risk-management activities for natural disasters[8] (see Aerts et al., 2014; Collier et al., 2021; Kunreuther, 2018; Klein & Wang, 2009; Michel-Kerjan, 2012; Michel-Kerjan et al., 2015; Mills, 2009). Jametti and von Ungern-Sternberg (2010) do not consider the observed risk selection between the private and public sectors as optimal in cases where the private sector keeps acceptable or lower losses, and the public sector is limited to extreme losses. Louaas and Picard (2021) propose a new characterization of optimal insurance coverage for low-probability catastrophic risks. They derive determinants of insurability and socially optimal risk sharing for events that have a low probability and high severity and that affect many individuals.

Born and Viscusi (2006) take a different approach to analyzing the effect of natural catastrophes on the insurance industry. Using data from the Swiss Re Sigma Reports for the 1984–2004 period, they show that small insurers are more likely to be affected, because they are less diversified. Finally, Born and Klimaszewski-Blettner (2013) affirm that some insurers tend to reduce their activities when they are subject to severe regulations or when they receive

[8]On risk management in the insurance industry, see Cummins et al. (2009), Bauer et al. (2013), and Hoyt and Liebenberg (2011).

unanticipated large claims. Such reduction-of-activities behavior is less frequent for large insurers that are better diversified.

5 | THEORY

5.1 | Borch theorem

Borch (1962) shows, in an expected utility (EU) framework, that value-maximizing risk-sharing transactions would leave all risk-averse insurers holding losses net of reinsurance portfolios defined solely on the market's aggregate loss, and, under certain conditions, that insurance would be priced solely on the first two moments of the aggregate portfolio. Each insurer holds a proportion of the aggregate loss, and all insurers' portfolios become perfectly correlated. This result is obtained assuming that transactions between insurers are costless.

Let L_i be the random loss or claim payment of insurer i, and Q_i its capital. $F_i(L_i)$ is the distribution of L_i. The utility function of insurer i can be written as

$$U_i(L_i) = U(Q_i, F_i(L_i)) = \int_0^{\infty} U_i(Q_i - L_i)dF_i(L_i). \tag{1}$$

Risk-averse insurers can increase their welfare by writing a treaty or collective agreement (L^P) with the N insurers in the industry:

$$L^P = \left(L_1^P(L_1 \dots L_N) \dots L_N^P(L_1 \dots L_N)\right), \tag{2}$$

where $L_i^P(L_1 \dots L_N) = L_i^P(\bar{L})$ is the sum of the payments insurer i must pay according to the treaty. The treaty must satisfy the resource allocation condition under full liability:

$$\sum_{i=1}^{N} L_i^P(\bar{L}) = \sum_{i=1}^{N} L_i.$$

A treaty is Pareto optimal (Borch, 1962) if there exist N nonnegative constants $k_1 \dots k_N$, such that

$$k_i U_i'\left(Q_i - L_i^P(\bar{L})\right) = k_1 U_1'\left(Q_1 - L_1^P(\bar{L})\right) \; for \;\; all \;\; i = 1 \dots N, \tag{3}$$

where U_i' is marginal utility of insurer i. It is important to observe that (3) is independent of $F_i(L_i)$ meaning that the optimal treaty does not depend on the loss distributions. Moreover, if $L_i^P(\bar{L})$ is differentiable, the Pareto-optimal treaty is only a function of the total claims amount $\sum_{i=1}^{N} L_i$ and not of the individual results.

Lemaire, (1977, 1991) shows that, for a set K of constants $(k_1 \dots k_N)$, there exists only one Pareto-optimal treaty. Finally, one can verify that, for exponential utility functions, each risk-averse insurer will pay a share of each claim that is inversely proportional to its constant risk-aversion parameter. The optimal treaty contains monetary side payments to compensate the least risk-averse companies that will have to pay higher shares. This condition is necessary to have all insurers participate in the treaty. See the Appendix for more details on the maximization problem.

5.2 | The Cummins et al. (2002) proposition

Extending Borch's result to a world with risk neutrality and limited liability, Cummins et al. (2002) show that the distribution of insurance liabilities, which minimizes insolvencies and therefore maximizes payments to policyholders, is similar to the Borch equilibrium. Their market structure provides a framework for measuring the insurance industry's available capacity to respond to major catastrophes.

Their objective is to develop an optimal sharing rule that maximize payouts to policyholders for a given loss scenario. Their starting point is the result of Borch (1962), namely, that a Pareto optimal risk-sharing arrangement is one of mutualization between insurers, where each insurer hold a proportional claim of total insured claims. The riskiness of the aggregate portfolio depends on the total number of individual policies and their correlations. In the presence of a high correlation between insured losses, for catastrophe risk, L is riskier. Let us define T_i as the terminal value of equity for insurer i. In the presence of limited liability,

$$T_i = \mathrm{Max}\left(\left(P_i + Q_i^0\right)(1 + r) - \alpha_i L \,;\, 0\right), \tag{4}$$

where Q_i^0 is the starting surplus of insurer i, P_i is premium income, r is the rate of return on investments, and α_i is the quota share of insurer's i total loss. $\alpha_i L = L_i$ from Borch's result. Without transaction costs, $P_i = E(L_i)/(1 + r)$. Writing $Q_i = Q_i^0(1 + r)$, (4) becomes

$$T_i = \mathrm{Max}(E(L_i) + Q_i - L_i \,;\, 0). \tag{5}$$

By aggregation, under limited liability, the total terminal equity of insurers is equal to

$$\sum_{i=1}^{N} T_i = \mathrm{Max}\left(E(L) + \sum_{i=1}^{N} Q_i - L \,;\, 0\right), \tag{6}$$

while the aggregate losses paid to policyholders L^P is equal to

$$\sum_{i=1}^{N} L_i^P = \mathrm{Min}\left(L \,;\, E(L) + \sum_{i=1}^{N} Q_i\right). \tag{7}$$

Insurers are exposed to two types of losses: idiosyncratic or diversifiable loss, d_i, and catastrophe losses, L_U. It is assumed that $\mathrm{cov}(d_i, d_j) = 0$ and that catastrophe losses, such as hurricanes losses, are correlated, so $L_i = c_i L_U + d_i$, where c_i is the proportion of the total catastrophe loss L_U belonging to insurer i.

5.2.1 | Proposition

A necessary condition for the average industry capacity per policyholder, $\sum_i E(L_i^P/n)$, where n is the number of policyholders, to be maximized is that all firms hold a net of reinsurance portfolio that is proportional to L_U and D, where $D = \sum_{i=1}^{N} d_i$.

The proof is in Cummins et al. (2002). From this proposition, the authors derive the following corollary.

5.2.2 | Corollary

When the necessary condition for the maximization of capacity per policyholder $\sum_i E(L_i^P/n)$ is satisfied, all insurers will hold net of reinsurance portfolios L_i that are perfectly correlated with the aggregate industry losses L.

Proof of the corollary is obtained when L_i is proportional to L_U, and d_i is diversifiable.

5.3 | Application to catastrophe losses

Under limited liability and risk neutrality, the ability of the insurer i to pay the total insured loss $L_i^p = \text{Min}(L_i; E(L_i) + Q_i)$ depends on its equity capital Q_i and the collected premiums without transaction costs $E(L_i)$, where L_i is the total insured loss of insurer i, and $E(L_i)$ its expected value. The insurer has a put option on L_i with a corresponding strike value equal to the available resources $E(L_i) + Q_i$, as illustrated in Figure 1.

Aggregating these values under limited liability, they show that the aggregate loss that will be paid by the insurance industry to policyholders will be the minimum of the value of aggregate losses L and the industry's total resources, as shown in (8):

$$\sum_{i=1}^{N} L_i^P = \text{Min}\left\{L; E(L) + \sum_{i=1}^{N} Q_i\right\}, \tag{8}$$

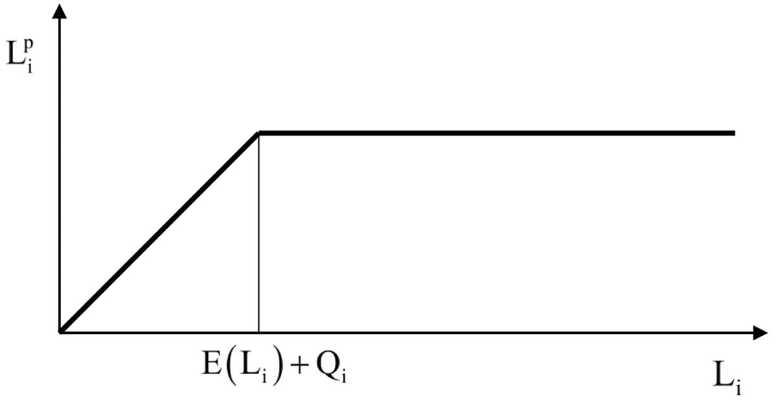

FIGURE 1 Limited liability of insurer i

where N is the total number of insurers in the market, and $E(L) + \sum Q_i$ measures the total resources in the industry for expected and unexpected losses. Consequently, they obtain the following definition for maximizing payouts to policyholders.

5.3.1 | Definition of the insurance industry's payment capacity

For any configuration of losses for which insurers are liable, the payment capacity of the insurance industry is the proportion of those liabilities that is deliverable, given the financial resources of the firms and given all arrangements (such as reinsurance, guarantee funds, etc.) for reallocating those losses among insurers.

This provides a reference for measuring industry capacity. Let us define the proportional payment of aggregate loss L by insurer i as

$$\alpha_i L = c_i L_U + k_i D = L_i, \tag{9}$$

where

α_i is the proportion of L paid by insurer i;

c_i is the proportion of the aggregate catastrophe risk L_U paid by insurer i;

k_i is insurer i's proportion of the aggregate industry diversifiable losses D.

They show that (9) maximizes industry capacity for a given industry surplus Q. This implies perfect correlation between L_i and L.

To estimate the industry's observed response function, we must make distributional assumptions about L. Using the normal distribution, the expected terminal equity value is equal to

$$E(T_i|Q_i, L) = (E(L_i) + Q_i - \mu_{L_i|L})N\left[\frac{E(L_i) + Q_i - \mu_{L_i|L}}{\sigma_{L_i|L}}\right] + \sigma_{L_i|L}\frac{1}{\sqrt{2\pi}}e^{-(1/2)\left((E(L_i)+Q_i-\mu_{L_i|L})/\sigma_{L_i|L}\right)^2}$$

where

$$\mu_{L_i|L} = \mu_i + \frac{\rho_i\sigma_i}{\sigma_L}(L - \mu_L) \quad \text{and} \quad \sigma^2_{L_i|L} = \sigma_i^2(1 - \rho_i^2), \tag{10}$$

and where T_i is the terminal equity of insurer i, $\mu_i = E(L_i)$, $\mu_L = E(L)$, and ρ_i is the correlation coefficient between L_i and L. The corresponding response function can be written as

$$R_i|L = E(L_i) + Q_i - E(T_i|Q_i, L) = (E(L_i) + Q_i)N(-C_i) + \mu_{L_i|L}N(C_i) - \sigma_{L_i|L}n(C_i), \tag{11}$$

where

$$C_i = \frac{E(L_i) + Q_i - \mu_{L_i|L}}{\sigma_{L_i|L}} \tag{12}$$

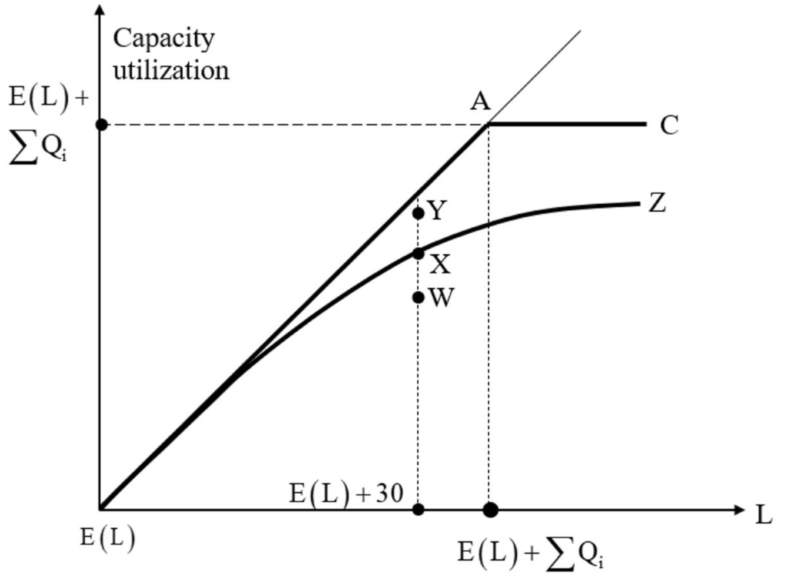

FIGURE 2 Empirical capacity utilization of the industry

is the standardized capacity, $N(C_i)$ is the standard normal distribution function, and $n(C_i)$ is the standard normal density function. Using (11), we can measure the capacity of the industry for any industry loss L, as a function of two industry variables, $\{E(L), \sigma(L)\}$, and three firm variables, $\{\sigma_i, \rho_i, Q_i\}$. One can show that the expected response value is decreasing in σ_i and positively related to ρ_i. This occurs because the value of the insurer's nonpayment option is increasing in σ_i and because the industry gets closer to optimal compensation as ρ_i gets higher.

In summary, since (9) maximizes the industry's payment capacity for a given initial industry surplus Q, the estimated empirical correlations will provide an empirical measure of the insurance industry's capacity utilization for a given Q.

However, many frictions in the market can reduce the conditions described in the corollary on capacity maximization, including small insurer size, geographical distribution of insurers, loading in insurance pricing, reinsurance costs, and other insurer diversification costs. For example, Cummins et al. (2002) estimate the average transaction costs for reinsurance (price − expectedloss)/expectedloss to be equal to 65% for the 10 years preceding their study.

Figure 2 represents such a measure of empirical average capacity E(L)Z that has to be estimated, where X is the estimated capacity utilization for an aggregate loss of $E(L)$ plus \$30 billion, and W would be the estimated capacity value for a less diversified industry while Y would be for a more diversified industry.

6 | EXTENSION OF THE CUMMINS ET AL. (2002) EMPIRICAL ANALYSIS

6.1 | Introduction

In their theoretical analysis, Cummins et al. (2002) show that the condition for capacity maximization, given a level of total resources in the industry, is for all insurers to hold a net of reinsurance underwriting portfolio that is perfectly correlated with aggregate industry losses. Such a measure of capacity relies on two broad components: the size of the capital and industry diversification. How much equity or surplus is available? And how effectively is the riskiness of insurance losses spread through the insurance market? The main objective of this study is to update the computation of this correlation coefficient and measure the capital capacity of the US insurance industry with new data up to the end of 2020.

We develop estimates of response functions for the US property liability insurance industry by selecting samples of insurers and estimating the parameters of Equation (11). The response functions are then calculated for various values of L, the total industry loss that can be observed in various years. The objective of the analysis is to determine the ability of the US insurance industry to respond to catastrophic losses, and to measure the industry's capacity to spread risk across the market. This section discusses the method we use to measure industry capacity, as well as sample selection, parameter estimation, and estimation results.

The fact that some insurers do not write insurance that covers catastrophes, or do not do business in catastrophe-prone areas, or happen to be lucky in suffering relatively low losses as a result of a given event is captured by the estimated correlation coefficient ρ_i between the losses of company i and those of the industry. To the extent that differences in loss correlations can be under- or overestimated for these features of industry loss exposure and experience, these estimates must be viewed as approximations.

The data for the study are taken from the regulatory annual statements filed by insurers with the NAIC. In Cummins et al. (2002), the capacity estimates are for 1997, the most recent report year available at the time the study began. To estimate parameters, Cummins et al. (2002) use data from the period of 1983 to 1997, providing 15 annual observations for the companies in the sample.

The losses used in estimating capacity are the net losses incurred, which are defined as direct losses incurred, plus losses due to reinsurance assumed, minus losses due to reinsurance ceded. Direct losses incurred are losses paid or owed directly to policyholders, while net losses incurred reflect the netting out of reinsurance transactions. Our analysis thus does not take into account the direct effects of the reinsurance industry on capacity. There may be some indirect effects, as discussed in the conclusion. We use the values from line 2 to line 11 of column 28 in "Schedule P – Part 1 – Summary" of the NAIC annual statements as our main source of data. These are the net losses and loss expenses incurred during 1 year. In what follows, "net losses" (for short) and "net losses plus loss expenses" should be considered synonymous.

6.2 | Sample selection and modeling approach

Cummins et al. (2002) used a 15-year period to estimate their parameters for the year 1997. Our objective, in this section, is to replicate their 1997 results and to add estimations for the years 2005, 2014 and 2020. It was not possible to create a 15-year database for the same time period as in Cummins et al. (2002) to make a direct comparison with the year 1997. Our data period is from 1990 to 2020, while their data period is from 1983 to 1997. One way to compare our results to theirs is to employ the observations from line 2 to line 11 in column 28 of "Schedule P – Part 1 – Summary" of the NAIC reports, that contain historical data on previous years and can provide 10 annual observations on the companies for the four years of our study. We label this sample "Sample 1." Note that Cummins et al. (2002) used 15 annual observations from line 11 only of the NAIC reports.

One question that then arises is how the results might differ from using 10 annual observations, rather than the 15 in their study, and from a different period. To answer this question, we first estimate our parameters over 10 years. We concentrate the comparison on three 10-year periods, respectively, from 1996 to 2005, from 2005 to 2014, and from 2011 to 2020, using this time the data at line 11 only, in column 28 of "Schedule P – Part 1 – Summary" of the NAIC reports, providing 10 annual observations on the companies. We label this sample "Sample 2." The details are presented in Supporting Information: Online Appendix OA2. We compare these results from Sample 2 with those from Sample 1, to verify how parameter estimates can be affected by the type of data used in the estimations (lines 2 to 11 in Sample 1, vs. line 11 only in Sample 2).

Second, again for the years 2005, 2014, and 2020, we estimate the parameters for three 15-year periods, from 1991 to 2005, from 2001 to 2014, and from 2006 to 2020, with the values from line 11 only of column 28 in "Schedule P – Part 1 – Summary" of the NAIC reports, providing 15 annual observations on the companies. We call this sample "Sample 3." The details are presented in Supporting Information: Online Appendix OA3. We then compare these results with those estimated from Sample 2, to verify how parameters can be affected by the length of the estimation period.

Two data series are available. Full-time series (FTS) are companies that are present in the samples for the entire period and have net losses and equity capital strictly greater than 0 each year. Regression models are then estimated from FTS data to provide parameter estimates for firms that are not in the full-time series (NFTS). Parameters for these companies are computed by inserting their 1997, 2005, 2014, and 2020 financial data into the regression models. Observations for net admitted assets and total liability had to be strictly greater than zero, while those for cash and short-term investments and for liquid assets had to be greater than or equal to zero.

All main estimates presented in the following discussion are derived from Sample 1. Sample 2 and Sample 3 are for robustness analysis. They show that results in Sample 1 are not dependent on the type of data (lines 2 to 11, instead of line 11 only) nor on the estimation methodology (10 years instead of 15 years).

6.3 | Raw data from Sample 1

Supporting Information: Tables OA1.1–OA1.4 in Online Appendix OA1 report net losses and capital for Sample 1 during the 1990–2020 period. We can see from Supporting Information: Tables OA1.1 and OA1.3 that the number of companies significantly decreases after 2015. Also, the mean of the net losses increases yearly with few exceptions. Summary statistics on equity capital, the other determinant used to compute industry capacity, are presented in Supporting Information: Tables OA1.2 and OA1.4 for the same period. Equity capital increased significantly during the period of analysis.

Tables 1 and 2 report net losses and equity capital for FTS and NFTS data in different years for all companies and for groups and unaffiliated companies. For the moment, only the number of firms differs between the two types of companies, but it will be interesting to observe their respective diversification behavior. Table 2 also compares our data with those of Cummins et al. (2002) for the year 1997. We observe that our estimates are quite similar. The net losses in 1997 are equal to $202 billion for 2256 insurance companies in their study, while it is equal to $210 billion for 2286 insurance companies in our database during the same period. Net losses

TABLE 1 FTS Sample 1 summary statistics: Net losses and equity capital ($000 omitted)

Sample	Net losses incurred	Equity capital	Number of firms
1997			
Groups and unaffiliated companies	201,252,911	355,097,195	877
All companies	201,252,911	355,097,195	1667
2005			
Groups and unaffiliated companies	301,274,767	496,797,400	853
All companies	301,274,767	496,797,400	1578
2014			
Groups and unaffiliated companies	343,463,626	780,443,239	844
All companies	343,463,626	780,443,239	1574
2020			
Groups and unaffiliated companies	455,137,413	1,085,524,198	841
All companies	455,137,413	1,085,524,198	1509

TABLE 2 NFTS Sample 1 summary statistics: Net losses and equity capital ($000 omitted)

Insurance industry	Net losses incurred	Equity capital	Number of firms
1997			
Cummins et al. (2002) study			
Groups and unaffiliated companies	201,905,979	370,993,421	1248
All companies	201,905,979	370,993,421	2256
Our database			
Groups and unaffiliated companies	209,800,900	373,035,693	1179
All companies	209,800,900	373,035,693	2286
2005			
Groups and unaffiliated companies	311,568,085	520,451,387	1200
All companies	311,568,085	520,451,387	2152
2014			
Groups and unaffiliated companies	349,123,503	803,479,225	1064
All companies	349,123,503	803,479,225	1923
2020			
Groups and unaffiliated companies	461,350,387	1,109,446,600	992
All companies	461,350,387	1,109,446,600	1787

increased to $461 billion for 1787 insurers in 2020, while capital increased more rapidly during the same period. The ratio of net losses over capital decreased over the years. For example, in Table 1 (Table 2), the ratio of net losses incurred over equity capital was 57% (56%) in 1997 and 42% (41.5%) in 2020.

6.4 | Capacity estimation

Let $L_t = \sum_{i=1}^{N} L_{it}$ be the total industry net losses in year *t*, and L_{it} the net loss of insurer *i* in period *t*. The estimator of the mean of net losses for the industry is equal to $\bar{L} = 1/T\sum_{t=1}^{T} L_t$ and the estimator of the variance of net losses for the industry is equal to $\hat{\sigma}^2 = \frac{1}{T-1}\sum_{t=1}^{T}(L_t - \bar{L})^2$. We write $\hat{\sigma}$ for the standard deviation of the net losses for the industry. Table Supporting Information: OA1.5 presents the total net losses, their means, and their standard deviations over the 1990–2020 period for the FTS population.

Detailed values for $\hat{\sigma}_i$ are presented in Supporting Information: Table OA1.6. The correlation coefficient between company *i*'s losses and the industry losses is estimated using the following formula:

$$\hat{\rho}_i = \frac{\frac{1}{T-1}\sum_{t=1}^{T}(L_{it} - \bar{L}_i)(L_t - \bar{L})}{\hat{\sigma}_i \hat{\sigma}}. \tag{13}$$

On average, the standard deviation of the net losses incurred by a company is less than $30 million from 1990 to 2001, increases to $44 million in 2008, decreases to $39 million in 2014, and increases again to about $50 million during the last 3 years of observation. We can see from Supporting Information: Table OA1.7 that, on average, the correlation coefficient between company *i*'s losses and the industry losses is 0.5996 in 1990, decreases to 0.4071 in 1999, decreases to 0.3683 in 2010, and increases beyond 0.4000 during the last 4 years.

6.5 | Detrended parameter estimates

The detrended estimates are based on the residuals from the time trend regressions. The reason for computing the detrended estimators is that property liability insurance losses are subject to a strong positive time trend. Thus, the raw estimates of the loss standard deviation capture trend-related growth in losses across the years. Differences in losses across the years due to this trend effect are thus anticipated loss fluctuations and should not be included when measuring the effect of catastrophes and other types of random shocks on the insurance market's capacity.

By measuring capacity using both the raw and detrended parameters, we can isolate potential time-trend bias. Detrended estimates of $\hat{\sigma}_i^2$ and $\hat{\sigma}^2$ are obtained by applying formulas (15) and (16) to the estimated residuals ε_{it} and ε_t, both obtained from (14). The detrended estimate of $\hat{\rho}_i$ is obtained by applying formula (17) to the estimated residual series ε_{it}, and ε_t from (14).

To obtain the detrended parameter estimates, we first conduct the following regressions:

$$L_{it} = \alpha_{0i} + \alpha_{1i} t + \varepsilon_{it},$$

$$L_t = \alpha_0 + \alpha_1 t + \varepsilon_t. \tag{14}$$

The detrended estimator of the variance of losses for the industry is equal to

$$\text{det}\hat{\sigma}^2 = \frac{1}{T-1}\sum_{t=1}^{T}(\hat{\varepsilon}_t - 0)^2. \tag{15}$$

We write *det* $\hat{\sigma}$ for the detrended estimator of the standard deviation of the losses for the industry. The detrended estimator of the variance of losses for company i is equal to

$$\text{det}\hat{\sigma}_i^2 = \frac{1}{T-1}\sum_{t=1}^{T}(\hat{\varepsilon}_{it} - 0)^2. \tag{16}$$

The detrended correlation coefficient between company i's losses and the industry losses is estimated using the following formula:

$$\text{det}\hat{\rho}_i = \frac{\frac{1}{T-1}\sum_{t=1}^{T}(\hat{\varepsilon}_{it} - 0)(\hat{\varepsilon}_t - 0)}{\text{det}\hat{\sigma}_i\text{det}\hat{\sigma}}. \tag{17}$$

On average, Supporting Information: Table OA1.8 indicates that the mean of the detrended standard deviation of the net losses incurred for a company is less than \$15 million from 1990 to 2000, increases up to \$22 million in 2007, and is beyond \$25 million afterward (with few exceptions), reaching \$28 million in 2020—this last value being about three times the value of 1990.

We can see from Supporting Information: Table OA1.9 that, on average, the detrended correlation coefficient between company i's losses and the industry losses is 0.2020 in 1990 and decreases to 0.0891 in 2007, then it increases from 0.1760 in 2008 to 0.2419 in 2020. The estimated detrended correlation coefficients in Supporting Information: Table OA1.9 are much lower than those observed in Supporting Information: Table OA1.7, indicating a real time-trend bias in the raw data.

6.6 | Regression models for parameter estimations

Regression models estimate the parameters of the companies that did not have data for the full time period covered by the study (NFTS companies). The procedure is to estimate regression models with the parameters of the FTS companies as dependent variables and companies' financial characteristics as regressors. The NFTS company parameters are computed by inserting the financial characteristics of these firms into the estimated equation to obtain fitted parameter values, which are used in estimating the insurance industry's capacity.

We need to estimate the parameters $\{\hat{\sigma}_i, \hat{\rho}_i\}$ for companies that do not have the FTS period covered. Since those parameters are censored at 0 for the standard deviation and censored to −1 and 1 for the correlation coefficient, we estimated the tobit model (censored normal regression) to obtain the parameters values.

For the 1997 market, we report the results of these regressions in Supporting Information: Table OA1.10a for the standard deviation, and in Supporting Information: Table OA1.11a for the correlation coefficient. For the 2005 market, we report the results of these regressions in

Supporting Information: Table OA1.10b for the standard deviation, and in Table Supporting Information: OA1.11b for the correlation coefficient. Similar results are obtained for the years 2014 and 2020. They are reported in panels c and d of Supporting Information: Tables OA1.10 and OA1.11.

By inserting the financial characteristics of the NFTS firms into the estimated equations, we obtain fitted parameters $\hat{\sigma}_i$ and $\hat{\rho}_i$. Supporting Information: Table OA1.12 presents the summary statistics for the standard deviation of the net losses incurred for a company, by year, for the NFTS sample. Supporting Information: Table OA1.13 presents the summary statistics for the correlation coefficient between company i's losses and the industry losses, by year, for the NFTS sample.

The average values of the raw and detrended parameter estimates for all companies and groups and unaffiliated companies are presented in Table 3 for the FTS and NFTS samples. As anticipated, the detrended values of sigma and correlation coefficients are much lower than the raw values. The detrended standard deviations and correlations are higher in 2020 than in previous years. Detrended sigmas are higher for groups and unaffiliated companies, while detrended correlations are lower after 2014.

As expected, detrending reduces the magnitude of loss standard deviations and the correlations between companies' and industry losses. Because detrending leads to larger reductions in correlations than in the standard deviations, we expect the estimated loss payments to be lower for the detrended parameter estimates than for the raw estimates.

6.7 | Response function for industry capacity

The response function is calculated for various values of L, the total industry potential net loss, as shown in Figure 2. The horizontal axis measures possible values for aggregate insurance industry net losses. The vertical axis measures the amount paid by all firms considered. The empirical response functions for the insurance industry (Sample 1) are shown in Figures 3 and 4 for 1997 and 2020, respectively. Those of 2005 and 2014 are reported in Supporting Information: Online Appendix 1 (Figures OA1.1 and OA1.2). This sample is made up of firms that have full time series (FTS). The corresponding four figures for the NFTS are in Supporting Information: Online Appendix 1 (Figures OA1.3–OA1.6).

The figures show the estimated amounts that would be paid for the industry losses, starting from the actual expected losses and adding unexpected losses for a given year: spanning from \$200 billion to \$500 billion in 1997; from \$300 billion to \$600 billion in 2005; from \$340 billion to \$740 billion in 2014; and from \$460 billion to \$1,260 billion in 2020. These limits were chosen from the total observed losses for the US property liability insurance industry during the corresponding year and the total equity capital for that year. Four response curves are shown in each figure based on raw and detrended parameters for group and company samples. Our main interpretation will be for detrended parameters for all companies.

The existing market capacity departs from the Borch theorem result that losses are perfectly correlated and that insurers are evenly capitalized under full liability. Figure 3 shows that the 1997 response curve with detrended FTS data begins to diverge from the 45° line at approximately \$220 billion. In Figure 4, the 2020 response curve begins to diverge from the 45° line at approximately \$620 billion, meaning that the insurance industry could easily cover an extra loss of \$200 billion in 2020.

TABLE 3 Detrended and raw parameter estimates: Property liability insurance industry with values from Sample 1

Case	Average				Number of firms
	Detrended sigma × 10^8	Detrended correlation	Raw sigma × 10^8	Raw correlation	
1997					
Insurance industry (FTS)					
Groups and unaffiliated companies	0.1766	0.1141	0.3703	0.5092	877
All companies	0.1311	0.1257	0.2536	0.4390	1667
Insurance industry (NFTS)					
Groups and unaffiliated companies	0.2066	0.1243	0.4320	0.4899	1179
All companies	0.0955	0.1004	0.2935	0.4376	2286
2005					
Insurance industry (FTS)					
Groups and unaffiliated companies	0.3198	−0.0077	0.6241	0.5110	853
All companies	0.2157	0.0545	0.3969	0.4609	1578
Insurance industry (NFTS)					
Groups and unaffiliated companies	0.3629	0.0352	0.7009	0.4765	1200
All companies	0.1582	0.0409	0.4245	0.4399	2152
2014					
Insurance industry (FTS)					
Groups and unaffiliated companies	0.3872	0.1162	0.6258	0.3927	844
All companies	0.2582	0.1621	0.3912	0.4039	1574
Insurance industry (NFTS)					
Groups and unaffiliated companies	0.4202	0.1233	0.6817	0.3489	1064
All companies	0.2113	0.1337	0.4156	0.3848	1923

TABLE 3 (Continued)

Case	Average				Number of firms
	Detrended sigma $\times 10^8$	Detrended correlation	Raw sigma $\times 10^8$	Raw correlation	
2020					
Insurance industry (FTS)					
Groups and unaffiliated companies	0.4135	0.1690	0.8693	0.4282	841
All companies	0.2804	0.2419	0.5348	0.4668	1509
Insurance industry (NFTS)					
Groups and unaffiliated companies	0.4299	0.1716	0.9699	0.4138	902
All companies	0.2368	0.2093	0.5811	0.4487	1787

Abbreviations: FTS, full time sample; NFTS, non full time sample.

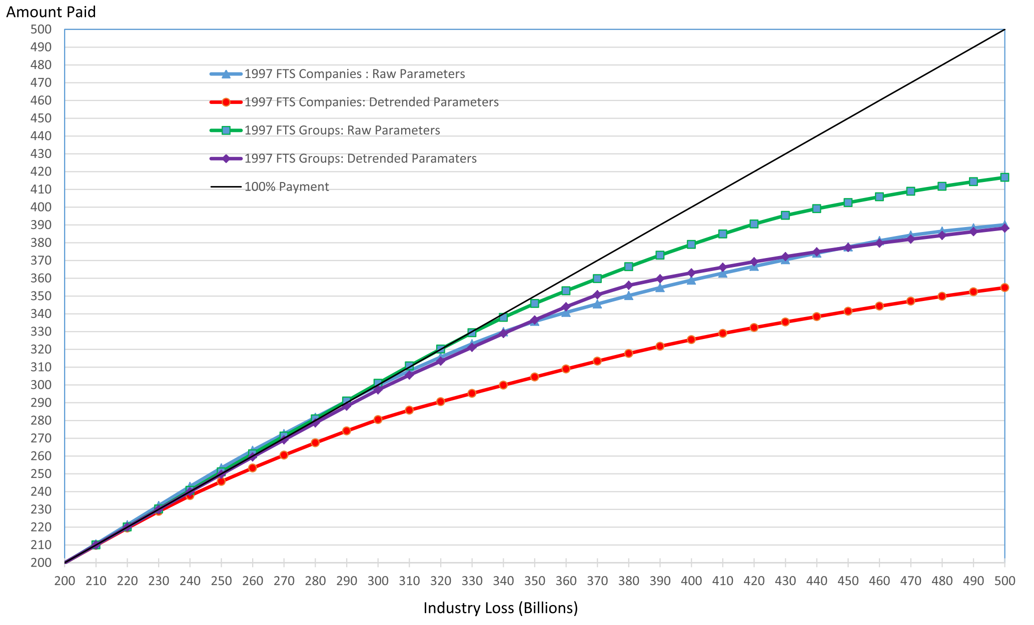

FIGURE 3 Industry capacity in 1997 (FTS sample 1)

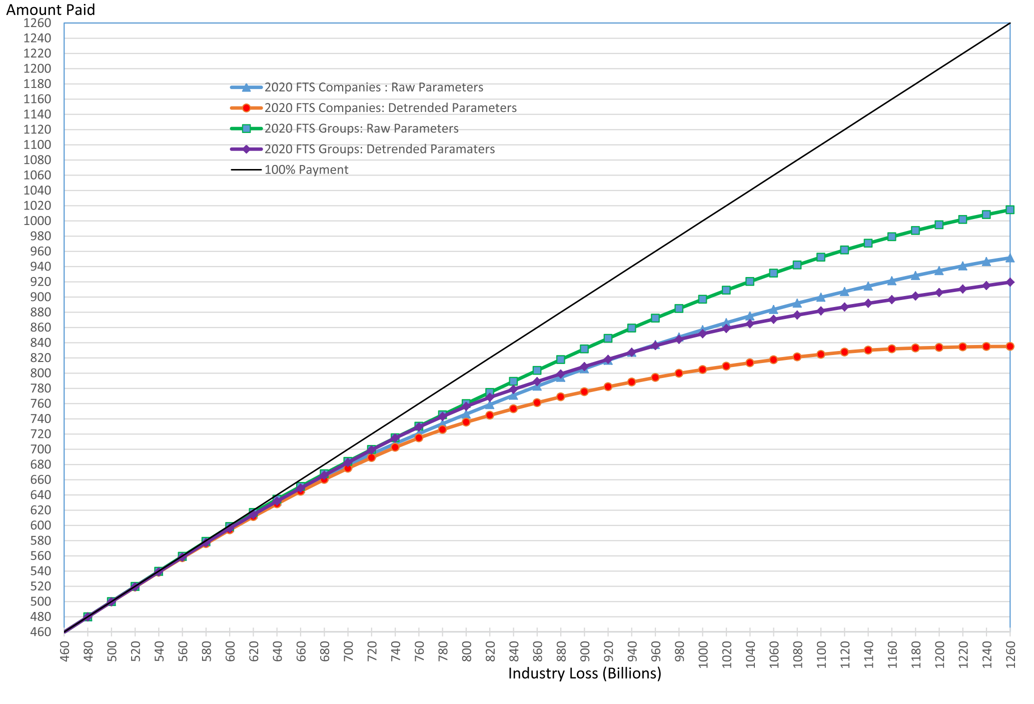

FIGURE 4 Industry capacity in 2020 (FTS sample 1)

TABLE 4 Capacity from Sample 1 with detrended values

	%			
	100 billion	**200 billion**	**300 billion**	**400 billion**
1997				
Insurance industry (FTS)				
Groups and unaffiliated companies	99.0	90.8	77.6	67.1
All companies	93.3	81.3	70.9	62.2
Insurance industry (NFTS)				
Groups and unaffiliated companies	94.7	87.9	77.3	67.0
All companies	94.6	82.8	72.4	63.5
2005				
Insurance industry (FTS)				
Groups and unaffiliated companies	97.9	90.5	82.2	75.3
All companies	95.3	85.1	74.3	65.0
Insurance industry (NFTS)				
Groups and unaffiliated companies	95.8	90.7	83.3	77.1
All companies	97.3	89.2	80.3	72.9
2014				
Insurance industry (FTS)				
Groups and unaffiliated companies	99.2	96.6	91.5	85.5
All companies	98.5	94.6	87.8	80.5
Insurance industry (NFTS)				
Groups and unaffiliated companies	97.7	94.8	90.5	85.2
All companies	99.0	95.7	89.7	83.1

	%					
	100 billion	**200 billion**	**300 billion**	**400 billion**	**500 billion**	**600 billion**
2020						
Insurance industry (FTS)						
Groups and unaffiliated companies	99.6	98.3	95.9	91.7	87.1	82.1
All companies	99.5	97.7	94.1	88.5	82.7	77.1
Insurance industry (NFTS)						
Groups and unaffiliated companies	98.9	97.3	94.9	91.2	86.6	82.1
All companies	99.9	98.8	95.9	91.0	85.8	80.8

The corresponding numbers for realized capacity are presented in Table 4. Realized capacity is obtained as the ratio, at the chosen loss level, of the value of the response curve E(L)Z to the value of the maximum curve E(L)AC, in Figure 2. We observe that all companies in the FTS sample were able to pay 93% of a $100 billion loss in 1997, but only 81% for a $200 billion loss. Cummins et al. (2002) obtained 93% and 79%, respectively, with their data in 1997 (see their Figure 4). In 2020, the percentages are 99.6% and 98%. We also observe that, in 2020, the industry seems to be able to cover 92% of a $400 billion event during one year, or possibly, two events of $200 billion each. Tables 5 and 6 show the robustness of our results from Sample 2 and Sample 3. We observe, in Table 6, that the percentages for a $100 billion loss are 99.9% (Sample 2) and 99.7% (Sample 3). The corresponding numbers for a $200 billion loss are 98.9% and 97.8%. For a $400 billion loss, they are, respectively, 93.5% and 89.6%.

7 | POTENTIAL SOURCES OF RELATIVE CAPITAL INCREASE

In this section we provide a preliminary discussion on possible sources of capital that may explain our results. As already mentioned, ILS products are more prevalent in the reinsurance industry than in the insurance industry. In 2021, alternative risk transfer represented 14% of the total reinsurance capital, with more than 95% being CAT bonds (American Academy of Actuaries, 2022). We start with the reinsurance demand. Figures 5 and 6 present the evolution of the reinsurance demand over our period of analysis. The two figures represent the evolution of the average demand for reinsurance over time for the US property-liability insurance industry. They update those provided by Desjardins et al. (2022). The data are from NAIC's annual financial statements. The data period ranges from 1990 to 2020, which gives us coverage

TABLE 5 Summary statistics from Sample 2 and Sample 3: Losses and equity capital ($000 omitted)

Sample	Insurance industry FTS: Net losses incurred	Insurance industry FTS: Equity capital	Number of firms
2020 Sample 2 FTS			
Groups and unaffiliated companies	455,145,860	1,087,840,856	877
All companies	455,145,860	1,087,840,856	1570
2020 Sample 2 NFTS			
Groups and unaffiliated companies	461,350,387	1,109,446,600	992
All companies	461,350,387	1,109,446,600	1787
2020 Sample 3 FTS			
Groups and unaffiliated companies	448,309,430	1,069,230,397	784
All companies	448,309,430	1,069,230,397	1407
2020 Sample 3 FTS			
Groups and unaffiliated companies	461,350,387	1,109,446,600	992
All companies	461,350,387	1,109,446,600	1787

TABLE 6 Capacity from Sample 2 and Sample 3 with detrended values

	%					
	100 billion	**200 billion**	**300 billion**	**400 billion**	**500 billion**	**600 billion**
2020 Sample 2						
Insurance industry (FTS)						
Groups and unaffiliated companies	99.9	98.9	96.3	93.5	90.5	86.9
All companies	99.4	97.3	92.3	85.8	79.4	73.0
Insurance industry (NFTS)						
Groups and unaffiliated companies	98.8	97.4	94.8	90.9	86.2	81.4
All companies	99.4	97.5	92.8	86.3	79.9	73.5
2020 Sample 3						
Insurance industry (FTS)						
Groups and unaffiliated companies	99.7	97.8	97.1	89.6	85.2	80.8
All companies	99.3	96.2	90.4	84.2	78.6	73.4
Insurance industry (NFTS)						
Groups and unaffiliated companies	98.3	96.4	93.1	89.6	85.3	81.6
All companies	99.5	96.9	91.4	85.2	79.6	74.4

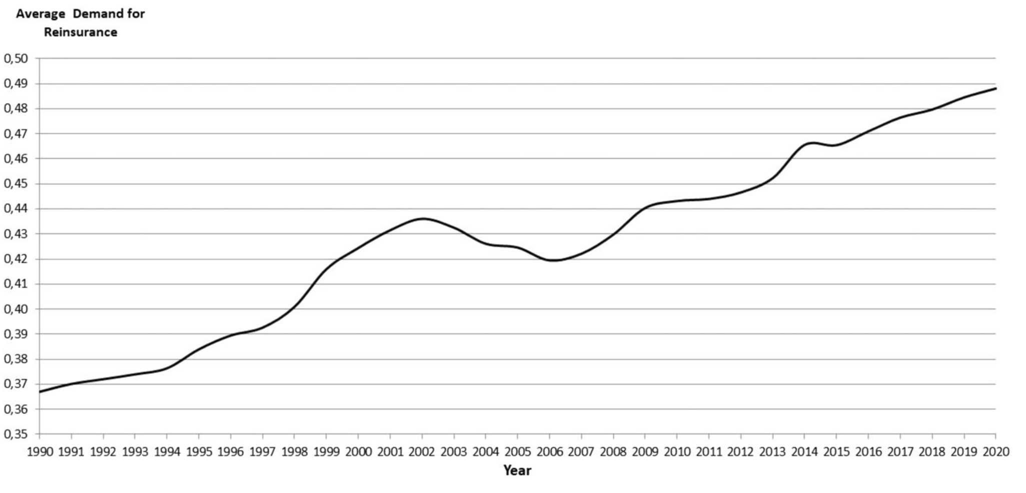

FIGURE 5 Demand for reinsurance by all insurers. *Source*: Desjardins et al. (2022).

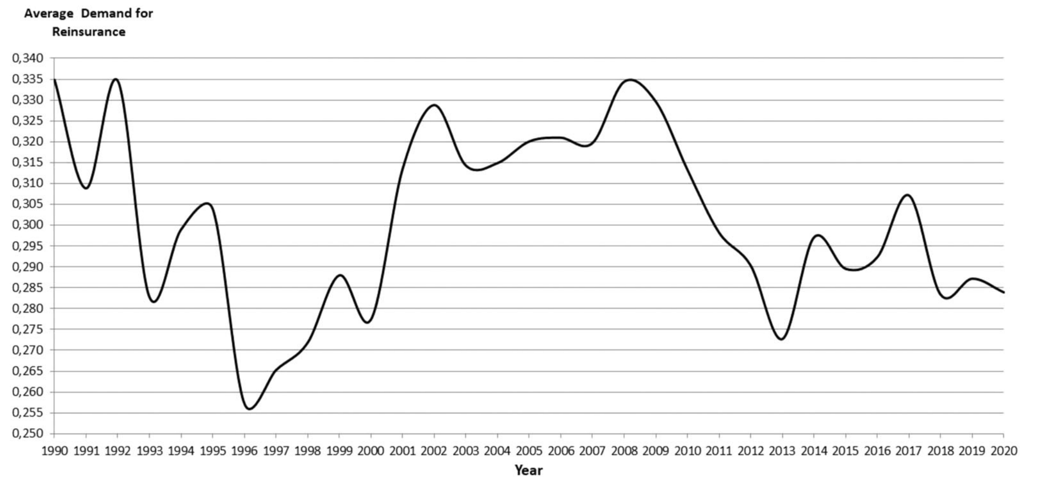

FIGURE 6 Demand for reinsurance by large insurers. *Source*: Desjardins et al. (2022).

of the 2007–2008 financial crisis and the 2001 recession. An insurer's demand for reinsurance is defined as the ratio of (affiliated reinsurance ceded + nonaffiliated reinsurance ceded)/(direct business written plus reinsurance assumed). Figure 5 is for all insurers, while Figure 6 is for large insurers. Large insurers have total admitted assets greater than \$3 billion and small insurers have total admitted assets less than \$1 billion.

We observe in Figure 5 that the mean value of reinsurance demand increases steadily from about 37%–49% over the period, with a small decrease during the years 2004–2008. Small insurers seem to use larger amounts of reinsurance to mitigate risk as time increases. During the same period the average demand for reinsurance by large insurers fluctuates heavily between 33.5% in 1990 and 28.5% in 2020. This seems to indicate that large insurers use other diversification instruments than reinsurance.

Another potential explanation for the capital capacity increase is related to the relative growth of insurance premiums over time. Figure 7 presents four premium indexes over the period 1998–2021. We observe that the general P&C Premium Index is very similar to the CPI Index during the period. In fact, the mean CPI Index is significantly higher, at 5%. The Life Premium Index is statistically lower than the other three indexes, while the Home P&C Premium Index is statistically higher. The mean and variance values are presented in Table 7. So, home insurance premiums could have been a source of capital increase, particularly for states with extreme weather and wildfire events.

Figure 8 shows the evolution in the number of mergers and acquisitions in the life and nonlife industries between 1990 and 2021. We observe a parallel trend before 2012 and then a significant relative decrease in the life insurance industry. Dionne et al. (2022) are studying the causes of this structural change over time. It may be that climate change affected the P&C insurance industry more than the life insurance industry during these years. Other explanatory market causes are also investigated.

Additional capital regulation for the property and liability insurance industry was also introduced after the 2007–2009 financial crisis, even though the insurance industry was not directly affected, with few exceptions. For example, in 2012, the NAIC adopted The Risk Management and Own Risk Solvency (ORSA) Model Act, which includes new economic risk measures of capital, as compared to before, when capital regulation was mainly based on

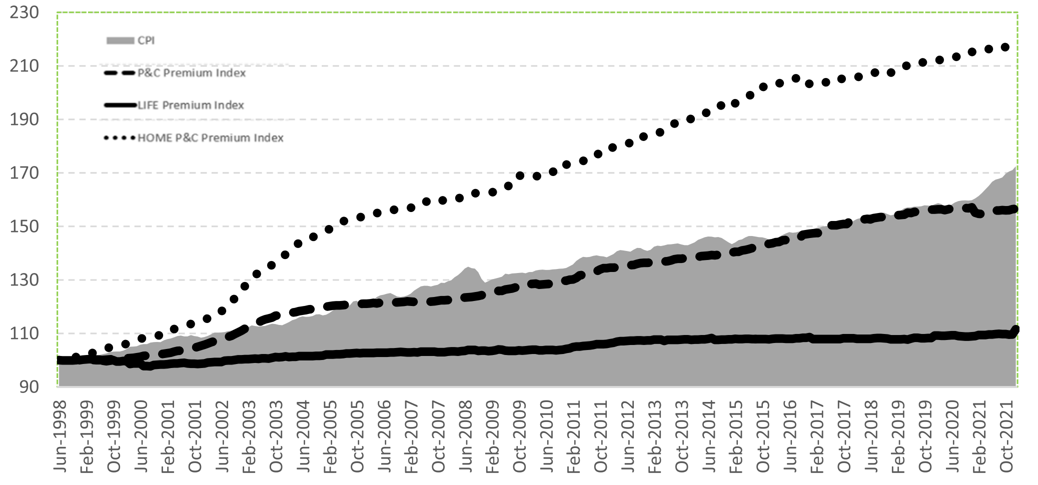

FIGURE 7 Increase in different premium indexes during the 1998–2021 period. *Source*: Dionne et al. (2022).

TABLE 7 Mean and variance of different indexes during the period 1998–2021

	P&C premium index	CPI	Life premium index	Home P&C premium index
Mean	129.39	132.79	104.58	167.02
Variance	320.92	354.56	12.69	1307.70

Source: Dionne et al. (2022).

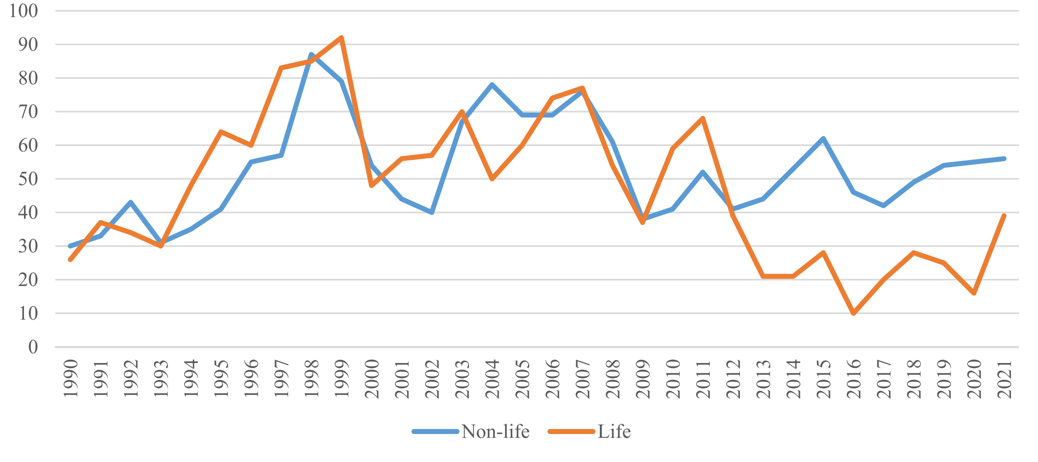

FIGURE 8 Mergers and acquisitions in the life insurance and P&C insurance industries. *Source*: Dionne et al. (2022).

accounting risk measures. New capital adequacy tests were also proposed to detect insurers that may not be adequately capitalized (Hartwig et al., 2015). These regulatory measures may have increased the average capital in the insurance industry.

Finally, some insurers may have reduced their financial responsibility for weather risk events because these events are more severe and frequent (Hunter, 2012). This last potential explanation would account for the lower relative increase in the net insured losses incurred when compared to total capital.

Overall, the evolution in P&C insurance capital during our period of analysis may have various explanations, including a combination of all of these. Future research is underway to identify the most significant explanation (Dionne et al., 2022).

8 | CONCLUSION

The main objective of this study was to estimate the observed capacity of the US property liability insurance industry to cover catastrophic losses in 2020 and verify how this capacity has evolved since 1997. We also presented all the important steps in data management and model estimation for those wanting to replicate the analysis or update the results, given that climate risk will undoubtedly become an increasingly important research subject over the coming years.

Cummins et al. (2002) use Borch's theorem as a starting point for defining industry capacity. They extend the theorem to a limited liability framework with risk neutrality. Capacity maximization is obtained when each insurer has an underwriting portfolio that is perfectly correlated with the industry's aggregate loss. At Pareto optimality, the industry would pay 100 percent of losses, up to the point where industry net premiums and equity are exhausted. This theoretical result does not consider the different frictions in the insurance market, including transaction costs, asymmetric information, and insurers' relative exposure to climate risks. Moreover, insurers are unevenly capitalized, such that some may go bankrupt for relatively low levels of industry losses. Finally, most insurers are not perfectly diversified geographically and may have their exposures concentrated in a subset of states that are disproportionately exposed to weather events. The estimated correlations should consider all these imperfections and be used to estimate the industry's real capacity.

Equity capital in the US insurance industry increased from $355 billion in 1997 to $1.1 trillion in 2020 in the FTS sample, and the ratio of net losses over capital decreased from 57% to 42%, indicating a better capitalization in 2020. These ratios do not necessary measure the capacity of the insurance industry to cover additional unforeseen large events in a given year, because they do not consider the correlations between individual loss and aggregate loss.

Although the insurance industry's available capital has increased significantly since 1997, the market's ability to adequately insure catastrophic risks can be still problematic. The total available capital is earmarked for all types of insurable risks, not only disasters.

The industry response curves for 2020 are presented in Figure 3 for the FTS data. The curves assume that insurer losses are normally distributed and are estimated over a period of 10 years. The figure shows the response curves for industry losses going from $460 billion (total losses in 2020) to a maximum of $1.1 trillion (total capital in 2020). As documented in Table 4, results with detrended parameters indicate that the insurance industry can cover 98% of a $200 billion loss and 94% of a $300 billion loss. Table 4 also indicates that the capacity for a $300 billion loss would have been 71% in 1997 (74% in 2005 and less than 90% in 2014). Table 5 and Table 6 show the robustness of the results from two other samples.

Table 4 shows that the capacity available to groups and unaffiliated companies is always higher than for all companies with FTS data. The increased capacity can be attributed to the higher absolute value of industry capitalization and, probably, the higher concentration of equity among the largest reinsurers as a result of consolidations. Other possible explanations are under investigation, as discussed in Section 7.

Many extensions of our analysis can be considered. Reinsurance is important, to diversify climate risks around the world over time (Cummins & Weiss, 2000, 2004). To date, the two levels of industry capacity have been studied separately in the literature. It has been documented that the presence of reinsurance can affect insurers' behavior (Desjardins et al., 2022). It would be interesting to analyze how insurers with more reinsurance coverage can obtain more capital and be more aggressive in tackling weather events. The opposite causality link is also of interest.

Assuming normality for catastrophic losses is a strong assumption. Cummins et al. (2002) assumed a normal distribution to simplify the aggregation of individual losses. The true empirical distribution should have a loss distribution with a relatively high probability for extreme outcomes. Fat tails imply that extreme observations strongly influence expected future risk. By using the same assumption in this study, for replication purposes, we may have overestimated the industry's capacity.

Cummins and Weiss (2000) explicitly consider the effect of reinsurer industry consolidation on the industry's capacity to cover catastrophe risks and verify a positive statistical link. Two research questions can be considered for the insurance industry: Is catastrophe risk a causal factor of industry consolidation? If so, how could this consolidation affect the insurance industry's capacity to cover disaster risks, improve insurer value, and modify the demand for reinsurance?

Another issue concerns life insurance. Are life insurers prepared to deal with this increasing risk? How could extreme losses related to climate risks and involving many deaths affect the future viability of life insurers' current business and investment portfolios? Another interesting research topic is how life insurers manage their investments in green technologies, since these important investors can influence global warming in the long run. Other financial market participants can also affect climate risk coverage, as well as global warming, in the long run.

Finally, the starting point of Cummins et al. (2000) is coverage for the "big one." But many big ones, in a given year, or even simultaneously, must be considered in the near future, for instance a hurricane in Florida and an earthquake in California. This requires a more dynamic view of the evolution of industry capacity, particularly for losses associated to climate risk, because many of these losses are related to global warming, which, it is suspected will increase both the frequency and severity of weather disasters.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX

Additional theoretical analysis

Borch (1960, 1962) presents the basic model of risk sharing between insurance firms. For simplicity, we limit the presentation to an economy with two insurers. The generalization is straightforward. In fact, the Borch model can be viewed as a principal-agent model. The objective of the allocation program is to maximize the welfare of one insurer under two constraints: the other insurer must participate, and total resources are limited. Suppose that the welfare of insurer i, i = 1,2, is measured by (1) in Section 5.

A treaty between insurer i and insurer j can be written as

$$L^P \equiv L_i^P(L_i, L_j) + L_j^P(L_i, L_j) = L_i + L_j \equiv L, \tag{A1}$$

since all claims must be paid under full liability. The maximization program for obtaining the best treaty can be written as

$$\underset{L_1^P(\bar{L})L_2^P(\bar{L})}{\text{Max}} \int_0^\infty \int_0^\infty U_1\left(Q_1 - L_1^P(L_1, L_2)\right) dF(L_1, L_2), \tag{A2}$$

under these constraints:

$$k_2\left(\int_0^\infty \int_0^\infty U_2\left(Q_2 - L_2^P(L_1, L_2)\right) dF(L_1, L_2) - U_2(L_2) = 0\right), \tag{A3}$$

$$k_3\left(L_1^P(L_1, L_2) + L_2^P(L_1, L_2) - L_1 - L_2 = 0\right). \tag{A4}$$

Parameters $k_1 = 1$, $k_2 > 0$, $k_3 > 0$, and $L_i^P(\bar{L})$ is written for $L_i^P(L_i, L_j)$.

At the optimum, the functions $L_1^P(\bar{L})$ and $L_2^P(\bar{L})$ must satisfy

$$U_1'\left(Q_1 - L_1^P(L_1, L_2)\right) = k_2 U_2'\left(Q_2 - L_2^P(L_1, L_2)\right), \tag{A5}$$

$$L_1^P(L_1, L_2) + L_2^P(L_1, L_2) = L_1 + L_2. \tag{A6}$$

As shown by Lemaire (1977) with exponential utilities,

$$L_i^P(L_1, L_2) = q_i L + L_i(0). \tag{A7}$$

where the quota share of insurer i is equal to $q_i = c_i^{-1}/\left(c_1^{-1} + c_2^{-1}\right)$, c_i is the constant risk-aversion parameter of insurer i, and $L_i(0)$ is a side payment to compensate the less risk-averse insurer and obtain its participation in the treaty. Moffet (1977) interprets q_i as a coinsurance contract and show that a deductible contract cannot be optimal under the assumptions used in the program, particularly assuming that transaction costs between insurers are very low.

Cummins et al. (2002) assume risk neutrality and limited liability for each insurer. Without a treaty, the payoff of insurer i is equal to

$$T_i = \text{Max}(E(L_i) + Q_i - L_i, 0), \tag{A8}$$

or

$$T_i = \int_0^{z_i} (E(L_i) + Q_i - L_i)\ dF(L_i), \tag{A9}$$

where $z_i \equiv E(L_i) + Q_i$.

It is clear that we cannot directly apply the Borch (1960) maximization program to this environment because the resource constraint will not be satisfied in all states of the world. In fact, under limited liability, we must write

$$L^P \equiv E(L) + \sum_{i=1}^{2} Q_i \leq L_1 + L_2 \equiv L, \tag{A10}$$

with strict equality only when both insurers can pay L. Moreover, Cummins et al. (2002) do not show that the optimal form of the treaty is proportional or like a coinsurance contract. They assume this form of contract following the Borch (1962) result to obtain their condition of maximal compensation. More recently, Bergesio et al. (2021) show that a limited liability firm can buy a coinsurance contract at the optimum. However, they also assume this contract form instead of explicitly deriving it. Developing the optimal form of the treaty under limited liability and risk neutrality is beyond the scope of this article.[9] For our purpose of updating the results of Cummins et al. (2002), we assume that each insurer's compensation is proportional to the aggregate loss so long as all insurers can pay, as in Cummins et al. (2002). Otherwise, the industry capacity falls short of the total claims.

[9]For the derivation of contract forms with ex-post moral hazard and risk-neutral entrepreneurs, see Caillaud et al. (2000).