Earnings Dynamics and Selection in Health Insurance Markets*

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Abstract

This paper uses Utah All-payer Claims Data linked to noise-infused earnings records to estimate an insurance demand model that jointly considers earnings dynamics and medical risk. Including earnings dynamics reduces the estimated insurance take-up rate by 10.3% and the deadweight loss by 6.5%. Heterogeneous earnings dynamics influence the willingness to pay (WTP) for health insurance, even among individuals with identical medical risks, thereby weakening the connection between expected medical costs and WTP. Simulations show that means-tested subsidies increase equilibrium take-up less than equivalently costly uniform subsidies. Combining public insurance expansion with means-tested subsidies significantly boosts welfare.

Keywords: Health insurance; Adverse selection; Earnings risks; Means-tested subsidy policy

JEL Classifications: G22; I11; I13; I18.

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1 Introduction

Because adverse selection results in welfare loss (Akerlof, 1978; Rothschild and Stiglitz, 1978; Einav et al., 2010), subsidies are commonly used as a policy response to adverse selection (Einav and Finkelstein, 2011). Therefore, many developed and developing countries, including the United States of America (Handel and Ho, 2021; Handel and Kolstad, 2022), the Netherlands (de Ven and Schut, 2008), Switzerland (Holly et al., 1998), and Chile (Atal, 2019; Cuesta et al., 2019) provide premium subsidies for private insurance.

Relative to simple theoretical models of insurance demand that abstract from income risk, individuals do not just face medical risks but also considerable *economic* risks, including health-related earnings risks (Dobkin et al., 2018; Meyer and Mok, 2019; Nardi et al., 2023; Lockwood, 2024; Blundell et al., 2024). Due to limited information about earnings dynamics in most medical claims data, existing studies of health insurance demand typically assume a utility function with Constant Absolute Risk Aversion (CARA) and incorporate income heterogeneity in risk preferences (Einav et al., 2013; Handel, 2013; Marone and Sabety, 2022).

However, understanding how earnings dynamics affect adverse selection is crucial for designing effective public policies to combat adverse selection. In the ''textbook" adverse selection model, subsidies *always* significantly reduce adverse selection. This is because subsidies *always* attract healthier consumers, who have a lower willingness to pay (WTP) for health insurance than sicker consumers. However, when incorporating earnings dynamics, individuals' WTP also depends on earnings dynamics and its correlation with medical risk. One potential scenario arises: sicker consumers might have a lower WTP for health insurance than healthier ones. Sicker consumers may remain uninsured, and subsidies may induce sicker consumers to take up insurance. Consequently, subsidies may reinforce adverse selection.

This paper is one of the first to empirically examine how both expected earnings and earnings uncertainty influence adverse selection in health insurance markets. Furthermore, it investigates the implications for the design of means-tested subsidies. While prior studies indicate that individuals with higher incomes tend to have higher insurance demand (Mahoney, 2015; Finkelstein et al., 2019b; Nardi et al., 2016; Geruso et al., 2023), researchers have paid less attention to how the interaction between health risks and earnings risks affects insurance demand and market-level adverse selection. One exception is Lockwood (2024), who studies individual-level valuation of health insurance using sufficient statistics. He highlights how the interaction between healthcare costs and other risks alters the risk protection provided by health insurance.

My paper studies the impact of earning dynamics on adverse selection in health insurance markets by incorporating individuals' WTP for health insurance into a market-level analysis. Using Utah All-payer Claims Data and noise-infused earnings records, I empirically estimate individual-level WTP via a binary insurance demand model that jointly considers earnings dynamics and medical risks. Individuals face uncertainty about their health risk, job mobility, earnings levels, and earnings volatility when deciding whether to purchase insurance or not. My modeling approach relates to the literature that models earnings dynamics using employer-employee-matched databases (Abowd et al., 1999, 2019; Addario et al., 2023; Bonhomme et al., 2019) and survey data (Meghir and Pistaferri, 2004; Altonji et al., 2013). However, my model differs by incorporating health status to capture the joint dynamics of earnings and medical expenditures. Furthermore, I discuss how subsidy policy design can be improved, taking into account earnings dynamics which can influence the joint distribution of WTP and expected medical costs.

Conceptually, even if individuals face the same medical risk, their WTP for health insurance may differ if they predict different future earnings dynamics. How earnings dynamics affect WTP for health insurance is theoretically ambiguous. Because the expected utility of being uninsured is lower for individuals whose earnings are more volatile, it leads to a higher WTP for health insurance. Simultaneously, individuals with more volatile earnings are more likely to face low-resource states, that is, economic hardship. Thus, the same premium reduces consumption utility by a greater amount when earnings are low. This reduces individuals' WTP for health insurance. Moreover, the correlation between earnings and medical expenditures affects the WTP. When individuals are likely to face low earnings and high medical spending at the same time, WTP is higher than in a model that assumes zero correlation between earnings and medical spending realizations. The intuition is that the negative correlation reallocates resources from low-resource states to high-resource states, which is undesirable for risk-averse individuals.

Because savings provide an alternative to insurance for smoothing consumption over time, I further simulate asset accumulation using a life-cycle model of optimal consumption and savings. Additionally, to account for the social safety net, I consider a consumption floor. The literature has provided evidence of its impact on the demand for health insurance, including protection from bankruptcy (Mahoney, 2015) and uncompensated care (Garthwaite et al., 2018). Building on this insight, my model points out that an individual with lower expected earnings or higher earnings uncertainty expects a higher probability of receiving transfers from the consumption floor, implicitly reducing her incentive to purchase insurance.

My findings show that introducing earnings dynamics to insurance demand models leads to changes in the joint distribution of the WTP and expected medical costs. Relative to a classical model, incorporating heterogeneity in assets, expected earnings, and earnings uncertainty leads to significant and different changes in consumers' WTP. The WTP reduction is especially large for sicker consumers. Specifically, a large share of consumers have a WTP that is *lower* than their expected medical costs, which is consistent with the findings in the literature (Finkelstein et al., 2019a,b). I contribute to the literature by linking this finding to adverse selection and subsidy design in private health insurance markets.

Then, I study adverse selection by aggregating individual-level WTP to the market level. Relative to standard models, incorporating earnings dynamics shifts the demand curve downward. Consequently, the estimated equilibrium take-up rate *decreases* and premiums *increase*. However, considering earnings dynamics also attenuates the relationship between WTP and expected medical costs. The average cost curve exhibits a flatter slope compared to a standard model, leading to an *increase* in the equilibrium take-up rate and a *decrease* in premiums. On net, the estimated equilibrium take-up rate decreases by 10.3%, premiums increase by 3.3%, but the deadweight loss from selection decreases by 6.5% per person.

The weakened relationship between WTP for insurance and expected medical costs is particularly relevant for the design of subsidy policies. Uninsured individuals are now no longer always healthier and subsidies could potentially increase adverse selection by attracting sicker consumers. To assess the efficiency of means-tested subsidy policies, I compare an ACA-style subsidy policy with a uniform subsidy of equivalent costs. Interestingly, uniform subsidies yield a large increase in take-up rate rates. I also explore an alternative policy that combines a public insurance expansion (e.g. Medicaid expansion) with means-tested subsidies (e.g. ACA Exchange subsidies). Relative to the case when only means-tested subsidies are provided, this counterfactual policy results in a 33.0% increase in the equilibrium take-up rate, a 23.8% reduction in premiums, and a 3.5% decrease in deadweight loss. Despite the higher costs associated with this two-step policy, net welfare increases by 73.5%. This is primarily due to public insurance expansion covering a significant number of low-income individuals, who are also more likely to be in poorer health. Hence, subsidies can operate more effectively by attracting healthier consumers.

Finally, I study a scenario specific to the US market: individuals may gain access to employer-sponsored insurance (ESI) if they join firms offering ESI and leave the private health insurance market, influencing the duration consumers remain in need of private health insurance. This transition results in private insurers facing lower expected costs for covering each consumer. Accounting for this employment transition effect increase take-up by 20.1%, and reduces premiums and the deadweight loss by 38.1% and 16.8%, respectively, compared to the standard model without ESI status transitions.

My results have policy implications for the U.S. and other regions. Through a case study of the US ACA-style private insurance market, my research underscores the critical importance of jointly considering earnings, job mobility, and health risks when evaluating policies aimed at combating adverse selection. This study therefore contributes to the growing literature on improving subsidy design in health insurance markets (Jaffe and Shepard, 2020; Finkelstein et al., 2019b; Decarolis, 2015; Decarolis et al., 2020). Geruso et al. (2023) highlight how adverse selection affects higher-income employees within a large employer and suggests integrating distributional consequences into subsidy designs. My work further explores the influence of earnings uncertainty and job mobility on adverse selection and subsidy design at the extensive margin within ACA-style markets. Another closely related paper is Tebaldi (2024), which proposes offering more subsidies to young consumers in the context of the ACA market. My paper evaluates a different counterfactual policy combining means-tested subsidies with public insurance expansion for low-income individuals, who are often sicker. This mirrors the key idea in Tebaldi (2024): designing subsidies in a way that attracts healthier consumers improves welfare.

2 Literature Review

This paper contributes to the literature on modeling short-term insurance demand. As mentioned previously, some studies exclude the income effect by assuming the CARA utility function and incorporate some degree of income heterogeneity in risk preferences to deal with data limitations (Einav et al., 2013; Handel, 2013; Marone and Sabety, 2022). Other studies follow Einav et al. (2010) and use price variations to estimate the WTP for insurance. One advantage of this method is that it does not require the researcher to make assumptions about consumer preferences or ex-ante information about the distribution of earnings. However, these methods limit our ability to investigate how earnings dynamics affect adverse selection and evaluate means-tested subsidy policies. My model explicitly incorporates the joint distribution of earnings and medical spending into insurance demand. This aims to separate risk preference and earnings dynamics, making it more suitable for evaluating means-tested policies in regulating the health insurance market, particularly in scenarios where income fluctuates.

This paper also contributes to the literature on how insurance markets function in reality, including the importance of multidimensional private information (Fang et al., 2008), administrative costs and preference heterogeneity (Einav and Finkelstein, 2011), uninsurable background risk (Doherty and Schlesinger, 1983), liquidity constraint (Ericson and Sydnor, 2018), behavior biases such as lack of information and inertia (Handel, 2013; Domurat et al., 2021; Drake et al., 2022;

Saltzman, 2021), and selection on moral hazard (Einav et al., 2013). My paper studies earnings dynamics in insurance markets, which is essential. First, it helps to improve means-tested health insurance policies like subsidies and individual mandates. Second, modeling earnings dynamics enables us to understand the role of safety nets and labor market shocks in health insurance markets. For example, individuals' earnings uncertainty might be unevenly affected by an economic downturn. How policymakers modify health insurance policies when a financial crisis occurs requires knowledge of the impact of earnings dynamics on adverse selection.

Further, this paper contributes to the literature on the interaction of health insurance systems and the labor market. Several studies investigate the economic consequences of health shocks (Dobkin et al., 2018; Charles, 2003; Poterba and Wise, 2017; Meyer and Mok, 2019; Fadlon and Nielsen, 2021). In particular, some studies focus on job lock, which is unique under the context of the US employer-sponsored insurance system (Currie and Madrian, 1999; Gruber and Madrian, 2002). My work differs by integrating the evidence of correlated health and economic risks into an insurance demand model and by studying the impact of earnings dynamics on adverse selection in health insurance markets.

Other studies adopt an equilibrium approach. Seminal papers like Aizawa (2019) and Fang and Shephard (2019) estimate equilibrium job search models and study the impact of the ACA on the labor market. Aizawa and Fu (2024) estimate an equilibrium model with heterogeneity in local markets, households, and firms and simulate a counterfactual policy that cross-subsidizes employer-sponsored insurance and individual health insurance. My paper complements this literature by introducing uncertainty of earnings to insurance demand models. I model the uncertainty of earnings via employment transitions, firm-to-firm transitions, and uncertainty in on-the-job earnings. To incorporate the rich heterogeneity, I model the joint dynamics of earnings and medical spending in a relatively simple way without explicitly modeling labor supply decisions, job search behaviors, and firm ESI offering decisions. This approach is therefore also relevant to private health insurance markets outside of the United States. However, it comes with a cost. I would interpret policy implications from my model as short-run effects rather than long-run equilibrium effects.

Finally, this paper also relates to the literature that studies reclassification risks and *long-term* health insurance (Handel et al., 2015; Ghili et al., 2024; Atal et al., 2023; Fleitas et al., 2018). Reclassification risk occurs when persistent poor health leads to increased premiums if pricing based on health status is allowed. As pointed out by Ghili et al. (2024), lifetime income profiles and income uncertainty are important in long-term health insurance designs. In particular, the value of long-term health insurance contracts is higher for people without steeply rising age-income profiles. My model focuses on *short-run* health insurance with a typical one-year maximum length and highlights that income levels and uncertainty also play an important role in insurance demand. This is partly because people in low-resource states suffer from higher utility costs of paying premiums, making them less willing to pay for health insurance. Moreover, earnings levels and risks largely affect protections from the consumption floor, therefore impacting WTP for health insurance. Detailed theoretical discussion can be found in Section 3.

3 Conceptual Framework

This section introduces a model that captures individual insurance choices while incorporating earnings dynamics. I develop a binary insurance choice model inspired by Einav et al. (2010). The key difference between this model and Einav et al. (2010) is that I explicitly allow consumers with the same risk preference to differ in medical risks, earnings levels, and earnings volatility. This framework enables a discussion on why, in models with earnings dynamics, individuals facing the same medical risk may have different WTP for insurance.

3.1 A Model of Insurance Choice

At the beginning of year $t+1$, individual i is characterized by two variables: $f(w_{t+1}, m_{t+1})$ and A_{t+1}. For simplicity, henceforth, I omit subscript i. The first variable, $f(w_{t+1}, m_{t+1})$, represents the probability density function (PDF) of the joint distribution of earnings and medical spending that an individual expects for the period $t+1$. The PDF of the marginal distribution of earnings and medical spending is denoted as $f(w_{t+1})$ and $f(m_{t+1})$. The second variable is A_{t+1}, representing the assets that an individual holds at the beginning of $t+1$.

Prior to the realization of earnings and medical spending, individuals face a binary insurance choice $I_{t+1} \in \{0, 1\}$. Individuals can either purchase health insurance covering ξ of the medical costs at a cost of p per year or remain uninsured. Earning reductions are not insurable in this model, as health insurance only covers medical spending. The earnings and medical spending for period $t+1$ are realized after the insurance choice is made.

Assuming individuals are risk-averse expected utility maximizers with the von Neumann-Morgenstern (vNM) utility function denoted as $u(.)$, the individual also encounters a consumption floor $\underline{c}$. If the individual's resources fall below the consumption floor, they receive a monetary transfer to ensure their resources remain above $\underline{c}$. Following these assumptions, if individual i chooses to be uninsured ($I_{t+1} = 0$), the expected utility is:

$$EU_{I_{i,t+1}=0} = \int_w \int_m u(\max[A_{t+1} + w_{t+1} - m_{t+1}, \underline{c}]) f(w_{t+1}, m_{t+1}) dmdw \tag{1}$$

However, if she purchases health insurance $(I_{t+1} = 1)$ priced at p, her expected utility is:

$$EU_{I_{t+1}=1}(p) = \int_w \int_m u(\max[A_{t+1} + w_{t+1} - (1-\xi)m_{t+1} - p), \underline{c}]) f(w_{t+1}, m_{t+1}) dmdw \tag{2}$$

The individual will purchase the insurance plan if their WTP is greater than or equal to the price offered by insurers. Therefore, her WTP (g_{t+1}) for the insurance plan is given by:

$$g_{t+1} = \max\{p : EU_{I_{t+1}=1}(p) \geq EU_{I_{t+1}=0}\} \tag{3}$$

To estimate individuals' WTP in this binary choice model, it is essential to estimate the joint distribution of earnings and medical spending as well as assets. Section 5.1 provides a detailed discussion on how I model and empirically estimate the joint distribution of earnings and medical spending. This includes the methods used for predicting possible combinations of (w_{t+1}, m_{t+1}) and determining the probability of realizing each combination. Additionally, in Section 5.2, I outline my approach for estimating the assets that individuals hold when making insurance choices.

3.2 How Earnings Dynamics Influence WTP

In this section, we explore the conceptual reasons behind the potential differences in individuals' WTP when earnings dynamics are integrated into insurance choices, even if they face the same medical risk: Take the joint distribution of earnings and medical spending, with a focus on three key parameters: (1) the mean of earnings denoted as $\mu_w = \int w_{t+1} f(w_{t+1}) dw$, (2) the variance of earnings represented by $\sigma_w^2 = \int (w_{t+1} - \mu_w)^2 f(w_{t+1}) dw$, and (3) the correlation between earning and medical spending denoted as ρ.

3.2.1 Joint Distribution of Earnings and Medical Spending

I begin by assuming that earnings and medical spending are independent, that is, $\rho = 0$.

The variance of earnings σ_w^2 has an ambiguous effect on WTP. — I compare individuals who face the same earnings mean but have a different earnings variance. It is tempting to think that people with a higher earning variance are willing to pay more for health insurance because they face more volatile consumption. However, the impact of earning variance on the WTP for health insurance is ambiguous. I explore two opposing forces: changes in (1) the expected utility of being uninsured; (2) the expected utility cost of a premium.

First, a higher earnings variance leads to higher consumption volatility.[1] Thus, risk-averse individuals experience lower expected utility when faced with volatile consumption. Figure 1 provides a visual representation of this concept. For individuals who face a higher earnings variance, the uninsured option can lead to two consumption realizations with equal probability: c_1^H and c_2^H. For those whose earning variances are lower, the possible consumption realizations change

[1] To see this mathematically, the variance of consumption when choosing to be uninsured is $\sigma_{w-m}^2 = \sigma_w^2 + \sigma_m^2$, which increases with the variance of earning σ_w^2. This assumes that both earnings and medical spending are independent and normally distributed.

to c_1^L and c_2^L. In both cases, the average consumption is $\bar{c}$. When consumption is more volatile, the expected utility is lower: $E(u(c^H)) < E(u(c^L))$. Therefore, individuals with a higher earning variance are worse off if they choose to be uninsured, making them more willing to purchase health insurance.

Second, a higher earnings variance increases the expected utility cost of premiums. Individuals with a higher earning variance are more likely to face a low-resource state. In a low-resource state, a fixed nominal insurance premium reduces the consumption utility by a greater amount. Therefore, these individuals are expected to give up more utility for the same premium. Such "expensive" insurance leads to a lower WTP.[2]

The mean of earnings μ_w has an ambiguous effect on WTP. — How the average earnings affect the WTP can also be explained by two opposing forces. First, individuals with lower earnings derive a lower expected utility from the uninsured choice. Therefore, they have a higher incentive to purchase health insurance. As illustrated in Figure A1 (Appendix A), when facing the same level of earnings volatility, if the average consumption equals $\bar{c}_L$, the expected utility is $E(u(c^L))$. This is lower than $E(u(c^H))$, which is the expected utility when the average consumption is $\bar{c}_H$.

Second, individuals with a lower mean of earnings consider insurance more expensive in terms of utility.[3]

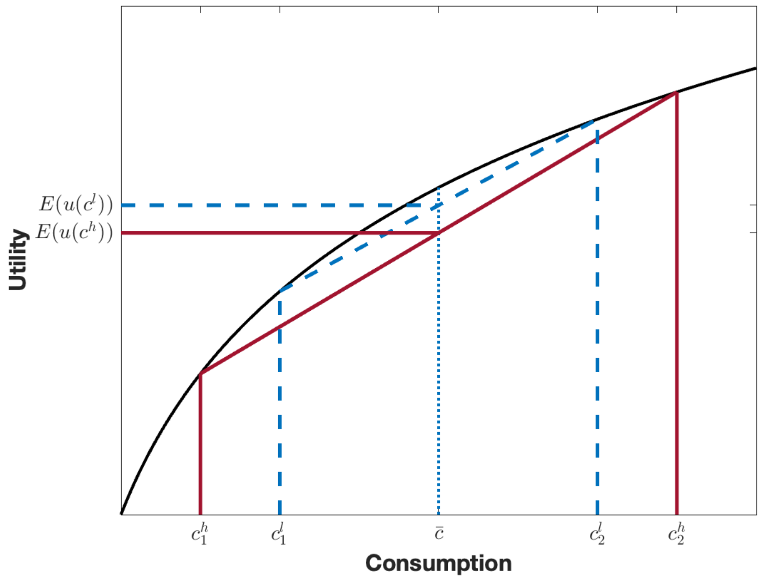
Correlation between earnings and medical spending ρ — If earnings and medical spending are correlated, how does WTP change? The answer is important because the literature has provided evidence that these two factors are correlated (Dobkin et al., 2018; Charles, 2003; Meyer and Mok, 2019; Poterba and Wise, 2017).

A negative correlation between earnings and medical spending unambiguously increases the WTP. The intuition is that the negative correlation reallocates resources from low-resource states to high-resource states, which risk-averse

[2]When the utility function is differentiable, the utility foregone to pay for insurance when the resource is w can be represented by $u'(w)$. Because individuals are risk averse, utility function $u(.)$ is concave and the marginal utility $u'(.)$ is convex. Thus, $E((u'(w^H)) > E((u'(w^L))$ holds, where w^H is the case that earning variance is higher.

[3]The marginal utility cost of insurance premium at earning w can be represented by $u'(w)$. Because people are assumed to be risk averse, the utility function is concave. Therefore, $u'(w)$ decreases in w.

Figure 1: Earnings Variance and WTP



Source: Own illustration. *Notes:* This figure illustrates the impact of earnings variance on the expected utility of being uninsured. For individuals who face higher earning variance, the uninsured option can lead to two consumption realizations with equal probability: c_1^H and c_2^H. For those whose earning variances are lower, the possible consumption realizations change to c_1^L and c_2^L. In both cases, the average consumption is $\bar{c}$. When consumption is more volatile, the expected utility is lower: $E(u(c^H)) < E(u(c^L))$.

individuals do not favor.

However, a positive correlation increases individuals' expected utility of being uninsured because it is a form of implicit insurance that reallocates resources from high-resource states to low-resource states.

3.2.2 Assets

Assets affect the WTP because individuals buy insurance to protect assets by reducing out-of-pocket medical spending and medical debt (Finkelstein et al., 2019a). Moreover, individuals who have different earnings dynamics can accumulate different levels of assets for two reasons. First, they have different savings motives. Secondly, negative earnings shocks can reduce the wealth levels that households have previously accumulated.

3.2.3 Consumption Floor

So far, my discussion regarding how earnings dynamics affect WTP assumes that the consumption floor is never reached. The consumption floor transfers wealth to individuals when they encounter extremely low-resource states. The consumption floor further impacts the WTP for health insurance because individuals with different earnings dynamics vary in the level of protection they receive from the consumption floor. For instance, individuals with a lower mean of earnings, more volatile earnings, or a negative correlation between earnings and medical spending are more likely to encounter states with lower resources than the consumption floor.

4 Data

As discussed in Section 3, earnings dynamics can theoretically affect WTP for health insurance. Thus, an empirical analysis of how earnings dynamics affect adverse selection requires individual-level panel data on earnings and medical utilization.

I use data from the 2013-2015 All-Payer Claims Database (APCD). These are linked to aggregated noise-infused earnings records derived from administrative earnings records for UI-covered jobs in Utah. Data from the APCD provide information about the medical spending of Utah residents from 2013 to 2015, including insurance coverage, diagnoses of patients, and medical utilization records for inpatient, outpatient and prescription drug consumption. See Lavetti et al. (2023) for further information.

The earnings file was constructed by the Utah Department of Workforce Services, who calculated each worker's total earnings from all jobs in each quarter. They then grouped workers into permilles (1000-quantiles) of the distribution of total earnings, and reported the average earnings level for each group. This aggregation procedure introduces some measurement error to increase privacy. See Lavetti et al. (2024) for additional details on data construction.

4.1 Sample Selection

Using APCD, I focus on individuals aged 26 to 64 who are insured for at least nine months between 2013 and 2015. Using individuals who are insured for at least nine months permits the introduction of uninsured consumers and the reliable estimation of health risk scores.[4] The sample is restricted to individuals under 65, as most people over 65 are retired and eligible for Medicare. Finally, I focus on individuals with positive earnings for at least two quarters from 2012 to 2013. This mitigates concerns about including too many individuals who have exited the labor force.[5]

4.2 Imputation of Medical Spending for Uninsured Periods

Only medical utilization during insured periods is reported in APCD. Thus, I adopt a multiple imputation method to impute the medical spending during uninsured months similar to Handel (2013). The imputation estimates total annual medical spending as if consumers were consistently insured throughout the year, under the assumption of no moral hazard. The details of the imputation are in Appendix B.

4.3 Health, Worker, and Firm Types

I assume that individuals are classified by worker types and health type in period t. Worker types reflect their ability level and health types reflect their expected medical spending. Individuals first predict the realization of health type, employed or not, and type of firms they work for before predicting the realization of earnings and medical spending for period $t+1$. In this section, I introduce health, worker, and firm types.

[4] I also explored a sample of individuals insured for at least six months each year and found similar parameters for the model of medical spending prediction (Table B2).

[5] Appendix B introduces more details in sample selection criteria. Table B1 outlines the changes in sample size as I select the sample step-by-step based on individuals' (1) age, (2) worker types, (3) labor force attachment, (4) health risk scores, (5) being insured for at least 9 months each year, (6) working for small firms that never have more than two workers, and (7) firm types.

Health Types. — First, I use the Johns Hopkins ACG software to calculate annual health risk scores in the APCD dataset. Researchers and commercial insurers widely use health risk scores to describe or predict patients' healthcare costs (Handel, 2013; Einav et al., 2013). Figure B2 (Appendix B) reveals the highly-skewed ACG risk score distribution.

Second, I categorize employees into four health-type groups based on their annual health risk scores from 2013 to 2015. Health types are assigned values of 1, 2, 3, and 4, representing individuals with risk scores each year below 0.5, between 0.5 and 1.5, between 1.5 and 2.5, and above 2.5, respectively. The choice of risk scores aims to reach a balance between having enough observations across groups and achieving a sufficiently accurate approximation of medical spending.[6]

Table B4 (Appendix B) provides descriptive statistics for person-quarter observations. Unobserved earnings are imputed as zero since workers may be unemployed, working zero hours, or out of the labor force in that quarter.[7] The sickest group (type 4) has an average annual medical spending of approximately $9,900, whereas the healthiest group's average is only $608. However, the sickest group's average quarterly earnings are $1,100, while the healthiest group earns around $1,300 on average. Individuals predicted to use more medical care tend to earn less per quarter and have a higher probability of being unemployed. The summary statistics suggest a potential negative correlation between earnings and medical spending.

Worker Types. — The worker type of individual i is interpreted as a combination of skills and other factors that are equally rewarded across employers.

I follow Abowd et al. (1999) by estimating a linear model with additive worker and firm fixed effects. I run the following regression on the sample of workers from 2013 to 2015.

$$ln(w_{ijt}) = \alpha_i + \psi_{j(it)} + X_{it}\beta + \eta_{ijt} \tag{4}$$

w_{ijt} stands for observed earnings of individual i who works for employer

[6]Because only annual risk scores are observed, I assume that individuals face the same health type in each quarter of the year.

[7]Self-employed and non-wage incomes are unobserved.

j in period t. α_i and $\psi_{j(it)}$ are person and firm fixed effects respectively. X_{it} are time-varying covariates, including age and risk scores, and indicators for missing risk scores. η_{ijt} is an error component.

I categorize workers into ten groups according to predicted worker fixed effects, ranging from lowest (1) to highest (10) types. Figure 2 (a) shows lower-type workers earn less than higher-type earners. For example, workers with type 1 earn approximately $\frac{1}{4}$ of high earners (type 10).

Firm Types. — Firm types are two-dimensional: (1) firm's ESI offering status, and (2) firm compensation types. I interpret firm compensation type as the pay premium paid by employer j.

To determine whether firms offer ESI, I use the share of workers with ESI in each firm. For small firms (2 to 10 employees), ESI provider status is assigned if the share exceeds 10%. Larger firms qualify if at least one worker receives ESI. This method's accuracy is supported by Table B5 (Appendix B), showing alignment with the 2013 KFF Employer Benefits Survey.

For firms offering ESI, I classify them into four groups based on estimated firm fixed effects $\hat{\psi}_{j(it)}$ estimated by equation (4), ranging from lowest (type 1) to highest (type 4) earning levels.[8]

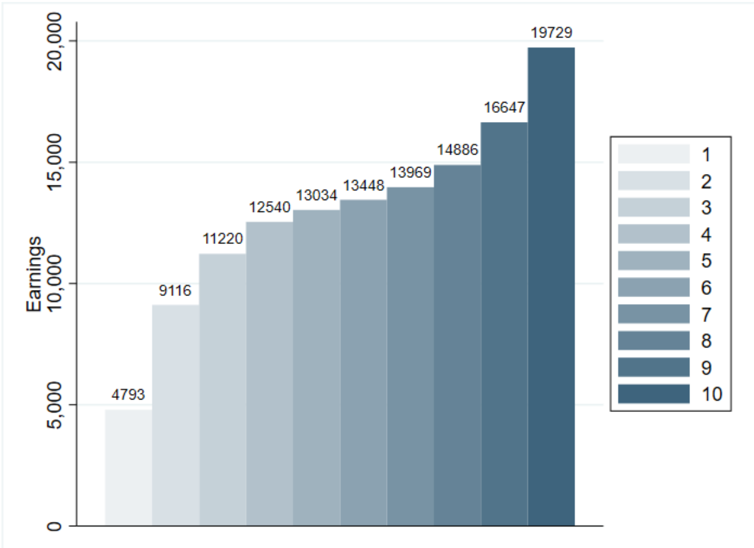
In Figure 2 (b), Workers in firms with higher earnings types earn more than workers in lower-type firms. For instance, among firms that offer ESI, workers in firms with type 4 earn approximately 1.6 times as much as workers in firms with type 1. Moreover, firms that do not offer ESI also tend to offer less compensation.

5 Empirical Model

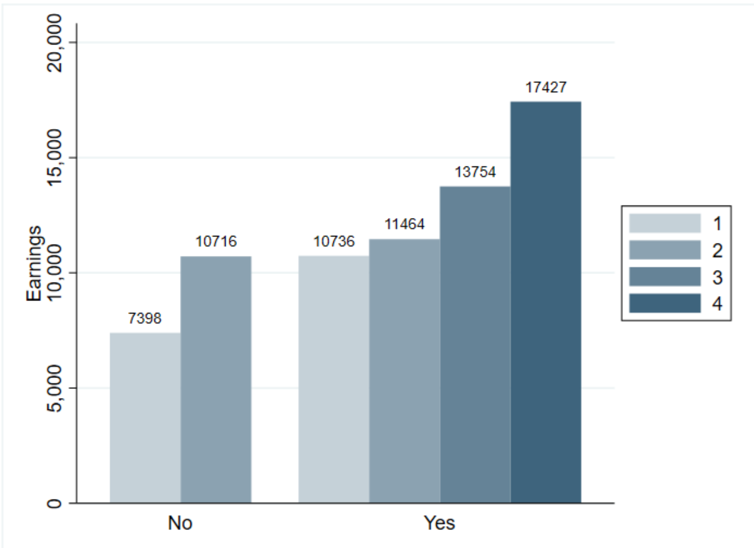
This section discusses two important dimensions for WTP estimation. I first discuss the estimation of the joint distribution of earnings and medical spending. Second, I develop a life-cycle model to simulate assets.

[8] I further categorize firms that do not offer ESI into two groups based on firm fixed effects, with type 1 representing the lower firm compensation level and type 2 representing the higher one.

Figure 2: Earnings by Worker and Firm Types



(a) By Worker Types



(b) By Firm Types

Notes: This figure shows the average quarterly earnings by worker types and firm types. Numbers are estimated by taking the average of all workers in each group. (a) shows the increases in average quarterly earnings when the estimated worker type is higher. (b) shows the increases in average quarterly earnings for workers in firms with higher estimated firm compensation types. Firms are categorized by whether or not they offer ESI. Because larger firms tend to offer ESI, firms that do offer ESI are divided into four groups, while those that do not are divided into two groups. Higher types are associated with higher values.

5.1 Model of Earnings and Medical Spending

Individuals first predict the probability of realizing possible health and earning types in the next period.[9] Then, conditional on each potential realization of health and earning types, they predict the possible realization of earnings and medical spending $f(w_{t+1}, m_{t+1})$. I empirically estimate the model using the data introduced in Section 4.

5.1.1 Health and Employment Transitions

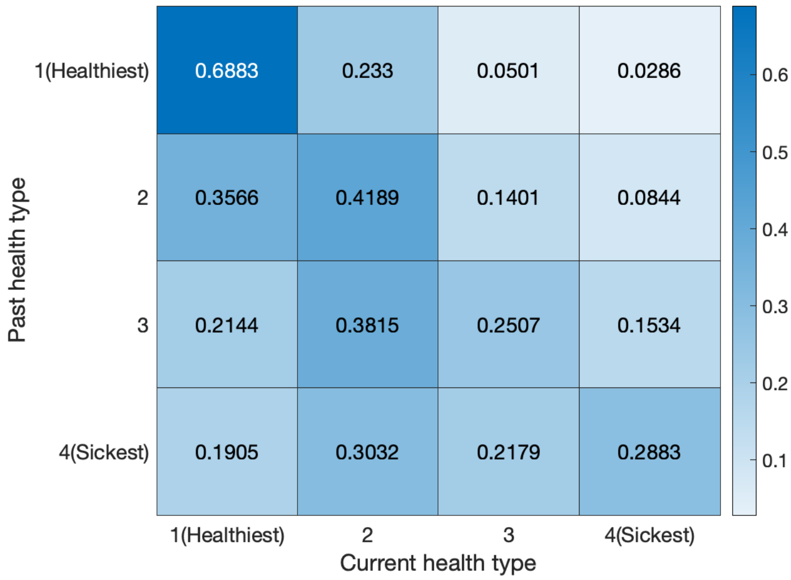
I assume that individual i predicts the probability of realizing each possible combination of earnings and medical spending in four steps. First, she predicts the probability of realizing the health types in period $t+1$, based on her past health type, gender, and age. Second, conditional on each possible realization of health type in period $t+1$, she predicts whether or not she is employed. Third, conditional on being employed, she predicts whether or not she changes employer. Finally, conditional on changing employer, she predicts the probability of ending up working in which type of firm. Following Atal et al. (2023), I estimate the probabilities by fitting the transitions observed in the data from 2013-2015 into a multinomial logit model. More details are in Appendix C.

Figure 3 displays the health-type transition matrices between t and $t+1$. The results indicate a high persistence of poor health. For instance, if an individual has health type 1 (the healthiest) at time t, the likelihood of transitioning to the sickest state (type 4) is 2.9%, while for a person with health type 4, the probability of remaining in the sickest health state is 28.9%

Table C5 (Appendix C) shows how health type transitions are correlated with the probability of being unemployed. For example, persistent sickest state is associated with a 1% increase in the likelihood of unemployment. Table C6 (Appendix C) shows that individuals with lower worker types tend to lose jobs and change employers. Figure C1 (Appendix C) shows strong persistence in firm transitions for job movers.

[9]The model, where individuals predict types before forecasting realizations of earnings and health spending, is inspired by Abowd et al. (2019) and Bonhomme et al. (2019).

Figure 3: Health Type Transitions



Source: 2013-2015 Utah All-payer Claims Data. *Notes:* Health type transition matrices, evaluated at means of control variables.

5.1.2 Earnings and Medical Spending

I consider that individual i predicts earnings and medical spending conditional on predicting health type $h_{i,t+1}$ and employment type $k_{i,t+1}$. Employment type includes both employed or not and what type of firms individual i works for.

If individual i predicts an unemployed state, she expects to get zero earnings. If individual i predicts an employed state, she predicts the earnings $w_{i,t+1}$ for next quarter t according to equation 5.

$$ln(w_{i,t+1}) = \phi(a_i, k_{i,t+1})\beta_\phi + H_{i,t+1}\beta_h + X_{i,t+1}\beta_x + \epsilon_{i,t+1} \tag{5}$$

where $\phi(a_i, k_{i,t+1})$ is the interaction term of worker type a_i and employment type $k_{i,t+1}$. H_{it} is health type transitions between t and $t+1$, and x_{it} are covariates including age type (in 5-year bin), gender, age, age squares, year and quarter fixed effects. Finally, ϵ_{it} is a transitory shock.[10]

[10]The ϵ_{it} is heteroscedastic and normally distributed with mean 0. I further assume that

Next, individual i predicts whether the medical spending is positive or not according to a logit model in equation (6).[11] Then, conditional on positive medical spending, she predicts the medical spending according to equation (7).

$$Pr(m_{iy(t+1)} > 0) = H_{iy(t+1)}\lambda_h + x_{iy(t+1)}\lambda_x + \eta_{iy(t+1)} \tag{6}$$

$$ln(m_{iy(t+1)}) = \gamma_m ln(m_{i,y(t+1)-1}) + \delta_{iy(t+1)}\gamma_0 + x_{iy(t+1)}\gamma_x + H_{iy(t+1)}\gamma_h + \nu_{iy(t+1)} \tag{7}$$

where $H_{iy(t+1)}$ are the health type transitions between past and current year. $m_{iy(t+1)}$ and $m_{iy,(t+1)-1}$ are the annual log total medical spending in current and past year. $\delta_{iy(t+1)}$ equals one if the previous year occurs zero medical spending. $x_{iy(t+1)}$ represents age, gender types and year fixed effects. Finally, $\nu_{iy(t+1)}$ is a transitory shock.[12]

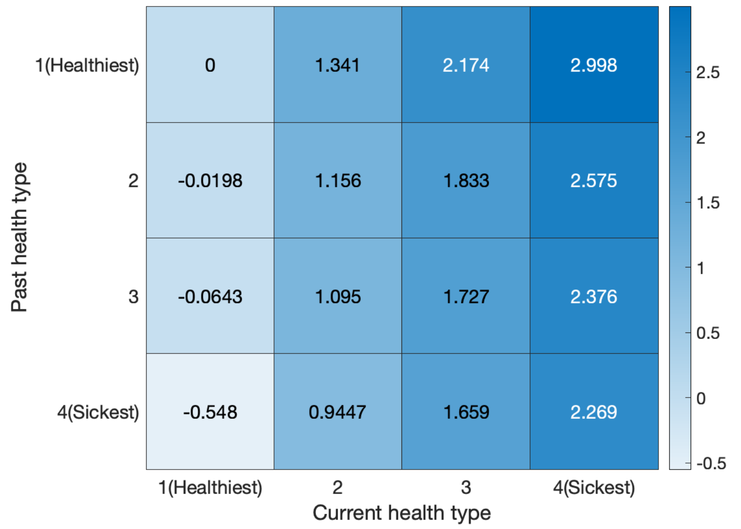
Figure 4 illustrates that predicted earnings are lower if individual i transitions to a sicker state. For instance, an individual with a past health type of 1 (healthiest) who transitions to the sickest state (type 4) in the next period is associated with a predicted higher log medical spending of 2.998 compared to remaining healthy. At the same time, individuals predict lower earnings: relative to remaining in health state 1, drawing a health type realization of 4 is associated with a -0.0209 decrease in the prediction of log earnings. This reveals a negative correlation between medical spending and earnings, which is consistent with other empirical evidences in the literature (Dobkin et al., 2018; Meyer and Mok, 2019; Nardi et al., 2023; Lockwood, 2024; Blundell et al., 2024).

individuals believe that the log earning residuals are random draws from a normal distribution $N[0, var(\hat{e}(k_{it}, a_i))]$, where $var(\hat{e}(k_{it}, a_i))$ is the sample variance of the estimated log-earning residuals by firm types and person types. Discussion of the impact of this assumption on prediction accuracy is discussed in Appendix C, Table C4.

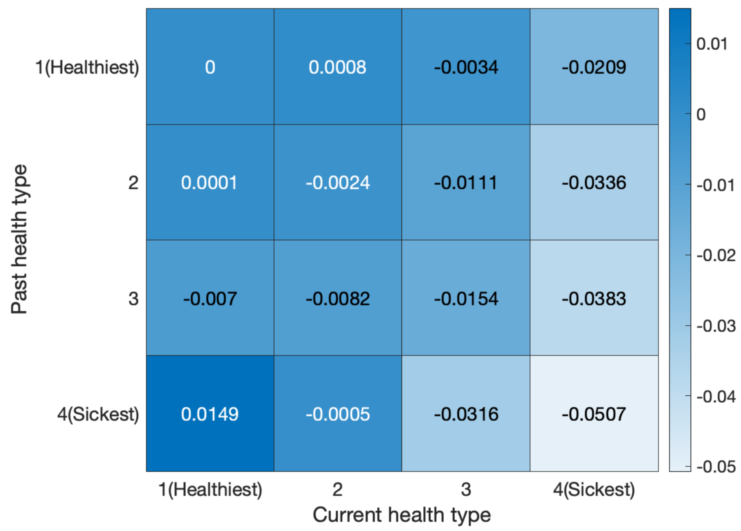
[11] Because health risk scores are calculated based on annual risk scores, individual i is assumed to predict medical spending at annually level for year that contains quarter $t+1$: $y(t+1)$.

[12] $\nu_{iy(t+1)}$ is heteroscedastic and normally distributed with mean 0. I further assume that individuals believe that the log medical residuals are random draws from a normal distribution $N[0, var(\hat{\nu}(H_{iy(t+1)}))]$, where $var(\hat{\nu}(H_{iy(t+1)}))$ is the sample variance of the estimated log medical spending residuals by health type transitions. Discussion of the impact of this assumption on prediction accuracy is discussed in Appendix C, Table C4.

Figure 4: Health Type Transitions and Medical Spending, Earnings Predictions



(a) Medical Spending



(b) Earnings

Notes: This figure shows estimated impact of health type transitions on medical spending and earnings predictions in equation (5), (6) and (7). (a) shows the how predicted log medical spending change when health type transits between past and current year. (b) shows the prediction of log earnings.

5.1.3 Model Fitness

Figure 5 (a) reports the distribution of earnings in data and in model. Overall, the fit is quite well. (b) reports the actual and predicted distributions of medical expenditure. The fit is again reasonably well. I tend to under predict the fraction of individuals who have no and low spending, but the difference is very small.

5.2 Life Cycle Model with Precautionary Savings

As discussed in Section 3, individuals hold assets before making insurance decisions. Assets are an important object for estimating the WTP for health insurance. However, I do not observe assets directly. Thus, I follow the literature to simulate wealth using a life-cycle model (Carroll, 2006; Nardi et al., 2010, 2016). I assume individuals save according to a life-cycle model, starting in the labor market at age 26 with zero assets. Individuals predict earnings dynamics according to the heterogeneous earnings dynamics of Section 5.1. All individuals die at age 100 with a probability of 100% and derive no utility from assets after deaths, implying no bequest motive in this saving model. The details of the life-cycle model and empirical parameter choices are in Appendix D.

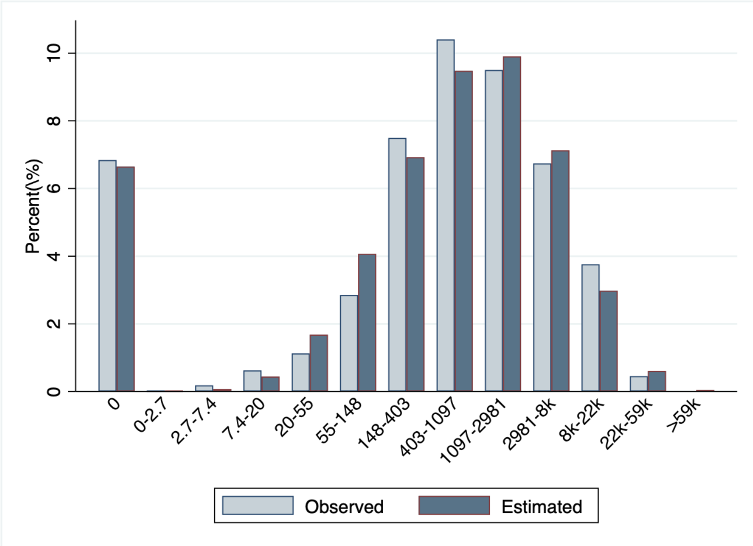
Figure 6 compares the median of simulated assets by age groups with a similar sample from the Panel Study of Income Dynamics (PSID), public use dataset.[13] I further assume that married couples equally share the households' assets.

As seen, the median assets simulated by the model match the cross-sectional distribution reasonably, particularly in capturing the general trend of increasing assets with age. However, the model tends to overestimate assets for younger individuals and underestimate them for older cohorts.

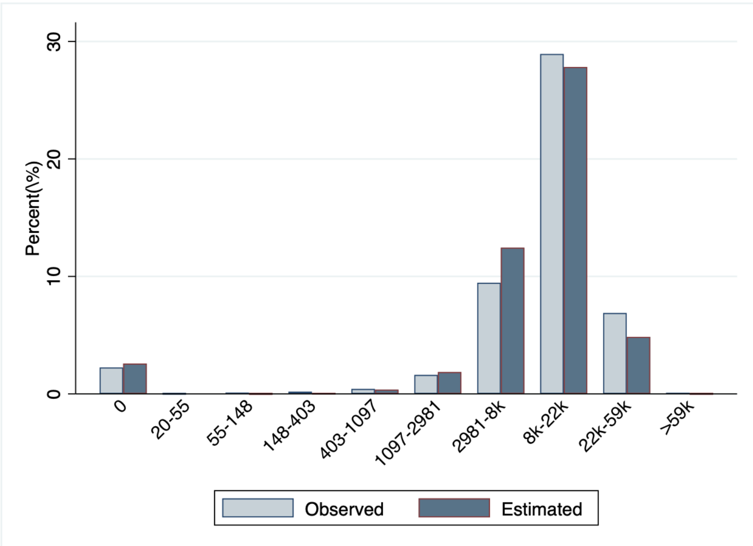
Several reasons explain why the estimated wealth distribution differs from the observed net worth data in the PSID. First, the PSID does not include precisely

[13]In the PSID I focus on individuals aged 26 to 64, you were ever insured and working for at least 1 quarter in 2015. The total assets that each family holds are constructed by summing the following asset types: business assets, checking and savings accounts, other real estate assets, stocks, vehicles, annuity/IRA, and other assets, net of debt values (business debt, other real estate debt, student loan debt, legal bills, credit card debt, family loan debt, and other debt), plus the value of home equity.

Figure 5: Model Fit: Earnings and Medical Spending Prediction



(a) Medical Spending

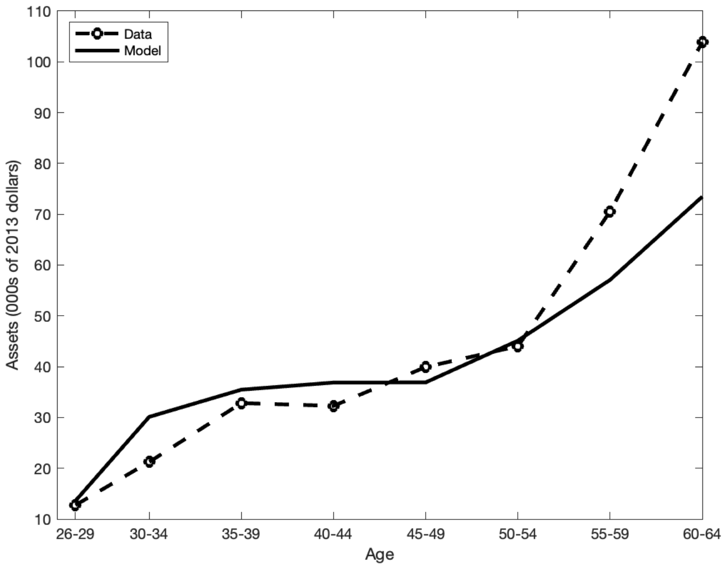


(b) Earnings

Notes: (a) presents the distribution of annual medical spending. (b) presents the distribution of total quarterly earnings, in the data and in model simulations based on the estimated parameters. The x-axis labels show the corresponding dollar amounts of selected bins.

the same information that I use to select my sample in the Utah data, such as months insured each year, employer-sponsored insurance access, and firm

Figure 6: Median Assets by Age Group



Source: 2015 Panel Study of Income Dynamics (PSID). Model Simulation. *Notes:* This figure compares median assets simulated by the life-cycle model in Section 5.2 and a similar sample from 2015 Panel Study of Income Dynamics.

linkages. Therefore, the two samples are similar but not identical. Second, the life-cycle model does not allow for borrowing or inter-generational transfers from parents, and it does not consider borrowing or house ownership, which is a significant component of net worth in US data. Moreover, the model does not perfectly account for social security changes and labor market variations across cohorts, as the joint earnings and medical spending dynamics are estimated using a short panel from 2013 to 2015.

6 Market Aggregation and Adverse Selection

To study how the incorporation of employment dynamics affects adverse selection, I aggregate individual-level WTP for health insurance to determine market demand. Specifically, I concentrate on a hypothetical market scenario involving the offering of one health insurance plan that covers 70 percent of medical costs, equivalent to the actuarial value of the Silver plan in the ACA

Marketplace.[14]

Individuals make their insurance decisions for year $y(t)+1$ during the last quarter of the previous year $y(t)$, without having information about their health and earnings types for year $y(t)$.[15] Additionally, I assume that individuals are perfectly liquid in year $y(t)$ and only consider combinations of employment types, rather than permutations. This assumption reduces the computational burden substantially from 2401 to 210 ($\frac{(7+4-1)!}{4!(7-1)!} = 210$ instead of $7^4 = 2401$). Additionally, I assume CRRA utility with a risk aversion parameter of 2, which is a common choice in the macroeconomics literature (Braun et al., 2017). The reason for considering individuals with the same risk preference is to isolate the impact of earnings dynamics from that of risk preference. Furthermore, I assume that individuals face a consumption floor at $5000 per year.

6.1 Models of Earnings Dynamics

As outlined in Section 3, various factors such as wealth levels and earnings dynamics can influence individuals' WTP for health insurance. To understand how each factor affects individuals' WTP for health insurance, I begin with the classical model and introduce different sources of heterogeneity among consumers. These include variations in wealth level, expected earnings, and earnings uncertainty. The models I consider are:

Model A: Classical Model. — I begin with the classical textbook model with a consumption floor. This model assumes that individuals only differ in their medical risks. Each individual i holds average assets of the sample $\bar{A} = \frac{1}{N}\sum_i A_i$. Moreover, each individual predicts that they will receive expected earnings $\bar{\mu}_{wt}$ with certainty. The calculation of $\bar{\mu}_{wt}$ involves two steps. First, individuals calculate the mean of their earning distribution.

[14]The decision to focus on this hypothetical market stems from two key reasons. First, it helps alleviate computational complexity, particularly in scenarios involving multiple plans within the market. Second, the majority of consumers opt for Silver plans in the marketplace. According to data from ASPE (2014), by March 2014, only 2% were enrolled in Catastrophic plans, 20% in Bronze plans (covering 60% of medical costs), 65% in Silver plans, 9% in Gold plans, and 5% in Platinum plans.

[15]Empirically, I focus on individuals without coverage from Medicaid or employer-sponsored insurance in the last quarter of 2014.

$$\mu_{iwt} = \int w_{it} f(w_{it}) dw_{it} \tag{8}$$

where w_{it} is earning realizations in different states. $f(w_{it})$ is the PDF of her predicted earning distribution. Second, the sample average is $\bar{\mu}_{wt} = \frac{1}{N}\sum_i \mu_{iwt}$.

Model B: Heterogeneous assets. — In this enhanced model, individuals face another source of heterogeneity: different initial accumulated assets A_i. Assets are simulated via the consumption-saving strategy in Section 5.2.

Model C: Heterogeneous Expected Earnings. — Individuals face differences in the expected earnings μ_{iwt} relative to the previous heterogeneous assets model.

Model D: Uncertainty in Earnings. — In this model, instead of facing the same expected earnings across states, individuals face the joint distribution of earnings and medical spending for period t as $f(w_{it}, m_{it})$. Individuals predict the joint distribution according to the model presented in Section 5.1.

6.2 Market Aggregation

In the health insurance market, N individuals must choose between a health insurance plan that covers 70% of medical expenses and being uninsured. Individual i calculates her WTP for the insurance plan as g_i. The expected medical costs of covering individual i is z_i. Insurers are assumed to be perfectly competitive.

Market Equilibrium. — The equilibrium premium p^* is thus the price under which insurers earn zero expected profits. The equilibrium take-up rate is the share of the people enrolled in insurance plan at the market equilibrium: $q^* = \frac{1}{N}\sum_i \mathbf{1}(g_i \geq p^*)$. where $\mathbf{1}(g_i \geq p^*)$ equals 1 if $g_i \geq p^*$. The consumer surplus at the equilibrium is $CS^* = \frac{1}{N}\sum_i[(g_i - p^*)\mathbf{1}(g_i \geq p^*)]$.

Because of the zero expected profits assumption, the producer surplus is 0. Therefore, the total surplus is simply the consumer surplus.

Social Efficiency. — The classical adverse selection model calculates the socially efficient take-up rate and premiums by finding the intersection between demand and marginal cost curves. However, when earnings dynamics are considered, the marginal cost curves may not be monotonic. Thus, an individual with a higher WTP does not necessarily face higher medical risk. This non-monotonicity creates difficulties when trying to identify the intersection.

Therefore, I consider a measure that requires no calculation of the intersection: it is socially efficient to cover individuals who are willing to pay more than their expected medical costs. The socially efficient take-up rate is $q^o = \frac{1}{N}\sum_i[\mathbf{1}(g_i \geq z_i)]$.

The deadweight loss under this measure is thus the consumer surplus of those who should be efficiently covered but who remain uninsured in the competitive equilibrium.

$$DWL^o = \underbrace{\frac{1}{N}\sum_i[(g_i - z_i)\mathbf{1}(g_i \geq z_i)]}_{\text{Socially Efficient CS}} - \underbrace{\frac{1}{N}\sum_i[(g_i - z_i)\mathbf{1}(g_i \geq p^*)]}_{\text{Competitive CS}} \tag{9}$$

6.3 Results

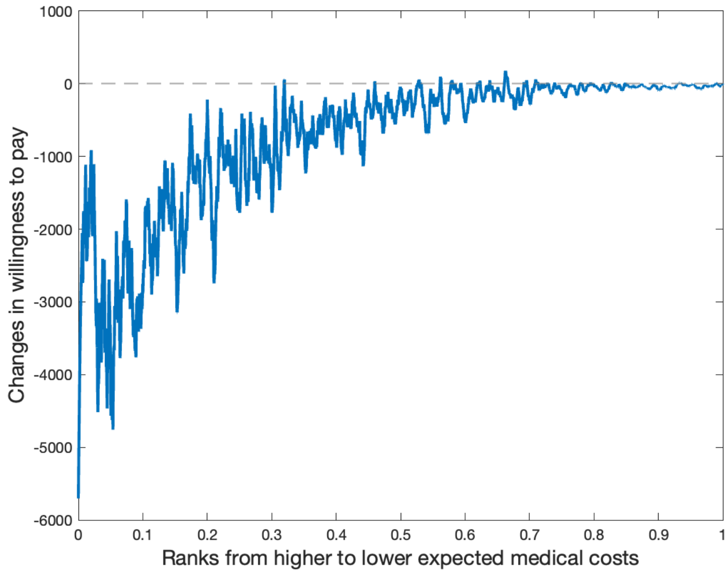
Changes in WTP Distribution. — Figure 7 presents heterogeneous changes in individuals' WTP, ranked by their expected medical costs.[16] As seen, introducing heterogeneity in assets, expected earnings, and earnings uncertainty results in a substantial reduction in the average WTP by −$461. Further, the decline is higher among individuals with higher medical costs.

One reason is that the consumption floor affects the WTP of sicker individuals more than healthier consumers. Further, the negative correlation between earnings and health risks implies that some sicker individuals earn lower incomes. Moreover, these individuals accumulate lower levels of assets due to adverse earning shocks that reduce their wealth. Given their disadvantaged financial situation, they are more likely to reach the consumption floor compared to healthier individuals.

Changes in Market Equilibrium. — As stated previously, employment dynamics significantly alter the WTP distributions. Thus, I will now discuss how the changes in WTP distributions affect adverse selection.

[16]The curves are smoothed with a Savitzky-Golay filter over each window of 30 points. This method smoothes according to a quadratic polynomial that is fitted over each window.

Figure 7: Impact of Earnings Dynamics on Willingness to Pay



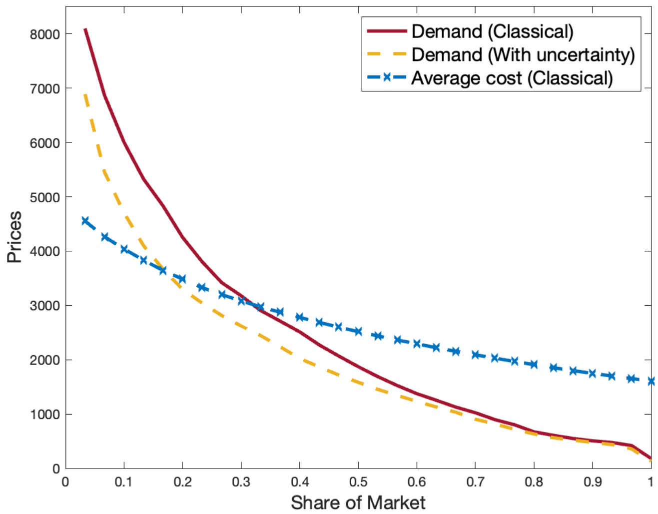
Source: Model simulation. *Notes:* This figure shows the changes in the WTP after introducing earnings dynamics (Model D) to Model A: Classical Model. The X-axis represents the rank of individuals by medical costs, ranging from the highest medical costs to the lowest. The details of the models are in Section 6.1.

In Figure 8(a), the demand curve shifts downward when introducing earnings dynamics to insurance demand, compared to the classical model where consumers only vary in medical risks. This is because the average WTP is lower after introducing earnings dynamics. This downward shift of the demand curve increases equilibrium prices and reduces the equilibrium take-up rate.

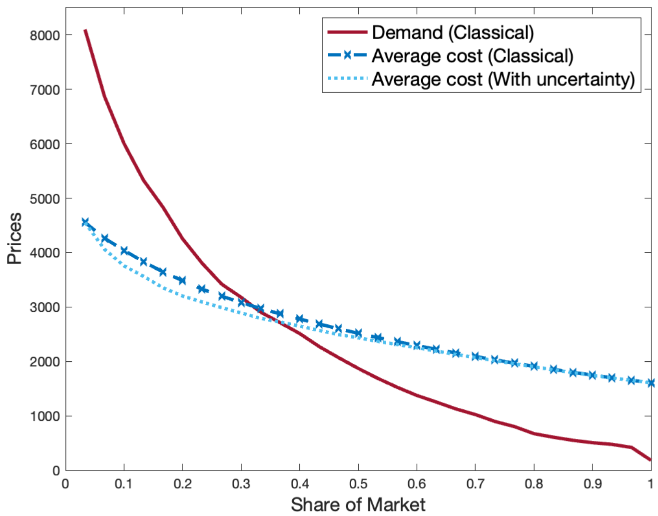
Additionally, earnings dynamics alter the pattern in the classical model where sicker consumers consistently have a higher WTP for health insurance. According to Figure 8(b), the average cost curve is flatter relative to the classical model. This is driven by higher WTP consumers now being a mix of sick and healthy individuals, resulting in reduced average costs. The effect counteracts the aforementioned changes to the demand curve: equilibrium price decreases, and equilibrium take-up rate rises. The net effect, theoretically, remains uncertain as to which force dominates, therefore empirical estimation is necessary.

Table 1 reports the main results for baseline scenarios (risk aversion $\gamma = 2$ and consumption floor $\underline{c} = 5000$) for Model A to Model D. Relative to the classical

Figure 8: Impact of Earnings Dynamics on Demand and Average Cost Curves



(a) Demand curve shifts



(b) Average cost curve changes

Source: Model simulation. *Notes:* (a) shows the demand curve changes and (b) shows the average cost curve changes. The details of the models are in Section 6.

model where consumers differ only in their medical risks, the introduction of heterogeneity in expected assets leads to a 2.1% increase in equilibrium take-up rate (column (1)) and a decrease in equilibrium premiums (column (5)) of $76. With the addition of differences in expected earnings, the equilibrium take-up decreases by 10.7%, accompanied by lower premiums of approximately $210. Next, when earnings uncertainty is added to the model, the equilibrium take-up rate drops by a further 1.78%. In total, relative to the classical model, the equilibrium take-up decreases by 10.3%, and premiums increase by around $100.

Furthermore, column (4) shows that employment dynamics also lead to a reduction in the socially efficient take-up rate by 15.6%. One driving factor is that the protection provided by the consumption floor significantly reduces WTP for health insurance. The negative correlation between earnings and medical spending makes protection from the consumption floor particularly valuable for low-income consumers. Therefore, some consumers' WTP, especially that of lower earners, is lower than the expected medical costs of insuring them, which echoes the findings of Finkelstein (2019a).

According to Table 1 column (6), the deadweight loss per person is just $17 relative to $259 in the classical model. The substantially lower deadweight loss comes from several sources. First, the lower WTP reduces the deadweight loss even when the socially optimal and market equilibrium allocation remains the same. Second, when it is socially optimal for fewer consumers to buy, the deadweight loss is reduced even when the WTP does not decrease and the market equilibrium allocation is unchanged. Third, consumers for whom it is socially efficient to purchase insurance but who refrain from doing so due to high prices now join the insured pool.

Finally, in Table F1 (Appendix E), I decompose the impact of the demand curve and the average cost curve. To understand how shifts in the average cost curve affect results, I keep the demand curve unchanged at the level of the classical model (Panel A). I find that a flatter average cost curve leads to a 3.8% higher take-up rate. According to Panel B, changes in the demand curve relative to the average cost curve in the classical model cause a decrease of around 15.94% in the take-up rate. These findings show the importance of considering both changes in the demand and average cost curves when evaluating how earnings

Table 1: Impact of Employment Dynamics on Market Equilibrium and Social Efficiency

	Equilibrium take-up			Socially efficient		
	Baseline	$\gamma = 3$	$\underline{c} = \$3000$	take-up	Premium	DWL
A. Classical model	0.3306	0.6106	0.3965	1	3075	259
	(0.0086)	(0.0088)	(0.0089)	(0.0000)	(41)	-7
B. Add heterogeneous assets	0.0211	0.0169	0.0192	0.0000	-76	-15
	(0.0053)	(0.0053)	(0.0053)	(0.0000)	(20)	-6
C. Add heterogeneous expected earnings	-0.1065	-0.0775	-0.0665	-0.0836	210	10
	(0.0068)	(0.0062)	(0.0071)	(0.0043)	(32)	(6)
D. Add uncertainty in earnings	-0.0178	-0.0306	-0.016	-0.0728	-34	-13
	(0.0053)	(0.0051)	(0.0069)	(0.0037)	(25)	(5)
Total	-0.1032	-0.0912	-0.0633	-0.1563	100	-17
	(0.0077)	(0.0070)	(0.0086)	(0.0055)	(34)	(6)
E. Allow ESI access to impact WTP	+0.0069	-0.0076	+0.0041	-0.0239	-75	-6
	(0.0041)	(0.0027)	(0.0042)	(0.0026)	(21)	(5)
F. Allow ESI access to impact insurers' costs	+0.2005	+0.1206	+0.1769	+0.0869	-1211	-41
	(0.0114)	(0.0072)	(0.0105)	(0.0045)	(56)	(10)

Source: Model simulation. *Notes:* This table shows the changes when adding earnings dynamics iteratively to the classical model, which only considers medical risks. More detailed introductions of the models are in Section 6.1. Furthermore, this table also shows the changes when ESI access is introduced iteratively to the model D. A detailed discussion of the model with ESI access and how I estimate the model can be found in Appendix G. γ is the risk aversion parameter of CRRA utility function. $\underline{c}$ is the consumption floor. In the Baseline model, $\gamma = 2$ and $\underline{c} = \$5000$ How to calculate equilibrium prices, take-up, socially optimal take-up rates, and deadweight loss are in Section 6.2. The standard deviations are generated using 50 bootstrap samples.

dynamics affect insurance market outcomes.

Robustness. — I begin by examining the robustness of my findings with a higher risk-aversion coefficient of 3; the results of which are in Table 1 column (2). Higher risk aversion increases WTP, resulting in a higher take-up rate in the classical model. However, the pattern of how earnings dynamics affect the market equilibrium take-up remains qualitatively similar to the baseline model.

I then explore how the level of the consumption floor affects my results by adjusting the consumption floor from \$5000 to \$3000 (column (3)). A lower consumption floor leads to an increase in WTP for insurance. However, the results still mirror the pattern observed in the baseline model. Overall, the impact of earnings dynamics on the equilibrium take-up rate is approximately 4% lower. This reveals that policies that alter the amount of protection individuals can receive from the safety net can influence the health insurance market.

Relation to Policy Designs. — When I incorporate earnings dynamics into the insurance demand model, sick individuals always have a high WTP for health insurance. This implies that the uninsured now include both healthy and sick individuals. This shift is particularly important in the context of subsidy design. Offering subsidies to the uninsured may attract both sick and healthy consumers, leading to a less significant reduction in average costs compared to the classical model. Section 7 will explore subsidy design in more detail.

6.4 Impact of Employer-Sponsored Insurance

One unique feature of the US health insurance market is that most people obtain health insurance through their employers. Consequently, if a consumer successfully finds a job in a firm that offers ESI, they can move from their current ACA private health insurance to ESI, which typically provides higher insurance coverage. Moreover, low-income individuals might qualify for Medicaid. A detailed discussion of the model with ESI access and how I estimate the model can be found in Appendix G.

Results. — Table 1 Model E shows that the changes in WTP due to employment transitions result in slight increases in the equilibrium take-up rate (column (1)) and minor decreases in equilibrium premiums (column (5)). These marginal effects are not surprising given the focus of this paper on uninsured individuals and those in firms without ESI. Additionally, employment is empirically stable over time. This stability results in a low likelihood of transitioning to ESI in subsequent years, thus having a limited impact on my findings. Furthermore, according to Model F, the possibility of transitioning to ESI and leaving the private insurance market reduces the expected annual cost of covering consumers in the private market. The equilibrium take-up increases by 20%, and premiums decrease by around $1211.

Comparison with Reality. —This counterfactual experiment diverges from the real-world ACA market in several aspects. First, in reality, employers are not obligated to provide ESI to all employees, even if they offer coverage to full-time workers. In the counterfactual analysis, I assume a 100% probability of obtaining ESI when transitioning to ESI-offering firms.[17] I make this assumption because of the lack of data on the part-time and full-time employment status of workers. Hence, I interpret the impact of employment transitions on WTP via coverage as an upper bound of the real impact.

Second, the Special Enrollment Period does not exist in my model. In reality, individuals losing ESI are eligible for a Special Enrollment Period to purchase ACA market insurance. If the share leaving and entering the ACA market is nearly equal, the insurer's costs should remain stable. My data limitation prevents accurate discussion of the above issues. Therefore, the extent to which employment transitions influence average costs is an empirical question for future investigation.

7 Subsidies in Models with Employment Dynamics

The Congressional Budget Office projected the Federal government would spend 1.1 trillion dollars for the nongroup marketplaces established under the ACA and the Basic Health Program over the 2024–2033 period (CBO, 2023). One

[17] According to the KFF Employer Benefit Survey (2013), about 80% of workers in firms offering ESI are eligible for it. However, employees at these firms tend to have a lower ability. Consequently, when they move to ESI-offering firms, they may be more likely to become part-time workers who are not eligible for ESI.

main economic objective of premium subsidies is to reduce adverse selection. In this section, I examine the efficiency of such a means-tested subsidy design in reducing adverse selection.

Subsidies influence adverse selection through several channels. First, lower premiums increase uninsured individuals' WTP and increase insurance take-up. I define the market equilibrium at this stage as "off-equilibrium".

Second, average insurance costs change as some uninsured individuals transition to being insured. In classical models, average costs typically *decrease* as switchers have lower expected healthcare spending. However, in models incorporating earnings dynamics, the impact on average costs is ambiguous.

Third, equilibrium premiums adjust based on changes in average costs. If premiums decrease, more consumers will purchase insurance. The process continues until insurers earn zero expected profits. I define the market equilibrium at this stage as "Equilibrium". A detailed descriptions of how subsidies work can be found in Appendix H.

Following Finkelstein et al. (2019b), I assume that WTP is the welfare-relevant metric for evaluating the welfare of the subsidy recipients. I also consider the social cost of taxation to fund the subsidies. Welfare per person is the difference between consumer surplus and the social cost of the subsidy. A detailed introduction of welfare calculation can be found in Appendix H.

Results. — Incorporating earnings dynamics, as discussed in Section 6, is likely to reduce the estimated WTP for sicker individuals, resulting in flatter average cost curves. This has theoretical implications for subsidy designs in private health insurance markets such as the ACA marketplace. In the classical model, subsidies consistently incentivize healthier consumers to enroll, reducing equilibrium premiums and deadweight loss significantly.

However, in models with earnings uncertainties, the group of uninsured may include sick consumers as well. As subsidies could induce sicker individuals to take-up insurance, the impact on equilibrium premiums, take-up rates, and deadweight loss is ambiguous. Moreover, means-tested subsidies, which offer higher subsidies to lower-income individuals, may not be as effective as in the classical model due to the negative correlation between health and earnings.

To shed light on this question, I first compare means-tested subsidies with a fixed subsidy that produces approximately the same costs for taxpayers.[18] Table 2 shows that an equivalently costly fixed subsidy, offered to all consumers, lowers take up by 47.2%—more than the 43.6% through a means-tested subsidy design. The deadweight loss is smaller and total welfare higher. Moreover, the changes between the off-equilibrium and equilibrium outcomes are much larger for the fixed subsidies than for means-tested subsidies.

Table 2: Counterfactual Subsidy Designs

	Off-equilibrium		Equilibrium		Public	DWL	Welfare
	Take-up	premium	Take-up	premium	cost	reduction	change
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Means-tested	0.3712	2511	0.4356	2491	114	96	781
	(0.0076)	(32)	(0.0075)	(31)	(4)	(7)	(19)
Fixed	0.3559	2822	0.4721	2570	114	100	785
	(0.0104)	(44)	(0.0087)	(31)	(4)	(9)	(19)
Public HI expansion	0.5745	2333	0.7654	1899	198	101	1355
	(0.0069)	(33)	(0.0062)	(29)	(5)	(9)	(22)

Source: Model simulation. *Notes:* This table compares three subsidy designs: means-tested, fixed, and a subsidy that combines both means-tested subsidies and public Health Insurance (HI) expansion. The off-equilibrium columns show the market equilibrium before adjustment of average costs due to new enrollees. The Equilibrium columns show the competitive market equilibrium after adjustment of average costs due to new enrollees. Public cost column reports the social cost of taxation to fund the subsidies, which is calculated by marginal cost of public funds (0.3 as in Einav et al. (2010)) and subsidies. Welfare per person is the difference between consumer surplus and the social cost of the subsidy. Welfare changes column shows how the welfare changes after subsidy is implemented. The standard deviations are generated using 50 bootstrap samples.

Motivated by the idea that subsidies granted to sicker consumers can reduce the effectiveness of subsidies in reducing adverse selection, theoretically, expanding public insurance to cover more low-income individuals–who are also more likely to be sicker on average–may improve the efficiency of ACA subsidies. I consider a two-step policy: First, policymakers offer individuals below 100% of the Federal Poverty Line (FPL) level with a 70% actuarial value public health insurance and then offer ACA income-based subsidies to the remaining eligible consumers.

[18] Empirically, the model only considers one health insurance plan with an actuarial value of 70%, which is the same for Silver plans in the ACA market. Details of ACA tax credit premiums is in Appendix E Table E1.

As seen in Table 2 column (7), such a policy would significantly increase welfare from \$781 to \$1355 per person. Several factors contribute to this welfare improvement. First, by extending public insurance to lower-income individuals who are often higher cost, the initial market becomes healthier. ACA subsidies incentivize healthier consumers to purchase insurance, significantly reducing market equilibrium premiums. Second, with lower equilibrium premiums, more subsidy-eligible consumers purchase insurance, resulting in a higher take-up rate. These findings underscore the importance of combining the Medicaid expansion with means-tested health insurance subsidies.

8 Conclusion

In this paper, I incorporate joint dynamics of earnings and medical spending into a standard model of individuals' insurance choices. First, from a theoretical perspective, I discuss how individuals decide between being uninsured and fully insured when facing uncertainty over earnings and medical spending. Second, using unique datasets—Utah All-Payer Claims Data and noise-infused earnings records—I empirically estimate individuals' WTP for health insurance. I then use a life-cycle model that accounts for earnings uncertainties to estimate their asset accumulation, given that wealth plays a key role in insurance decisions. Third, to study how earnings dynamics affect adverse selection, I aggregate individuals' WTP for health insurance to the market level. I document significant heterogeneity in the WTP distributions. Moreover, WTP is no longer a straightforward predictor of medical costs as in classical textbook models. By reducing the correlation between WTP and expected medical costs, I find that my model with earnings dynamics results in *lower* equilibrium take-up rates, and *higher* premiums, but a *lower* deadweight loss than a model abstracting from earnings dynamics.

Moreover, the fact that employment dynamics *reduce* the correlation between WTP and expected medical costs is crucial for policy design and subsidies. My counterfactual simulations show that ACA-style means-tested subsidies perform worse than an equivalently costly fixed subsidy. Furthermore, if public insurance covers everyone below 100% FPL (as originally foreseen by the ACA) and subsidies are only offered to people above 100% FPL, equilibrium take-up increases, premiums and the deadweight loss decrease significantly.

My findings point to several directions for future research. First, future work could incorporate moral hazard into a model of insurance demand with earnings risks. This is important for insurance demand models because wealthier people may demand more services than they need. Second, future work could incorporate marriage into the model. Marriage can be seen as one form of implicit insurance. Therefore, it may reduce insurance demand. However, assortative mating may also increase earnings dynamics heterogeneity at the family level, thereby making adverse selection worse in an insurance market. Third, my paper focuses on the extensive margin (the choice between being uninsured and insured). Allowing choices among plans with different levels of coverage could affect selection into different health insurance plans and corresponding optimal subsidy designs. Finally, future research could study the optimal adjustment of health insurance policies when the labor market is full of uncertainty, for example, during financial crises.

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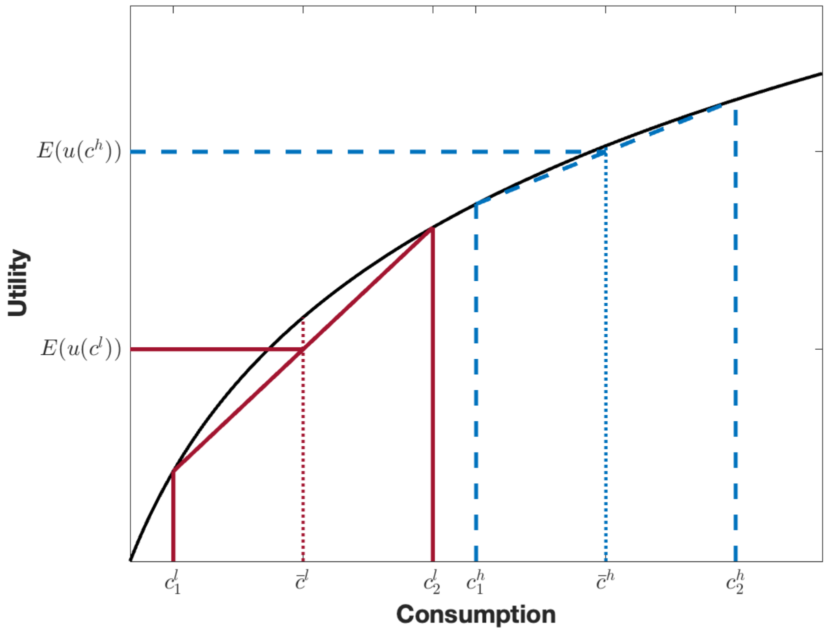
Appendix

A. Conceptual Framework: Further Details

Figure A1: Earnings Mean and Willingness-to-pay



Source: Own illustration. *Notes:* This figure demonstrates that individuals with a lower mean of earnings tend to have a lower expected utility of being uninsured. Facing the same level of earning uncertainty, if average consumption equals $\bar{c}^L$, the expected utility is $E(u(c^L))$. This is lower than $E(u(c^H))$, which is the expected utility when average consumption is $\bar{c}^H$.

B. Data: Further Details

Sample Selection: Further Details. — Table B1 shows sample size changes with sample selection steps.

Table B1: Sample Size Changes with Sample Selection Steps

Steps	Observations
Starting sample	2,999,382
Age 26 to 64	1,113,675
Person type construction	795,775
Labor force attachment	600,311
Observe health risk scores	473,783
Insured for at least 9 months	402,292
Never work for small firms	402,193
Firm type construction	402,123

Note: How sample size changes with sample selection steps.

Table B2 demonstrates the sensitivity of sample selection to the number of months insured. Utilizing a sample insured for at least 6 months each year yields similar parameters to those insured for at least 9 months when predicting medical spending using health type transitions. The estimation details can be found in Section 5.1.

Table B2: Sensitivity of Sample Selection on Insured Months

	h_t							
	1		**2**		**3**		**4**	
h_{t-1}	9 months	6 months	9 months	6 months	9 months	6 months	9 months	6 months
1	0.0000	0.0000	1.3405	1.3554	2.1744	2.1941	2.9976	3.0119
2	-0.0198	-0.0169	1.1561	1.1736	1.8334	1.8497	2.5746	2.5936
3	-0.0643	-0.0636	1.0948	1.1134	1.7268	1.7455	2.3759	2.3938
4	-0.5480	-0.5388	0.9447	0.9670	1.6586	1.6838	2.2686	2.2914

Notes: These parameters are estimated using equations 6 and 7, using health type transitions from h_{t-1} (year $t-1$) to h_t (year t) to predict log medical spending. This table compares the sample of people insured for at least 9 months (baseline) between 2013 and 2015, and a sample insured for at least 6 months.

Medical Spending Imputation. — Now I describe the details of how the medical spending for uninsured periods is imputed, which is summarized in

Section 4. The APCD dataset reports the utilization and corresponding medical spending related to inpatient care, outpatient care, professional services, and prescription drug fills. Total medical spending is calculated as the sum of these four categories. The imputed total spending is constructed using the multiple imputation method mentioned in the previous paragraph. This method aims to generate hypothetical total spending as if all individuals are always insured.

First, I calculate total medical spending per individual-month by summing over spending for inpatient, outpatient, professional services, and drug fills.

Second, I categorize the sample of interest into groups based on gender, age group, and health risk categories. I divide people into eight age groups based on their age in 2015: 26 to 29; 30 to 34; 35 to 39; 40 to 44; 45 to 49; 50 to 54; 55 to 59; and 60 to 64. Health risk categories are constructed based on risk scores calculated using Johns Hopkins ACG predictive medical software package. The sample is divided into seven health risk types with the following risk score threshold: below 0.25; 0.25 to 0.5; 0.5 to 1; 1 to 1.5; 1.5 to 2.5; 2.5 to 5; above 5. In total, individuals are grouped into 112 ($2 \times 8 \times 7$) cells.

Third, I construct the probability of incurring zero medical spending, the mean and variance of log total medical spending (sum of inpatient, outpatient, professional visits and prescription drug fills) for each cell. For each uninsured month, medical spending is simulated using the medical spending information of the same cell. I first simulate whether the month will incur positive medical spending. If simulated medical spending is positive, I simulate the medical spending using the estimated mean and variance of that cell.

Table B3 provides summary of variables used in medical spending imputation. The maximum values of medical spending are omitted to protect data privacy. The average age is 43.3 years in 2015. Roughly 50% are males. From 2013 to 2015, approximately 51% are always insured, while 57% have insurance for at least 9 months each year. The mean ACG risk scores are roughly 1.1, with the highest value around 19.

The average imputed medical spending falls roughly between the average total spending and the average total spending of always-insured individuals. This outcome is expected, as it successfully captures the different characteristics between the always-insured group and the rest, while imputing total spending as if individuals were insured for 12 months each year.

Figure B1 plots the joint distribution of log annual earnings and log annual medical spending of the sample using imputed medical spending. Both log earnings and log medical spending consist of observations stacked at zeros and a nearly normal-shaped component.

Table B3: Summary Statistics: 2013-2015 APCD

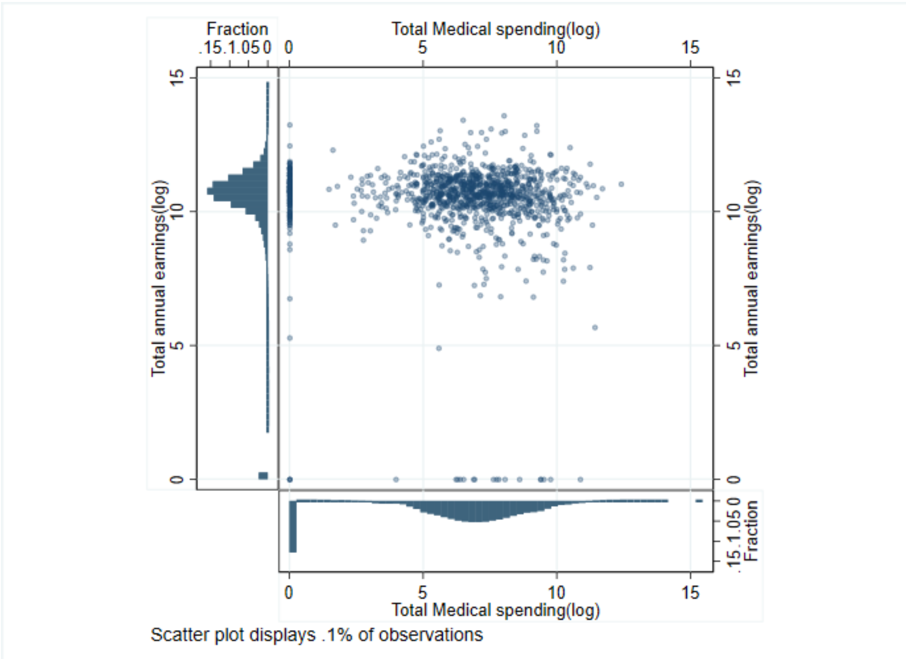
	Mean	Sd	Min	Max
Age (in 2015)	43.3488	11.2005	26	64
Male	0.4993	0.5000	0	1
Always insured	0.5142	0.4998	0	1
Insured for at least 9 months	0.5733	0.4946	0	1
Insured for at least 6 months	0.6145	0.4867	0	1
Insured months (in 2013)	8.6342	5.0183	0	12
Insured months (in 2014)	9.0239	4.7329	0	12
Insured months (in 2015)	9.6380	4.3067	0	12
ACG score (in 2013)	1.1185	2.3048	0	-
ACG score (in 2014)	1.1485	2.3416	0	-
ACG score (in 2015)	1.1890	2.4938	0	-
Inpatient	73.9168	4408.5527	0	-
Outpatient	93.6925	1023.1897	0	-
Professional services	121.7636	806.8555	0	-
Drug fills	73.3578	641.6271	0	-
Total spending	362.7307	4832.6572	0	-
Total spending(always insured)	424.0180	3331.0547	0	-
Total spending (imputed)	405.1293	4548.1675	0	-

Source: 2013-2015 Utah All-payer Claims Data. *Notes:* The maximum value of ACG score and medical spending in all categories are omitted for privacy protection.

Health, Worker, and Firm Types. — Figure B2 shows the distribution of ACG scores. The distribution is highly skewed, which is consistent with other papers in the literature (Atal et al., 2023).

Figure B3 presents the distribution of estimated worker and firm fixed effects using two-way fixed effects model. Both worker and firm fixed effects are approximately normally distributed.

Figure B1: Joint Distribution of Earnings and Medical Spending



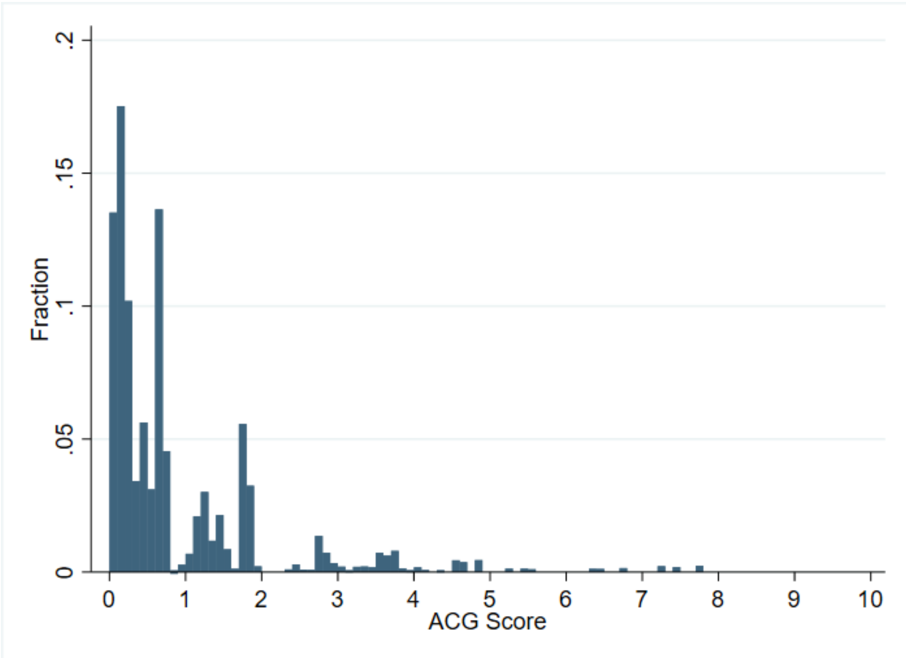
Notes: This figure shows the joint distribution of earnings and medical spending (in logs) (pooled years from 2013 to 2015).

Table B4: Descriptive Statistics by Health Status

	Total		Health type = 1		Health type = 2		Health type = 3		Health type = 4	
	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
Age (in 2015)	42.9865	10.7530	40.7891	10.2634	44.2649	10.6395	48.0698	9.7919	44.8891	11.7419
Male	53.7726	49.8575	61.9688	48.5464	50.2335	49.9995	41.4630	49.2659	34.7601	47.6209
Worker Type	5.4882	2.8304	5.9996	2.7842	5.2433	2.8018	4.4854	2.6548	4.6565	2.7569
Annual Medical Spending(000)	2.5466	4.4432	0.6076	1.5357	2.6597	3.6208	5.1356	5.1590	9.8909	6.9323
Quarterly Earnings	12916.8105	8886.0303	13190.3945	8889.4307	13024.8262	8860.5371	12827.8135	8959.8643	11136.8174	8660.8193
Quarterly Unemployed (%)	4.52	20.77	4.08	19.79	4.03	19.68	4.88	21.55	8.16	27.37
Work in ESI offer Firm	96.93	17.26	96.63	18.05	97.20	16.49	97.53	15.54	96.96	17.17
ESI offer firm: type 1 (%)	17.39	37.90	16.33	36.96	18.05	38.46	19.47	39.60	18.56	38.88
ESI offer firm: type 2 (%)	16.51	37.13	16.79	37.38	16.39	37.02	16.04	36.70	15.90	36.57
ESI offer firm: type 3 (%)	37.05	48.29	36.05	48.01	37.85	48.50	38.42	48.64	38.25	48.60
ESI offer firm: type 4 (%)	22.08	41.48	23.91	42.66	21.44	41.04	19.31	39.48	17.32	37.84
No ESI firm: type 1 (%)	1.39	11.69	1.50	12.16	1.28	11.25	1.14	10.60	1.40	11.74
No ESI firm: type 2 (%)	1.56	12.40	1.75	13.10	1.42	11.82	1.23	11.02	1.42	11.85
N	4,060,476		2,023,560		1,247,136		424,292		365,488	

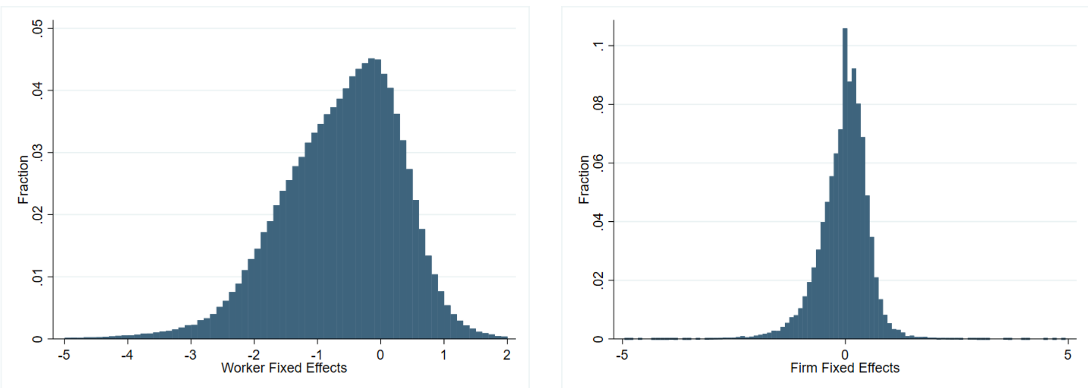
Notes: Larger health type stands for sicker consumers. Details of type construction are in Section 4.

Figure B2: Distribution of ACG Scores



Source: Utah 2013-2015 APCD dataset. *Notes:* This figure shows the distribution of ACG health risk scores (pooled years from 2013 to 2015). The distribution is cut under 10 (0.26% of individuals ever have an ACG risk score above 10).

Figure B3: Worker and Firm Fixed Effects Distribution



(b) Worker FE (c) Firm FE

Notes: This figure shows the distribution of estimated worker and firm fixed effects, estimated by equation (4) using two-way fixed effects model.

Table B5: Share of Firms Offering Employer-sponsored Insurance

Firm size	This paper	KFF Employer Benefit Survey (2013)
2-9	49%	45%
10-199	72%	75%
More than 200	100%	99%
All firms	59%	57%

Source: KFF Employer Benefit Survey (2013). *Notes:* ESI offer status is constructed according to the share of workers who have employer-sponsored insurance from their employers in each firm. For firms with employees between 2 and 10, firms are classified as ESI providers if the share of workers who have ESI exceeds 10%. Firms with more than 10 employees are classified as ESI providers if at least one worker receives ESI from her employer.

C. Model of Earnings and Medical Spending: Further Details

Estimation of Earnings and Medical Spending. — In practice, I exclude the top 2.5% of high medical spenders and the top 1% of high earners in the sample to reduce the impact of extreme values.

Table C1 presents the probability of realizing zero medical spending, while Table C2 reports the additional selected parameters in earnings and medical spending predictions. Individuals with higher ability types tend to predict higher earnings. Working in a higher-paying firm is associated with higher predicted earnings. Moreover, firms that do not offer employer-sponsored insurance are associated with relatively lower earnings, indicating a positive correlation between non-wage compensation and earnings level.

Table C3 reports the standard deviation of errors in medical spending and earning predictions. A lower ability type is associated with a higher variance in earnings errors.

Table C1: Probability of Realizing Zero Medical Spending

	h_{t+1}			
h_t	**1**	**2**	**3**	**4**
1	0.2959	0.0009	0.0005	0.0003
2	0.1332	0.0004	0.0001	0.0000
3	0.1088	0.0002	0.0001	0.0001
4	0.1281	0.0006	0.0002	0.0001

Source: Utah 2013-2015 APCD dataset. *Notes:* These parameters are estimated using equation (6) for the impact of health type transitions between h_t (year t) and h_{t+1} on realizing zero medical spending.

Estimations of Employment Transition Probabilities. — First, the probability of employed depends on health type transitions $H_{i,t+1}$, past employment type l_{it} and k_{it}, person ability types a_i, age groups, and gender, according to the

Table C2: Extra Parameters for Earnings and Medical Spending

Panel A: Earnings Prediction

Person type		Employment type	
2	0.8346	2	0.4855
	(0.0043)		(0.0047)
3	1.2362	3	0.8935
	(0.0040)		(0.0040)
4	1.5213	4	1.3224
	(0.0039)		(0.0043)
5	1.7624	5	-0.0273
	(0.0038)		(0.0111)
6	1.9580	6	0.7218
	(0.0039)		(0.0095)
7	2.1538		
	(0.0038)		
8	2.3537		
	(0.0038)		
9	2.5751		
	(0.0037)		
10	2.9350		
	(0.0037)		
Constant	4.0166		
	(0.0139)		

Panel B: Medical Spending Prediction

	Coefficients
Past year had zero medical spending	1.2325
	(0.0106)
Past year log medical spending	0.2697
	(0.0015)
Male	-0.3720
	(0.0105)
Constant	4.3839
	(0.0113)

Notes: These parameters are estimated using equations (6) and (7). For Panel A, the reference type is person type 1 and employment type 1.

Table C3: Errors in Medical Spending and Earnings Predictions

Panel A: Medical Spending Errors

	h_t			
h_{t-1}	**1**	**2**	**3**	**4**
1	1.3429	1.0998	1.0833	0.9238
2	1.3093	1.0069	0.9372	0.8840
3	1.3370	1.0075	0.8883	0.8262
4	1.3763	1.0710	0.8996	0.8341

Panel B: Earnings Errors

	Employment type					
Person type	**1**	**2**	**3**	**4**	**5**	**6**
1	0.7089	0.6405	0.5604	0.5242	0.6702	0.7340
2	0.4797	0.3692	0.2970	0.3300	0.5584	0.4452
3	0.4126	0.3235	0.2766	0.3044	0.5264	0.4205
4	0.3778	0.3157	0.2711	0.2890	0.4990	0.4279
5	0.3471	0.2995	0.2624	0.2880	0.5347	0.4107
6	0.3477	0.2890	0.2520	0.2781	0.5215	0.4057
7	0.3252	0.2681	0.2381	0.2662	0.4905	0.3712
8	0.3139	0.2545	0.2225	0.2593	0.4920	0.3454
9	0.2966	0.2400	0.2224	0.2655	0.5025	0.3423
10	0.3507	0.3185	0.3011	0.2926	0.5420	0.3402

Notes: This parameters are the sample standard deviations of prediction errors in equation (6) and (7).

Table C4: Test: Error assumptions

Panel A: Medical Spending				
	Mean	Sd	Min	Max
Errors	0.0000	1.1473	-7.0761	5.8517
Simulated errors	0.0005	1.1470	-6.0147	5.9306
	(0.0020)	(0.0016)	(0.3668)	(0.3107)
Panel B: Earnings				
	Mean	Sd	Min	Max
Errors	0.0000	0.3527	-3.3579	3.0086
Simulated errors	0.0000	0.3527	-3.0763	3.0713
	(0.0002)	(0.0016)	(0.2144)	(0.2163)

Notes: This table compares the estimated transitory errors for medical spending and earnings according to equations (6) and (7) with the simulated errors based on the assumption they are normally distributed. Details can be found in Section 5.1.

following logit regression:

$$Pr(I_{i,t+1}) = \gamma_0 + H_{i,t+1}\gamma_h + a_i\gamma_a + f(l_{it}, k_{it})\gamma_k + X_{i,t+1}\gamma_x + \epsilon^I_{i,t+1} \tag{10}$$

where $Pr(I_{i,t+1})$ is the probability of being employed in quarter $t+1$, given information at time t. $H_{i,t+1}$ represents transitions between past health type and current health type. $f(l_{it}, k_{it})$ represents the employment type defined by employment status I_{it} and firm types k_{it}. a_i is the person ability type. $X_{i,t+1}$ includes age group, gender and time fixed effects.

Second, conditional on being consistently employed from period t to $t+1$, I consider the probability of changing employers, which is assumed to depend on past firm types, age group, person ability type, and health type transitions.

$$Pr(d_{i,t+1}) = \beta_0 + H_{i,t+1}\beta_h + a_i\beta_a + k_{it}\beta_k + X_{i,t+1}\beta_x + \epsilon^d_{i,t+1} \tag{11}$$

where $Pr(d_{i,t+1})$ is the probability of being job movers in quarter $t+1$.

Finally, conditional on being employed, individuals further predict the types of their new employers in period $t+1$ if they change employers from t to $t+1$. There is no need to predict the firm-type transitions if the individuals are stayers because the firm types will remain unchanged. I assume that, for movers, the transition probabilities of firm types depend on gender, age group, person ability types, current health type, past employment types. The transitions are estimated using a multinomial logit model as follows:

$$Pr(k_{i,t+1}) = \omega_0 + H_{i,t+1}\omega_h + a_i\omega_a + f(I_{it}, k_{it})\omega_k + X_{i,t+1}\omega_x + \epsilon^k_{i,t+1} \tag{12}$$

where, $Pr(k_{i,t+1})$ is the probability of working for firms with type $k_{i,t+1}$ in quarter $t+1$. $f(I_{it}, k_{it})$ is employment types of past period t.

Table C5: Probability of Unemployment and Job Changes by Health Transitions

Panel A: unemployment				
	h_{t+1}			
h_t	1	2	3	4
1	0.0148	0.0135	0.0162	0.0277
2	0.0155	0.0140	0.0158	0.0225
3	0.0176	0.0148	0.0163	0.0206
4	0.0240	0.0197	0.0188	0.0238
Panel B: job mover				
	h_{t+1}			
h_t	1	2	3	4
1	0.0189	0.0191	0.0184	0.0142
2	0.0213	0.0204	0.0188	0.0176
3	0.0244	0.0217	0.0201	0.0201
4	0.0182	0.0223	0.0233	0.0218

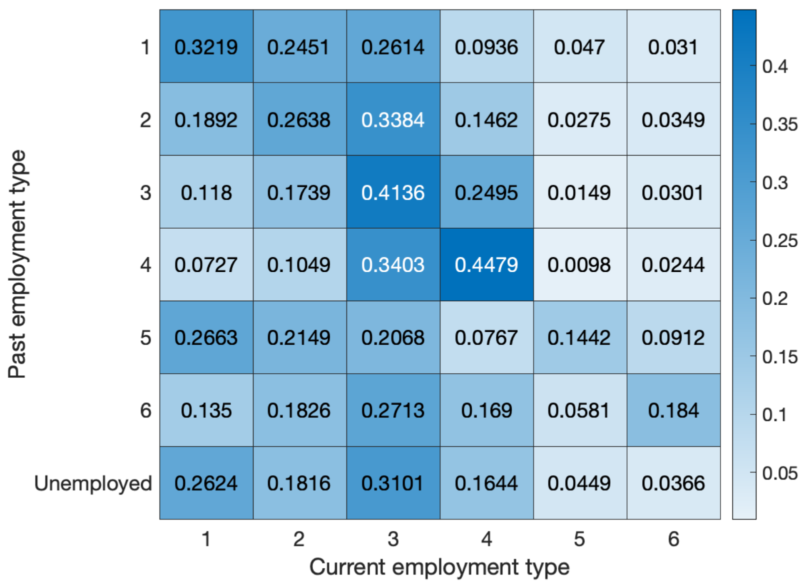
Notes: These parameters are the probability of unemployment and being a job mover by health status (transitions from h_t to h_{t+1}). The transitions are evaluated at the means of all variables except year, which is set to 2015. 1 stands for the healthiest group, and 4 stands for the sickest group.

Table C6: Probability of Unemployment and Job Changes by Worker Types

Worker type	Unemployment	Job mover
1	0.0613	0.0476
2	0.0319	0.0352
3	0.0253	0.0285
4	0.0203	0.0241
5	0.0167	0.0209
6	0.0134	0.0186
7	0.0105	0.0158
8	0.0086	0.0141
9	0.0073	0.0122
10	0.006	0.0086

Notes: These parameters are the probability of unemployment and being a job mover by worker types. The transitions are evaluated at the means of all variables except setting year to 2015. 1 refers to the lowest worker type, and 4 indicates the highest worker type. Details of type construction are in Section 4.

Figure C1: Firm Transitions



Notes: Firm type transition matrices, evaluated at the means of control variables. Details of type construction can be found in Section 4.

D. Life-cycle Model: Further Details

This section offers more details about the life-cycle model used to estimate assets in Section 5.2.

Individual i aims to maximize her expected lifetime utility from the tth quarter of her life after birth until the last quarter at age 100. Individuals optimize their expected lifetime utility by choosing consumption c. Each quarter, the individual's utility depends solely on consumption, with the flow utility from consumption represented by the Constant Relative Risk Aversion (CRRA) utility function.

Since assets are not directly observed in the data, I assume individuals save according to a life-cycle model, starting in the labor market at age 26 with zero assets. All individuals will die at age 100 with a probability of 100% and derive no utility from assets after death, implying no bequest motive in this saving model.

Retirement begins in the first quarter of age 65, and individuals receive constant paychecks from social security each quarter until their death. I assume individuals' earnings predictions follow the earnings determination equation 5 and the transition matrices in Section 5.1.[19] Further, I assume individuals to have health insurance with zero premiums and an actuarial value of π (covering the π share of all medical spending).

The next period's assets are then given by:

$$A_{t+1} = A_t + \tau_t(rA_t + w_t) - (1-\pi)m_t + b_t - c_t \tag{13}$$

Where w_t stands for earnings at period t and A_t are assets at the beginning of t. $\tau_t(rA_t + w_t)$ denotes post-tax income, with $\tau_t(.)$ standing for a function that maps pre-tax with post-tax income. Assets have to satisfy a borrowing constraint: $A_t \geq 0$. βm_t is the out-of-pocket medical spending. b_t denotes government transfers. I also assume government transfers b_t to individuals to provide a consumption floor at $\underline{c}$.

[19]This implies that individuals make current saving decisions without adjusting their beliefs about: (1) the person earning level types and the firm's earning level types; (2) the transition matrices of job mobility and health statuses.

$$b_t = \max\{0, \underline{c} - [A_t + \tau_t(rA_t + w_t) - (1-\pi)m_t]\} \tag{14}$$

The value function for a single individual of type δ_t is then given by

$$V_t(A_t, \delta_t, w_t, m_t) = \max_{c_t, A_{t+1}} \{u(c_t) + \beta s_t E_t V_{t+1}(A_{t+1}, \delta_{t+1}, w_{t+1}, m_{t+1})\} \tag{15}$$

subject to equations 13 and 14. s_t stands for the probability that an individual is alive at period $t+1$, conditional on gender and being alive at period t. w_{t+1} are the predicted earnings in $t+1$ that are associated with possible type realization δ_{t+1} and random draws of log earnings residuals. m_{t+1} is the predicted medical spending for the next quarter.

When estimating, the problem is redefined in terms of cash on hand x_t to save on state variables. I then rewrite the problem as follows. The value function for a single agent is:

$$V_t(x_t, \delta_t, w_t, m_t) = \max_{c_t, x_{t+1}} \{u(c_t) + \beta s_t E_t V_{t+1}(x_{t+1}, \delta_{t+1}, w_{t+1}, m_{t+1})\} \tag{16}$$

subject to:

$$x_t = A_t + \tau(rA_t + w_t) + b_t - (1-\pi)m_t \tag{17}$$

$$A_{t+1} = x_t - c_t \tag{18}$$

$$x_{t+1} = x_t - c_t + \tau(r(x_t - c_t) + w_{t+1}) + b_{t+1} - (1-\pi)m_{t+1} \tag{19}$$

To enforce the consumption floor, I impose that for all t: $x_t \geq \underline{c}$. And the non-negative assets require $c_t \leq x_t$.

Empirically, I estimate consumption and savings using a risk aversion parameter of 2, a consumption floor of $\bar{c} = 1250$, $r = 0.5\%$ (with annual interest rate of 2%), $\beta = 0.9951$, and $\pi = 80\%$. After age 65, women receive \$3293 and men receive \$4589 per quarter.[20]

[20] I calculate these numbers using Table 5.J3 from the Annual Statistical Supplement, 2014: https://www.ssa.gov/policy/docs/statcomps/supplement/2014/5j.html$#$table5.j3

E. Affordable Care Act Introduction

This section summarizes the subsidy, known as the Premium Tax Credit, under the Affordable Care Act (ACA). The ACA caps the amount that individuals who eligible for the tax credit must pay for monthly insurance premiums in the Health Insurance Marketplace. The amount of the tax credit an individual receives is based on their income and household information. The eligibility criteria and generosity of this subsidy in 2017 are detailed in Table E1. The final amount of the tax credit each person receives is determined by their actual yearly income, and any adjustments are made when they file their federal income tax return.

Table E1: Affordable Care Act Tax Credit Premium Cap for Single Individuals, by Income in 2017

Income % Poverty Level	Income $	Premium Cap
<100%	<11,880	No Cap
100% - 133%	11880 - 15800	2.04%
133% - 150%	15800 - 17820	3.06% - 4.08%
150% - 200%	17820 - 23760	4.08% - 6.43%
200% - 250%	23760 - 29700	6.43% - 8.21%
250% - 300%	29700 - 35640	8.21% - 9.69%
300% - 400%	35640 - 47520	8.21% - 9.69%
Over 400%	Over 47520	No Cap

Source: Kaiser Family Foundation. *Notes*: This table presents the tax credit premium cap by income in 2017 under the Affordable Care Act. The premium cap is the maximum percent of the income one must pay for the second-lowest Silver plan available to their area.

I then present an example to help illustrate how the tax credit is calculated. We consider a person with an income of $\$30,000$, which is 253% of the federal poverty level. This person's income contribution is 8.28% of income, which means that the maximum premium this person will have to pay is $\$2,485 = \$30,000 \times 8.28\%$ annually for the second-lowest-cost Silver plan. This person can receive a tax credit if that plan's premium is higher than $\$2,485$. If the premium is $\$4,485$, then this person receives $\$4,485 - \$2,485 = \$2,000$ in annual tax credits.

In summary, if a person's income is too high to be eligible for the subsidy, even if his willingness to pay for the plan is low, he will not receive the tax credit. However, if an individual's willingness to pay for the plan is higher than the equilibrium premium, but he is eligible to receive the tax credit, he would still benefit from a price reduction.

F. Adverse Selection: Further Details

Table F1: Separate Impact of Demand Curves and Average Cost Curves Changes

Panel A: changes in Average cost curves

	Equilibrium take-up			Premiums	Deadweight
	Baseline	$\gamma = 3$	$\underline{c} = \$3000$		Loss
A.Classical model	0.3306	0.6106	0.3965	3075	259
	(0.0086)	(0.0088)	(0.0089)	(41)	(7)
B.Add heterogenous assets	+0.0008	+0.0018	+0.0039	-8	-2
	(0.0011)	(0.0018)	(0.0018)	(7)	(2)
C.Add heterogenous expected earnings	+0.0315	+0.0132	+0.0193	-237	-4
	(0.0060)	(0.0041)	(0.0042)	(27)	(7)
D.Add uncertainty in earnings	+0.0055	-0.0005	+0.0063	-38	-18
	(0.0037)	(0.0011)	(0.0028)	(23)	(6)
Total	+0.0379	+0.0145	+0.0295	-283	-24
	(0.0054)	(0.0047)	(0.0045)	(23)	(6)

Panel B: changes in Demand curves

	Equilibrium take-up			Premiums	Deadweight
	Baseline	$\gamma = 3$	$\underline{c} = \$3000$		Loss
A.Classical model	0.3306	0.6106	0.3965	3075	259
	(0.0086)	(0.0088)	(0.0089)	(41)	(7)
B.Add heterogenous assets	+0.0198	+0.0155	+0.0161	-64	-11
	(0.0052)	(0.0051)	(0.0053)	(18)	(5)
C.Add heterogenous expected earnings	-0.1412	-0.1056	-0.0955	+530	-12
	(0.0108)	(0.0074)	(0.0081)	(58)	(10)
D.Add uncertainty in earnings	-0.0381	-0.0422	-0.0416	+184	+0.73
	(0.0073)	(0.0060)	(0.0069)	(38)	(8)
Total	-0.1594	-0.1323	-0.1210	+650	-22
	(0.0098)	(0.0077)	(0.0097)	(58)	(88)

Source: Model simulation. *Notes:* This table shows the changes when adding earnings dynamics iteratively to the classical model, which only considers medical risks. More detailed introductions of the models are in Section 6.1. γ is the risk aversion parameter of the CRRA utility function. $\underline{c}$ is the consumption floor. In the Baseline model, $\gamma = 2$ and $\underline{c} = \$5000$. How to calculate equilibrium prices, take-up, socially optimal take-up rates, and deadweight loss is described in Section 6.2.

G. Model with Employer-sponsored Insurance (ESI) Access

This section introduces the details of the insurance demand model with ESI access.

I consider an ACA-style insurance product that covers ξ of the medical costs when the individual is enrolled. Individuals do not have to stay enrolled in this insurance for an entire year. They will switch to ESI that covers ξ^E of total medical spending at p^E per quarter if they move to a firm that offers employer-sponsored insurance. If they lose their ESI, as long as they purchase the insurance at the beginning, they can freely rejoin the private insurance plan. However, if they choose not to buy the insurance, regardless of changes in their employment status, they will never have access to this private insurance plan during the year. I abstract the impact of Medicaid into a consumption floor without explicitly modeling it.

Their decision problem changes to the following. If the individual i chooses to be uninsured ($I_t = 0$), the expected utility is:

$$EU_{I_{it}=0} = \int_{w_t} \int_{m_t} u(\max[A_t + w_t - (1 - \frac{q^E \xi^E}{4})m_t - q^E p^E, \underline{c}]) f(w_t, m_t) dm dw \tag{20}$$

Where, $\frac{q^E \xi^E}{4}$ is the coverage individual i receives at period t, which varies with employment realizations. $q^E p^E$ is the premium paid for q^E quarters under the coverage of employer-sponsored insurance.

However, if he purchases health insurance ($I_t = 1$) priced at p, his expected utility is:

$$EU_{I_t=1}(p) = \int_{w_t} \int_{m_t} u(\max[c_t, \underline{c}]) f(w_t, m_t) dm dw \tag{21}$$

where $c_t = A_t + w_t - (1 - \frac{q^E \xi^E + (4-q^E)\xi}{4})m_t - (q^E p^E + (4 - q^E)p)$

Because individual i chooses to be insured with the insurance product that covers ξ of medical costs, the coverage changes to $\frac{q^E \xi^E + (4-q^E)\xi}{4}$, and the premium to be paid changes to $q^E p^E + (4 - q^E)p$.

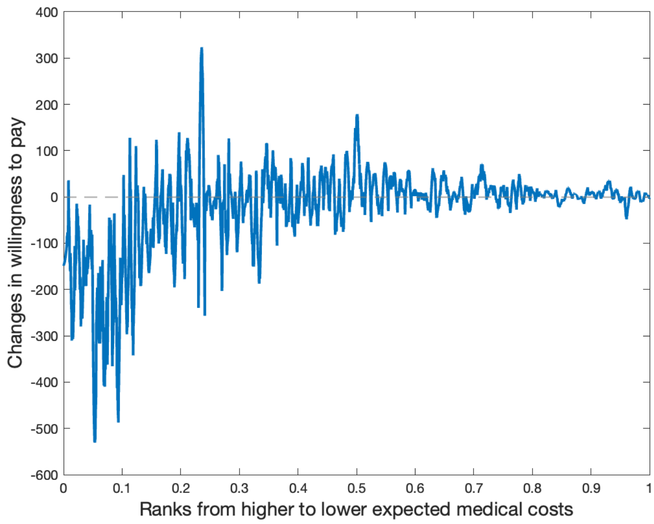
Note that the impact of employment transitions on WTP is theoretically ambiguous. Choosing not to purchase the specific product of interest reduces the duration of periods an individual remains uninsured, affecting WTP for health insurance. This implicit protection reduces the incentive to buy private health insurance. Moreover, individuals do not have to commit to paying the premium for private insurance for the entire year, unlike in a model excluding ESI access. Consequently, individuals may accept a higher quarterly price.

Additionally, insurers' costs in covering individuals in the private insurance market may change if they account for employment dynamics. Individuals may leave the private insurance market upon acquiring ESI. I analyze the costs of private insurers, assuming they only participate in an ACA-style private insurance market. In that context I assume individuals cannot enroll outside the open enrollment period.

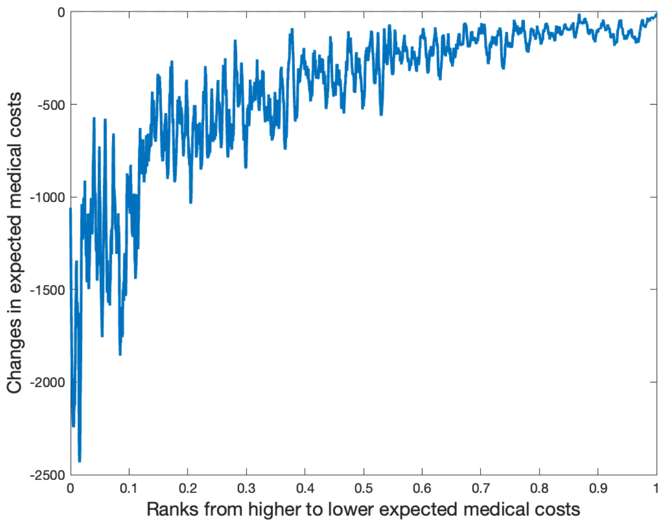
In the empirical analysis ξ is set at 70%, which is the actuarial value of the Silver plan in the ACA market. All employers offer the same employer-sponsored insurance that covers $\xi^E = 77.8\%$ of the total medical costs at a price of $p^E = \$162.45$ per quarter. [21]

[21] ESI actuarial value is inferred from the out-of-pocket payment and medical spending of employees in Utah, and 77.8% is the average of all observed employer-sponsored plans. The premiums are not directly observable in the dataset. Therefore, the premium of employer-sponsored insurance plan is estimated in the following steps: first, I calculate the average expected medical costs of all employees in employer-sponsored offering firms. The value is 1044$ per quarter. Second, I assume workers contribute to 20% of the total costs covered under an ESI that covers 77.8% of all total medical costs. The final premium per quarter is thus $1044 \times 0.778 \times 0.2 = \$162.45$.

Figure G1: ESI Access and Changes in WTP Distribution



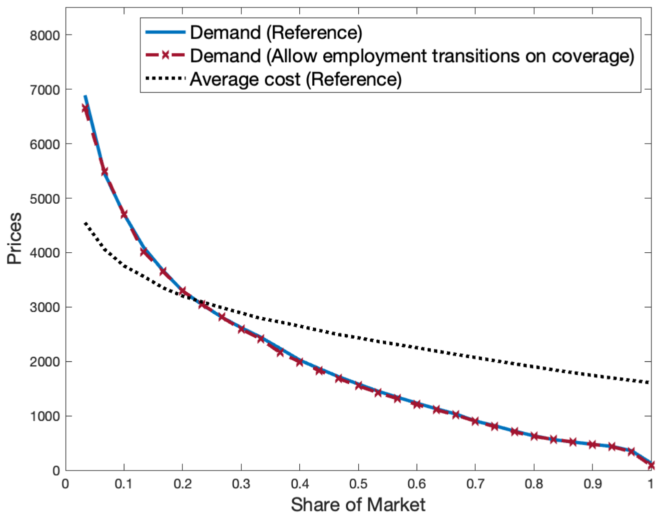
(a)



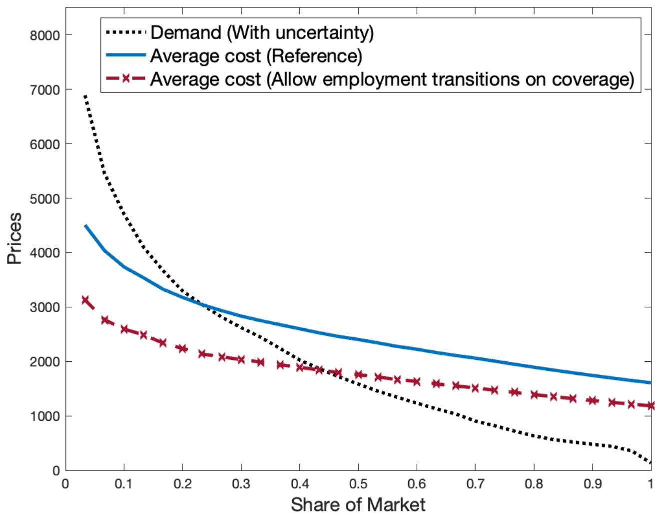
(b)

Source: Model simulation. *Notes:* (a) presents the WTP changes when considering how employment transitions affect the length under private insurance coverage. (b) shows the expected medical cost of covering each individual when allowing employment transitions to affect private insurance coverage.

Figure G2: ESI Access and Adverse Selection



(a)



(b)

Source: Model simulation. *Notes:* (a) and (b) show the changes in demand curve and average cost curves, respectively.

H. How Subsidies Work

In this section, I introduce the details of how subsidies work to reduce adverse selection.

I define the new equilibrium premium after subsidies as p^*_{after}. The change in the equilibrium premium because of subsidies is $\Delta p^* = p^*_{after} - p^*$. Individuals now face individualized premiums, on the basis of p^*_{after}, which is $\hat{p}^*_{i,after} = \max(p^*_{after} - k_i, 0)$.

The changes in equilibrium take-up rate:

$$\Delta q = \underbrace{\frac{1}{N}\sum_i \mathbf{1}(g_i \geq \hat{p}^*_{i,after})}_{\text{Equilibrium take-up after subsidies}(q_{after})} - \underbrace{\frac{1}{N}\sum_i \mathbf{1}(g_i \geq p^*)}_{\text{Equilibrium take-up before subsidies}(q_{before})} \tag{22}$$

The changes in consumer surplus are:

$$\Delta CS = \underbrace{\frac{1}{N}\sum_i (g_i - \hat{p}^*_{i,after})\mathbf{1}(g_i \geq \hat{p}^*_{i,after})}_{\text{Consumer surplus after subsidies}(CS_{after})} - \underbrace{\frac{1}{N}\sum_i (g_i - p^*)\mathbf{1}(g_i \geq p^*)}_{\text{Consumer surplus before subsidies}(CS_{before})} \tag{23}$$

The reductions in deadweight loss are $\Delta DWL = DWL_{before} - DWL_{after}$, where the deadweight loss before subsidies is:

$$DWL_{before} = \frac{1}{N}\sum_i (g_i - z_i)\mathbf{1}(g_i \geq z_i) - \frac{1}{N}\sum_i (g_i - z_i)\mathbf{1}(g_i \geq p^*) \tag{24}$$

The deadweight loss after subsidies is:

$$DWL_{after} = \frac{1}{N}\sum_i (g_i - z_i)\mathbf{1}(g_i \geq z_i) - \frac{1}{N}\sum_i (g_i - z_i)\mathbf{1}(g_i \geq \hat{p}^*_{i,after}) \tag{25}$$

I also consider the social cost of taxation to fund the subsidies. Only individuals who are both eligible for subsidies and purchase insurance will receive subsidies. The social cost of the subsidies is thus:

$$\lambda \frac{1}{N} \sum_i (p^*_{after} - \hat{p}^*_{i,after}) \mathbf{1}(g_i \geq \hat{p}^*_{i,after}) \tag{26}$$

where λ is the marginal cost of public funds. I use $\lambda = 0.3$ as the (standard estimate of) the marginal cost of public funds (Einav et al., 2010). Welfare per person is the difference between consumer surplus and the social cost of the subsidy.