Earnings Dynamics and Selection in Health Insurance Markets*

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February 28, 2025

Abstract

This paper uses Utah All-payer Claims Data linked to 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 14.7% and increases the premium by 3.8%. 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 dynamics; Means-tested subsidy policy

JEL Classifications: G22; I11; I13; I18.

*I am grateful to Kurt Lavetti and Nicolas R. Ziebarth for their guidance and support. I would like to extend thanks to Tamar Oostrom, Bruce Weinberg, Alex Hollingsworth, Meta Brown, Véra Zabrodina, Justin Sydnor, Ashley Swanson, Keith M. Ericson, and seminar participants at the Ohio State University, ZEW Mannheim, O'Neill School of Public and Environmental Affairs at Indiana University, 2020-2021 CSWEP Health Econ/Health Policy Mentoring Workshop, 2023 ASHEcon Conference, 2023 European Winter Meeting of the Econometric Society, 2024 Annual Conference of the European Society for Population Economics, 2024 EEA-ESESM conference, and 51st Seminar of the European Group of Risk and Insurance Economists. I am grateful to the Utah Office of Health Care Statistics for the data that made this research possible and would like to also thank the William Green Memorial Fellowship for their financial support. All errors are my own.

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1 Introduction

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 (Abowd and Card, 1986; Meghir and Pistaferri, 2004a; Hoffmann et al., 2022; 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 insurance market equilibrium is crucial for designing effective public policies to combat adverse selection. In the classical model where individuals only differ in medical risks, 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 than healthier ones.[1] Sicker consumers may remain uninsured, and subsidies may induce sicker consumers to take up insurance. Consequently, subsidies may theoretically reinforce adverse selection.

This paper is among the first to empirically examine how expected earnings

[1] Even if individuals face the same medical risks, their WTP for health insurance may differ if they face different earnings dynamics. The correlation between earnings and medical expenditures affects WTP: when individuals expect to experience low earnings and high medical expenses simultaneously, their WTP is higher than in a model that assumes zero correlation between the two. The intuition is that a negative correlation reallocates resources from low-resource states to high-resource states, which is undesirable for risk-averse individuals. The consumption floor is also an important component of WTP. Specifically, earnings dynamics shape how much protection individuals can obtain from the consumption floor. See Section 2 for more theoretical discussion.

and earnings uncertainty influence insurance demand. I also explore how heterogeneity in earnings dynamics affects adverse selection and the design of means-tested subsidies. While prior studies suggest that higher-income individuals have greater insurance demand (Mahoney, 2015; Finkelstein et al., 2019b; Nardi et al., 2016; Geruso et al., 2023), less attention has been given to how earnings and health risks interact to shape demand and market-level adverse selection. One exception is Lockwood (2024), who studies individual-level valuation of health insurance using sufficient statistics and highlights how healthcare costs interact with other risks to alter insurance's protective value. Building on these insights, this paper examines the implications for adverse selection and subsidy design.

Using Utah All-Payer Claims Data and earnings records, I estimate individual-level WTP via a binary insurance demand model that jointly considers earnings dynamics and medical risks. Individuals face uncertainty about health risks, job mobility, and earnings levels when making insurance decisions. My approach relates to the literature on 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, 2004b; Altonji et al., 2013), but differs by incorporating health status to capture the joint dynamics of earnings and medical expenditures.

Since savings serve as an alternative to insurance for consumption smoothing, I simulate asset accumulation using a life-cycle model of optimal consumption and savings. To account for the social safety net, I incorporate a consumption floor, as prior literature has illustrated its influence on the demand for health insurance by providing protection from bankruptcy (Mahoney, 2015) and uncompensated care (Garthwaite et al., 2018). This paper highlights that earnings dynamics shape reliance on these transfers: individuals with lower expected earnings or higher earnings uncertainty anticipate a greater likelihood of receiving support from the consumption floor, potentially reducing their incentive to purchase insurance.

My findings show that incorporating earnings dynamics into insurance demand models significantly alters the joint distribution of WTP and expected medical costs. Compared to classical models, heterogeneity in assets, expected earnings, and earnings uncertainty leads to substantial reductions in WTP, especially among sicker consumers. Expected budget heterogeneity (assets + expected earnings) accounts for 78% of the total average WTP decline, while earnings uncertainty explains the remaining 22%. Additionally, many consumers

have a WTP *lower* than their expected medical costs, aligning with prior literature (Finkelstein et al., 2019a,b). I extend these insights by linking them to adverse selection and subsidy design in private health insurance markets.

Next, I aggregate individual WTP to the market level to analyze equilibrium and efficiency. Compared to classical models, incorporating earnings dynamics shifts the demand curve downward, reducing the estimated equilibrium take-up rate and increasing premiums. However, earnings dynamics also weaken the relationship between WTP and medical costs, flattening the average cost curve, which counteracts some of these effects by increasing take-up and lowering premiums. On net, the equilibrium take-up rate decreases by 14.7%, while premiums rise by 3.8%.

Moreover, introducing heterogeneity in earnings dynamics significantly reduces the socially optimal take-up rate. Since WTP changes when earnings dynamics are considered, deadweight loss (DWL) is not always a reliable measure of adverse selection—it can decrease either due to lower WTP or because the allocation becomes more socially efficient. To better assess efficiency, I use an alternative measure: the share of optimal total surplus gained, calculated as the ratio of equilibrium total surplus to socially efficient total surplus. This measure declines progressively as heterogeneity in assets, expected earnings, and earnings uncertainty are incorporated into the insurance demand model, highlighting the importance of accounting for earnings dynamics when estimating optimal health insurance allocations.

A key contribution of this paper is highlighting how the weakened relationship between WTP for insurance and expected medical costs affects subsidy policy design. Uninsured individuals are no longer necessarily healthier, meaning subsidies could increase adverse selection by attracting sicker consumers. To assess the efficiency of means-tested subsidies, I compare an ACA-style subsidy policy with a uniform subsidy of equivalent cost. I find that uniform subsidies significantly increase take-up rates. I also examine an alternative policy that combines public insurance expansion (e.g., Medicaid expansion) with means-tested subsidies. Compared to means-tested subsidies alone, this approach raises the equilibrium take-up rate by 16.2%, reduces premiums by 9.1%, and lowers deadweight loss by 10.9%. Despite higher costs, it increases net welfare by 38.3%, because public insurance expansion covers a large share of low-income, higher-risk individuals, allowing subsidies to attract healthier consumers more effectively.

These results have policy implications for the U.S. and other regions. Using

the ACA-style private insurance market as a case study, I underscore the need to jointly consider earnings, job mobility, and health risks when designing policies to mitigate adverse selection. This study contributes to the 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) examine adverse selection among higher-income employees and argue for integrating distributional consequences into subsidy design. My work extends this by analyzing how earnings uncertainty and job mobility influence adverse selection and subsidy design in ACA-style markets. Another closely related paper, Tebaldi (2024), proposes targeting subsidies toward younger consumers. My study instead evaluates a counterfactual policy that combines means-tested subsidies with public insurance expansion for low-income individuals, who are often sicker. This aligns with the central insight of Tebaldi (2024): structuring subsidies to attract healthier consumers improves overall welfare.

This paper contributes to the literature on short-term insurance demand modeling. Some studies address data limitations by assuming a CARA utility function to exclude income effects while incorporating income heterogeneity in risk preferences (Einav et al., 2013; Handel, 2013; Marone and Sabety, 2022). Others, following Einav et al. (2010), estimate WTP using price variations. 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 approaches limit analysis of how earnings dynamics influence adverse selection and means-tested subsidies. My model explicitly integrates the joint distribution of earnings and medical spending into insurance demand, allowing for a clearer distinction between risk preferences and earnings dynamics. This makes it more suitable for evaluating means-tested policies, especially in environments with income fluctuations.

This paper also contributes to the literature on the interaction between health insurance and labor markets. Prior studies examine the economic consequences of health shocks (Dobkin et al., 2018; Charles, 2003; Poterba and Wise, 2017; Meyer and Mok, 2019; Fadlon and Nielsen, 2021) and job lock under the U.S. employer-sponsored insurance system (Currie and Madrian, 1999; Gruber and Madrian, 2002). My work differs by integrating correlated health and economic risks into an insurance demand model and analyzing how earnings dynamics shape 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

to assess the ACA's labor market effects. Aizawa and Fu (2024) incorporates local market, household, and firm heterogeneity to evaluate cross-subsidization policies. My paper complements this literature by incorporating earnings uncertainty—stemming from employment transitions, firm changes, and on-the-job wage variation—into insurance demand models. While my approach captures rich heterogeneity in earnings and medical spending without explicitly modeling labor supply, job search, or employer insurance decisions, it is more applicable to private health insurance markets beyond the U.S. 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 contributes to the literature on real-world insurance markets that deviate from classical models. Previous work has examined multidimensional private information (Fang et al., 2008), administrative costs and preference heterogeneity (Einav and Finkelstein, 2011), background risks (Doherty and Schlesinger, 1983; Meyer, 1992; Hong et al., 2011; Deshpande and Lockwood, 2022; Loubergé and Dionne, 2024; Lockwood, 2024), market segments Dickstein et al. (2024), liquidity constraints (Ericson and Sydnor, 2018), behavioral biases (Handel, 2013; Domurat et al., 2021; Drake et al., 2022; Saltzman, 2021), selection on moral hazard (Einav et al., 2013), and reclassification risk (Handel et al., 2015; Ghili et al., 2024; Atal et al., 2025; Fleitas et al., 2018). I extend this literature by analyzing earnings dynamics, which are crucial for improving means-tested policies like subsidies and mandates. This focus helps assess how safety nets and labor market shocks affect health insurance markets, particularly during economic downturns when earnings uncertainty can amplify adverse selection problems.

2 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) and Hong et al. (2011). The primary distinction between this model and Einav et al. (2010) is that I explicitly allow consumers with identical risk preferences to differ in their medical risks, expected earnings, and earnings uncertainty. I further modify the framework presented in Hong et al. (2011) to analyze an insurance market with a single coverage option. This framework enables a discussion on why, in models with

earnings dynamics, individuals facing the same medical risk may have different WTP for insurance.

2.1 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 period $t+1$. The PDFs of the marginal distributions of earnings and medical spending are denoted as $f(w_{t+1})$ and $f(m_{t+1})$, respectively. The second variable, A_{t+1}, represents the assets that an individual holds at the beginning of period $t+1$.

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 that covers b of the medical costs at a price of p per year or remain uninsured. Earnings reductions are not insurable in this model, as health insurance covers only 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:

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

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

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

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 4.1 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 4.2, I outline my approach for estimating the assets that individuals hold when making insurance choices.

2.2 Intuition: Earnings Distribution and WTP

In this section, we examine the conceptual reasons why individuals' ex-ante WTP may differ even when they face the same medical risk, particularly when future earnings are incorporated into insurance decisions. For simplicity, I consider a *full* insurance model ($b = 0$) when earnings and medical spending are joint normally distributed, and discuss the intuition on why four key parameters matters for individual-level WTP: (1) the variance of earnings represented by $\sigma_w^2 = \int (w_{t+1} - \mu_w)^2 f(w_{t+1}) dw$, (2) the correlation between earning and medical spending denoted as ρ, (3) initial assets A_{t+1}, and (4) consumption floor $\underline{c}$.

2.2.1 The Variance of Earnings

I begin by assuming that earnings and medical spending are independent, that is, $\rho = 0$. On the one hand, earnings variance affects the the expected utility of being uninsured, on the other hand, it also influences the expected utility cost of a premium.

Proposition 1. Consider a risk-averse individual with a Constant Relative Risk Aversion (CRRA) utility function with risk aversion of γ: $u(x) = \frac{x^{1-\gamma}}{1-\gamma}$, with $\gamma > 0$ & $\gamma \neq 1$, and $u(x) = ln(x)$ when $\gamma = 1$. The individual's WTP for a full insurance plan is higher when $\sigma_w > 0$ than when $\sigma_w = 0$.[2]

[2]According to Eeckhoudt and Kimball (1992), the demand for insurance against one risk is not independent of the background risk, even when the risks are uncorrelated. Many seminal theoretical papers build on this insight and examine optimal insurance demand in the presence of background risk (e.g., Meyer, 1992; Dionne and Gollier, 1992; Eeckhoudt et al., 1996; Guiso

Proof. see Appendix. [3]

2.2.2 Correlation between Earnings and Medical Spending

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).

Proposition 2. A negative correlation between earnings and medical spending unambiguously increases the WTP, while a positive correlation reduces the WTP.
Proof. See Appendix. [4]

The intuition is that the negative correlation reallocates resources from low-resource states to high-resource states, which risk-averse 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. [5]

2.2.3 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.

2.2.4 Consumption Floor

So far, my discussion of how earnings dynamics affect WTP assumes that individuals never reach the consumption floor. However, the consumption

and Jappelli, 1998; Gollier, 1995; Tibiletti, 1995; Gollier and Pratt, 1996; Meyer and Meyer, 1998; Mahul, 2000; Loubergé and Dionne, 2024).

[3] Appendix, I also show that earnings variance does not affect WTP when utility function is Constant Absolute Risk Aversion (CARA) utility function.

[4] Under less restrictive conditions, correlation coefficient is not adequate to investigate insurance demand. See Hong et al. (2011) for more discussion.

[5] Notice, because of the potential correlation between earnings and medical spending, even if we assume CARA utility function, earnings distribution may still affect WTP.

floor serves as a safety net, transferring wealth to individuals who experience extremely low-resource states. Its presence further influences WTP for health insurance, as individuals with different earnings dynamics receive different level of protection from it. For instance, those with lower average earnings, more volatile earnings, or a negative correlation between earnings and medical expenses are more likely to encounter states with lower resources than the consumption floor.

2.3 Intuition: Heterogeneous WTP and Adverse Selection

In a model where all consumers in an insurance market differ *only* in medical risks, and no one ever reaches the consumption floor, consumers with higher medical risks will always have a higher WTP. This results in a monotonic linear marginal cost curve.

However, introducing heterogeneity in earnings distributions can change this dynamic. As discussed in the previous section, individuals facing the same medical risks may hold different WTP for health insurance if their earnings distributions differ. Consequently, in a market where consumers face varying joint distributions of earnings and medical spending, those with higher medical risks may have a lower WTP compared to those with lower medical risks. This deviation disrupts the monotonicity of the marginal cost curve. Furthermore, the average cost curve may also be affected. In Section 5, we will examine whether and how the average cost curve shifts when heterogeneous earnings among consumers are considered within the empirical setting of this paper.

3 Data

I use two primary data sources: (2) the Utah All-Payer Claims Dataset (APCD) from 2013-2015, (2) linked to aggregated noise-infused administrative earnings records for jobs covered by unemployment insurance (UI) constructed by the Utah Department of Workforce Services.

The Utah Office of Health Care Statistics constructed the APCD administrative database using records submitted by all commercial insurance companies. These records include detailed information on insurance enrollment plans, enrollment dates, individual demographics, and medical, drug, and dental claims. The APCD captures data for nearly all commercial insurance plans, including ACA exchange plans, employer-sponsored insurance, individual and small group

plans, and Medicaid managed care plans. While traditional Medicare enrollees are not included in the database, this limitation is not significant for this study, as the focus is on working-age adults (under age 65) who are generally ineligible for traditional Medicare.

I use administrative medical and drug claims records to calculate medical spending at individual level. The APCD includes basic demographic information for each individual, such as an (anonymized) individual identifier, gender, age, race, and ethnicity. However, as is common with administrative health records, in the 2013–2015 APCD, race and ethnicity data are missing or unknown for a substantial portion of the population-65%. As a result, this study does not utilize race or ethnicity information. To generate predictive risk scores summarizing expected healthcare spending, all claims are processed using the Johns Hopkins ACG Software v13.0. This software examines combinations of medical diagnosis codes, procedure codes, and prescription drug records to create these indicators.

Moreover, I use an earnings file customized by the Utah Department of Workforce Services. They begin by calculating each worker's total earnings from all jobs for each quarter. Next, they group workers into permilles (1,000-quantiles) based on their total quarterly earnings and report the average total earnings for each permille in that specific quarter. To protect privacy, this aggregation process introduces some measurement error. However, the error resulting from this process is significantly smaller than the typical measurement error associated with survey-based earnings data.[6]

The connections between workers and firms in each quarter are constructed as follows. A worker is associated with a firm if they earn a positive amount from that firm during the quarter. For workers with multiple jobs in a quarter, the Utah Department of Workforce Services defines a primary firm as the one providing the highest quarterly earnings among all jobs. Firm IDs are directly observed in the APCD for workers with employer-sponsored health insurance, which accounts for 81% of our analysis sample. For the remaining firms, Online Appendix A presents the details on the process used to construct firm IDs based on the structure of the earnings data. Ultimately, we achieve one-to-one matches between workers and firms for each working quarter.

[6]Between 2013 and 2015, the average width of a permille bin—representing the maximum potential measurement error introduced by binning—was \$17 for the median earner, equivalent to just 0.2% of the median quarterly earnings (\$7,288).[7] By contrast, Abowd and Stinson (2013) find that linking self-reported earnings in the Survey of Income and Program Participation (SIPP) to administrative W-2 records reveals an average discrepancy of 10–30%.

3.1 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.[8] 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.[9]

3.2 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 Online Appendix A.

3.3 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.

Health Types. — Recall that 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

[8] 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 A2).

[9] Online Appendix A introduces more details in sample selection criteria. Table A1 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.

costs (Handel, 2013; Einav et al., 2013). Figure A2 (Online Appendix A) reveals the highly-skewed ACG risk score distribution.

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.[10]

Table 1 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.[11] 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 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 1 (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).

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

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

Table 1: 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)	43	11	41	10	44	11	48	10	45	12
Male	53.78	49.86	61.97	48.55	50.2335	50.00	41.46	49.27	34.76	47.62
Worker Type	5.49	2.839	6.00	2.780	5.240	2.800	4.49	2.65	4.66	2.76
Annual Medical Spending(000)	2.55	4.44	0.61	1.54	2.66	3.62	5.14	5.16	9.89	6.93
Quarterly Earnings	12917	8886	13190	8889	13025	8861	12828	8960	11137	8661
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 3.

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 A4 (Online 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.[12]

In Figure 1 (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.

4 Preparation for WTP Estimation

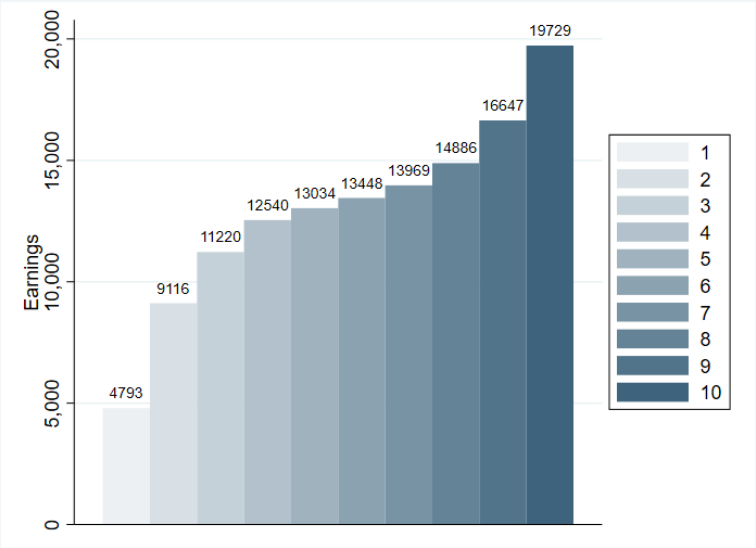
The estimation of WTP (g_{t+1}), as defined by the model in Section 2.1, requires estimating two key components. First, I estimate the joint distribution of earnings and medical spending. Second, I use this estimated distribution to develop a life-cycle model for simulating asset accumulation.

4.1 Model of Earnings and Medical Spending

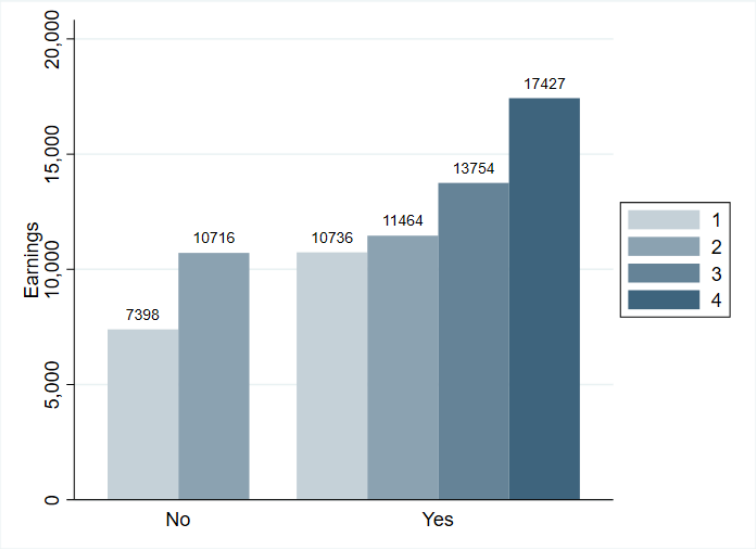
Given the complexity of how individuals predict joint distribution for next period, instead of modeling distribution with mean, variance, and correlation coefficient, I consider the following approach. First, individuals begin by predicting the probabilities of realizing various health and earnings types in the next period. Second, conditional on each potential health and earnings type, they then forecast the possible realizations of earnings and medical spending, $f(w_{t+1}, m_{t+1})$. This approach, where individuals first predict types before forecasting specific realizations of earnings and health spending, is inspired by

[12] 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 1: Earnings by Worker and Firm Types



(a) By Worker Types



(b) By Firm Types

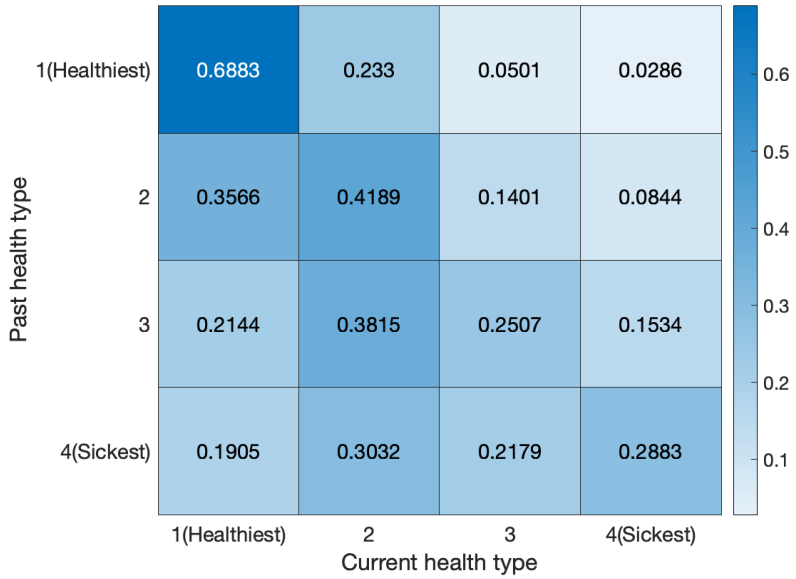
Notes: This figure shows the average quarterly earnings by worker types and firm types. Numbers are estimated by taking the average of all workers in each group. (a) shows the increases in average quarterly earnings when the estimated worker type is higher. (b) shows the increases in average quarterly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

Abowd et al. (2019), Atal et al. (2025) and Bonhomme et al. (2019).

4.1.1 Step 1: Health and Employment Transitions

Individual i is assumed to predict the probability of each possible combination of earnings and medical spending through two steps. First, the individual predicts the probability of transitioning to each health type in period $t+1$, based on their past health type, gender, and age. Second, conditional on each potential health type in $t+1$, the individual predicts whether they will be employed. If employed, they estimate the likelihood of changing employers. If they change employers, they predict the probability of working for each type of firm. Following Atal et al. (2025), I estimate these probabilities by modeling the transitions observed in the 2013–2015 data using a multinomial logit framework. Additional details are provided in Online Appendix B.

Figure 2: Health Type Transitions



Notes: Health type transition matrices, evaluated at means of control variables.

Figure 2 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 B5 (Online Appendix B) 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 B6 (Online Appendix B) shows that individuals with lower worker types tend to lose jobs and change employers. Figure B1 (Online Appendix B) shows strong persistence in firm transitions for job movers.

4.1.2 Step 2: Earnings and Medical Spending

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.[13]

Next, individual i predicts whether the medical spending is positive or not according to a logit model in equation (6).[14] Then, conditional on positive medical spending, she predicts the medical spending according to equation (7).

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

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

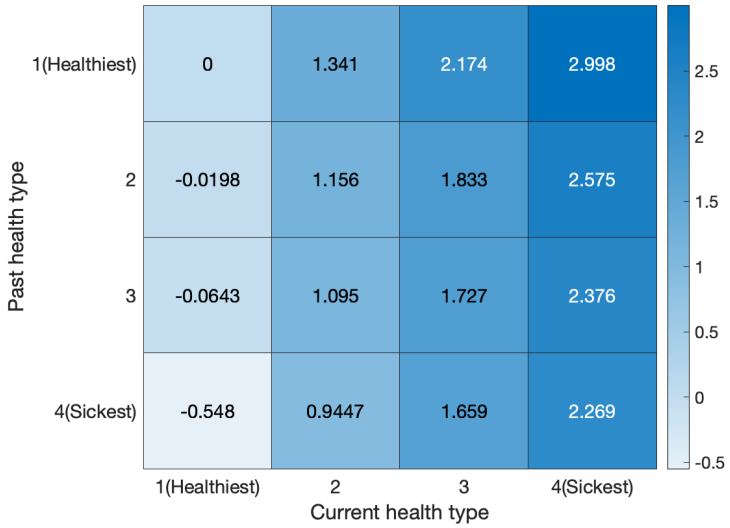
where $H_{iy(t+1)}$ are the health type transitions between past and current year. $m_{iy(t+1)}$ and $m_{iy,(t+1)-1}$ are the annual log total medical spending in current and past year. $\delta_{iy(t+1)}$ equals one if the previous year occurs zero medical spending. $x_{iy(t+1)}$ represents age, gender types and year fixed effects. Finally, $\nu_{iy(t+1)}$ is a transitory shock.[15]

[13] The ϵ_{it} is heteroscedastic and normally distributed with mean 0. I further assume that individuals believe that the log earning residuals are random draws from a normal distribution $N[0, var(\hat{\epsilon}(k_{it}, a_i))]$, where $var(\hat{\epsilon}(k_{it}, a_i))$ 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 Online Appendix B, Table B4.

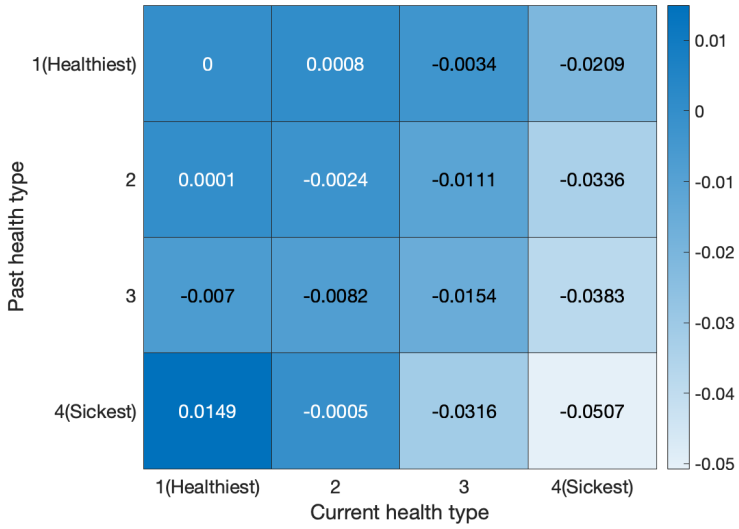
[14] Because health risk scores are calculated based on annual risk scores, individual i is assumed to predict medical spending at annually level for year that contains quarter $t+1$: $y(t+1)$.

[15] $\nu_{iy(t+1)}$ 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

Figure 3: 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.

Figure 3 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.

The correlation between medical spending and earnings appears small based on the estimates in Figure 3. However, this correlation is partially driven by the opposing effects of health transitions on these levels. Moreover, health transitions also influence employment transitions, as estimated in Section 4.1.1.

4.1.3 Model Fitness

Figure 4 (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.

4.2 Life Cycle Model with Precautionary Savings

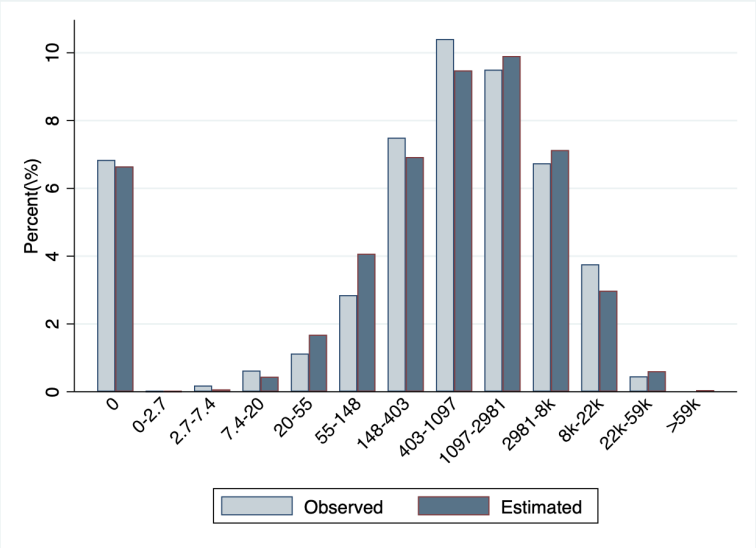
As discussed in Section 2, individuals hold assets before making insurance decisions. Assets are an important object for estimating the WTP for health insurance. However, I do not observe assets directly. Thus, I follow the literature to simulate wealth using a life-cycle model (Carroll, 2006; Nardi 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 4.1. 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 Online Appendix C.

Figure 5 compares the median of simulated assets by age groups with a similar sample from the Panel Study of Income Dynamics (PSID), public use dataset.[16] I further assume that married couples equally share the households'

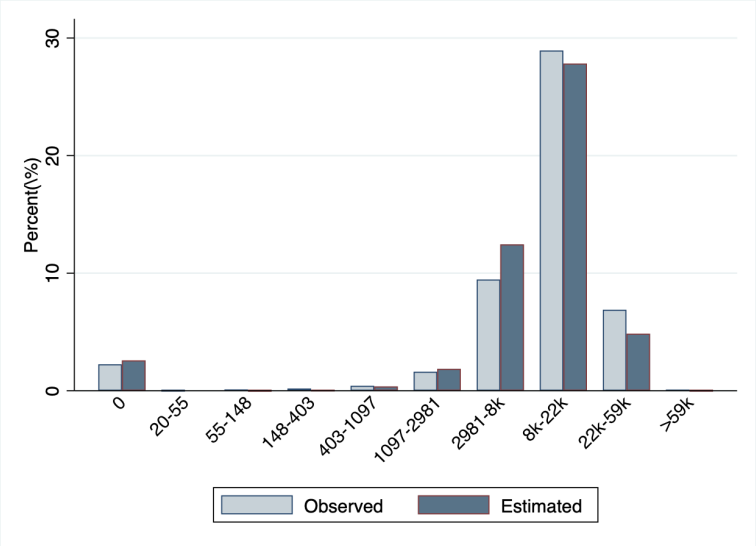
on prediction accuracy is discussed in Online Appendix B, Table B4.

[16] In the PSID I focus on individuals aged 26 to 64, that 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

Figure 4: Model Fit: Earnings and Medical Spending Prediction



(a) Medical Spending



(b) Earnings

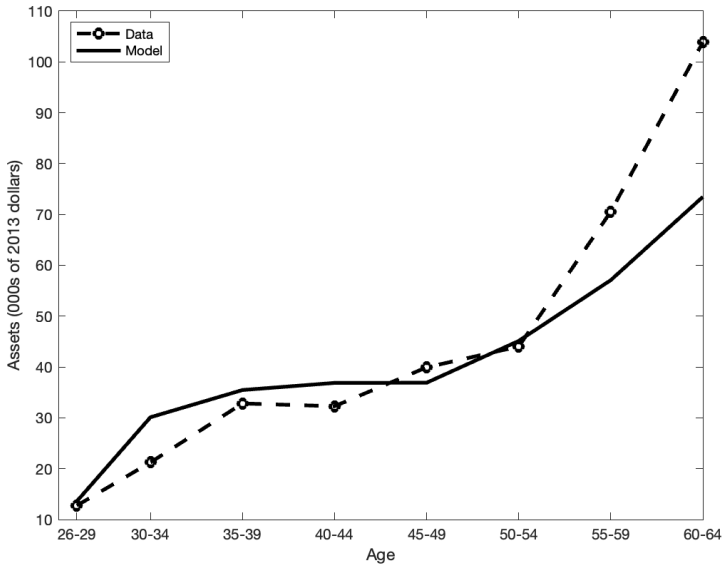
Notes: (a) presents the distribution of annual medical spending. (b) presents the distribution of total quarterly earnings, in the data and in model simulations based on the estimated parameters. The x-axis labels show the corresponding dollar amounts of selected bins.

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

estate debt, student loan debt, legal bills, credit card debt, family loan debt, and other debt), plus the value of home equity.

Figure 5: 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 4.2 and a similar sample from 2015 Panel Study of Income Dynamics.

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 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 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.

5 Market Equilibrium

In this section, I aggregate individual-level WTP for health insurance to study market equilibrium. Specifically, I study hypothetical market scenario offering a single health insurance plan that covers 70% of medical costs—-equivalent to

the actuarial value of the Silver plan in the ACA Marketplace.[17]

N individuals must make ex-ante insurance decision between a health insurance plan that covers 70% of medical expenses and being uninsured for year $y(t)+1$, based on the information of health and employment type in the last quarter of year $y(t)$.[18] Individual i will buy the plan if her WTP g_i is greater or equal to the market equilibrium premium p^*.[19]

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.

Moreover, I assume that individuals are completely liquid in year $y(t)$.[20] Additionally, I 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 $7^4 = 2401$).

Finally, insurers are assumed to be perfectly competitive and are not allowed to price on the pre-existing conditions. The expected medical costs of covering individual i is z_i.

5.1 Heterogeneous Earnings Dynamics and Market Aggregation

As outlined in Section 2, various dimensions of heterogeneity such as wealth levels and earnings dynamics can influence individuals' WTP for health insurance. To understand the impact of these heterogeneities, I begin with the classical case when the only difference among consumers are the medical risks. Then I introduce different sources of heterogeneity among consumers. These include variations in wealth level, expected earnings, and earnings uncertainty.

[17] I focus on this hypothetical market to mitigate computational complexity, particularly in cases involving multiple plans. Moreover, the hypothetical market reasonably reflects the real market, as most consumers in the ACA Marketplace choose Silver plans. According to data from ASPE (2014), as of March 2014, only 2% of enrollees selected Catastrophic plans, 20% chose Bronze plans (covering 60% of medical costs), 65% opted for Silver plans, 9% enrolled in Gold plans, and 5% selected Platinum plans.

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

[19] How to calculate WTP will be discussed in Section 5.1 and Online Appendix E.

[20] For a detailed discussion on the importance of liquidity in insurance demand, see Ericson and Sydnor (2018). Due to the computational complexity of this project, I leave the integration of liquidity and earnings dynamics to future research.

The details of how to calculate the individual-level WTP for each case can be found in Online Appendix E. The cases are:

Case 1: Classical. — I begin with the classical case, which 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.

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

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 $\bar{\mu}_{wt} = \frac{1}{N}\sum_i \mu_{iwt}$.
Case 2: Heterogeneous Assets. — In this case, individuals face another source of heterogeneity: different initial accumulated assets A_i. Assets are simulated via the consumption-saving strategy in Section 4.2.
Case 3: Heterogeneous Expected Earnings. — Individuals further face differences in the expected earnings μ_{iwt} relative to Case 2.
Case 4: Uncertainty in Earnings. — 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 4.1.

Notice that the earnings uncertainty here includes multiple reasons that cause deviations from the expected earnings, such as unemployment, job mobility, firm changes, and on-the-job variations in earnings. As this paper focuses on whether these deviations in total influence the market equilibrium, separating these individual causes of earnings uncertainty is beyond the scope of this paper.

I consider the following key statistics to analyze market equilibrium. The equilibrium premium p^* is 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.

In a model when consumers only differ in health risks, socially efficient take-up rate and premiums can be calculated by finding the intersection between demand and marginal cost curves. However, when heterogeneity in earnings dynamics are considered, an individual with a higher WTP does not necessarily face higher medical risk, which may lead to non-linearity in marginal cost curves. This non-linearity 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 (DWL) under this measure comprises two components. First, it arises from the loss of consumer surplus for individuals who should be efficiently insured but remain uninsured in the competitive equilibrium. Second, it reflects the efficiency of not insuring individuals whose WTP falls below the cost of providing coverage. DWL is defined as follows:

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

5.2 Results

WTP distributions.— As discussed in Section 2, the heterogeneous changes in WTP result from multiple interacting factors, making empirical analysis essential. Figure 6 presents the heterogeneous changes in individuals' WTP with the step-by-step introduction of heterogeneity in earnings dynamics.[21]

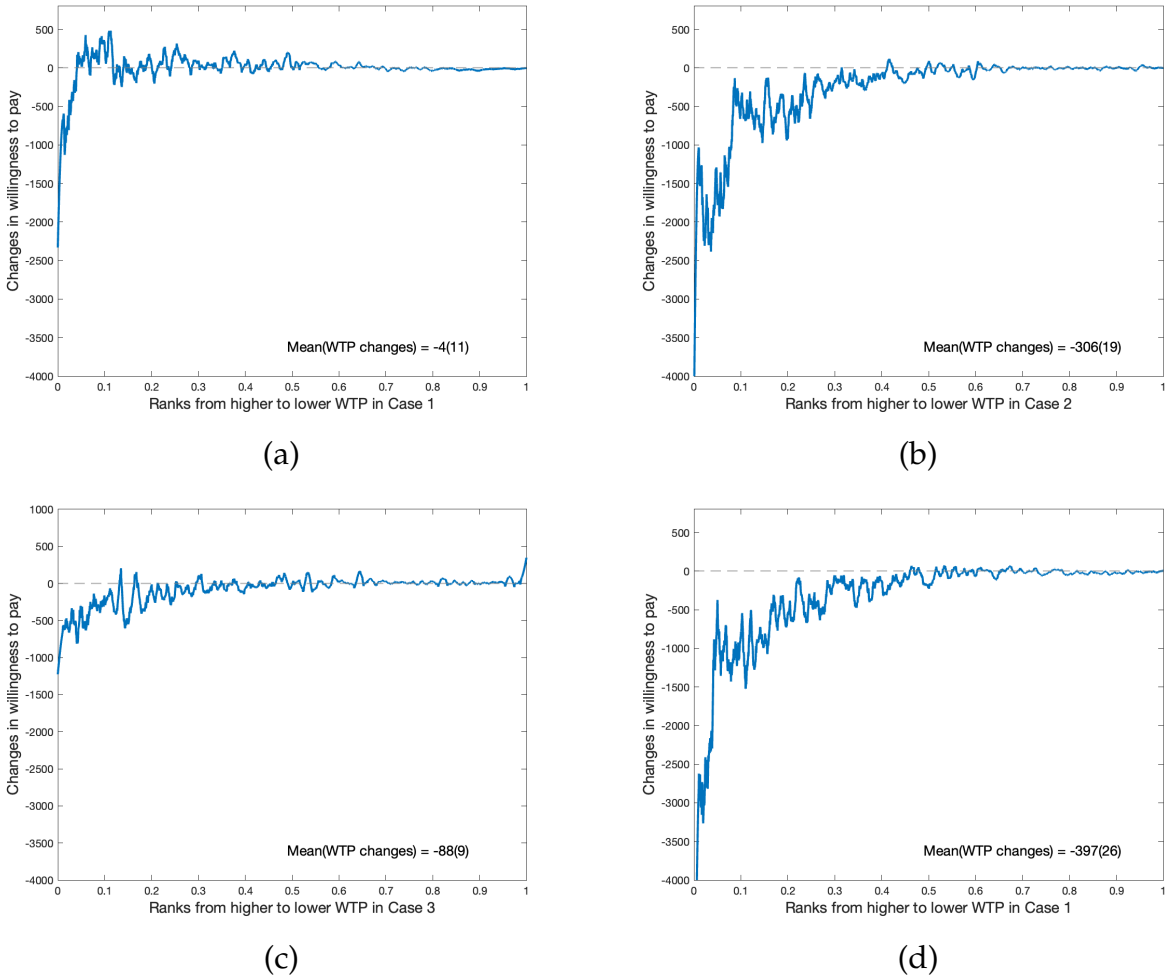
As seen, introducing heterogeneity in assets, expected earnings, and earnings uncertainty results in a substantial reduction in the average WTP by -$397.[22] As shown in Figures 6 (a) and (b), this decline is mainly driven by heterogeneity in the expected budget, which is the sum of assets and expected earnings; together, they account for approximately 78% of the total reduction in WTP. When earnings uncertainty is introduced, as shown in Figure 6 (c), the average WTP reduction is $88, which is also sizable—roughly 22% of the total decrease.

Another important observation from Figure 6 (d) is that consumers with

[21]The curves are smoothed with a Savitzky-Golay filter over each window of 50 points. This method smooths according to a quadratic polynomial that is fitted over each window.

[22]First, I calculate the average WTP reduction for all consumers in each simulation. Then, I compute the mean of these average WTP reductions using 50 bootstrap samples. The mean and standard deviations are also reported in each subfigure in Figure 6.

Figure 6: Effects of Earnings Dynamics on Willingness to Pay



Source: Model simulation. *Notes:* This figure shows the changes in the WTP after introducing heterogeneity in earnings dynamics to Case 1: Classical Model, where consumers only differ in medical risks. The X-axis represents the rank of individuals by WTP, ranging from the highest to the lowest. The Y-axis represents the changes in WTP. (a) compares the changes in WTP in Case 2 relative to Case 1. (b) compares changes in WTP in Case 3 relative to Case 2. (c) compares changes in WTP in Case 4 relative to Case 3. (d) compares the total changes in WTP in Case 4 relative to Case 1. The details of the models are in Section 5.

higher WTP in the classical case—-who also face higher expected medical costs—-have a higher probability of experiencing a larger drop in WTP. Notice, this pattern does not hold for every pair of consumers, as the WTP reduction curve is nonlinear with respect to WTP rank.

One key reason is that the consumption floor is more likely to affect the WTP of sicker individuals than that of healthier ones. In the classical case when consumers only differ in medical risks, sicker consumers almost always have higher WTP than healthier ones.[23]

However, when we consider the heterogeneity in earnings dynamics, sicker consumers often hold lower expected budget, leading to a higher probability of reaching the consumption floor compared to healthier individuals.[24] Since the consumption floor provides financial protection, it effectively reduces their WTP for health insurance. This aligns with the reduced-form findings in Finkelstein et al. (2019b).

Furthermore, uncertainty in earnings plays a crucial role in shaping changes in the WTP distribution. Earnings volatility further exacerbates financial constraints, making some consumers even more reliant on the consumption floor. This, in turn, contributes to the substantial heterogeneity in WTP reductions across individuals.

Other reasons beyond consumption floor may also contribute to the WTP changes at individual level. See Section 2 for further discussion. While these factors jointly explain the observed WTP changes, isolating their individual contributions is beyond the scope of this paper and offers limited policy relevance. The key takeaway is that ignoring earnings dynamics and the consumption floor can lead to an incomplete understanding of WTP heterogeneity and insurance demand.

Market Equilibrium.— Now, we move to the discussion of market equilibrium and efficiency.

The demand curve represents the share of consumers willing to purchase insurance at each possible price. In Figure 7(a), the demand curve shifts downward when earnings dynamics are introduced into insurance demand, compared to

[23]The classical case in this project can be viewed as a textbook model (consumers only differ in medical risks and consumption floor will never hit) with a consumption floor. Due to the consumption floor acting as implicit insurance, some sicker consumers may have lower WTP than healthier ones, but such cases are very rare.

[24]This is because 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.

the classical case where consumers differ only in medical risks. This shift occurs for two main reasons. First, the average WTP decreases with the introduction of earnings heterogeneity. Second, heterogeneous changes in individual WTP alter their relative positions on the demand curve. As a result, the downward shift in the demand curve leads to higher equilibrium prices and a lower equilibrium take-up rate.

The average cost curve represents the average medical costs of all consumers who choose to purchase the plan at each given premium. According to Figure 7(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.

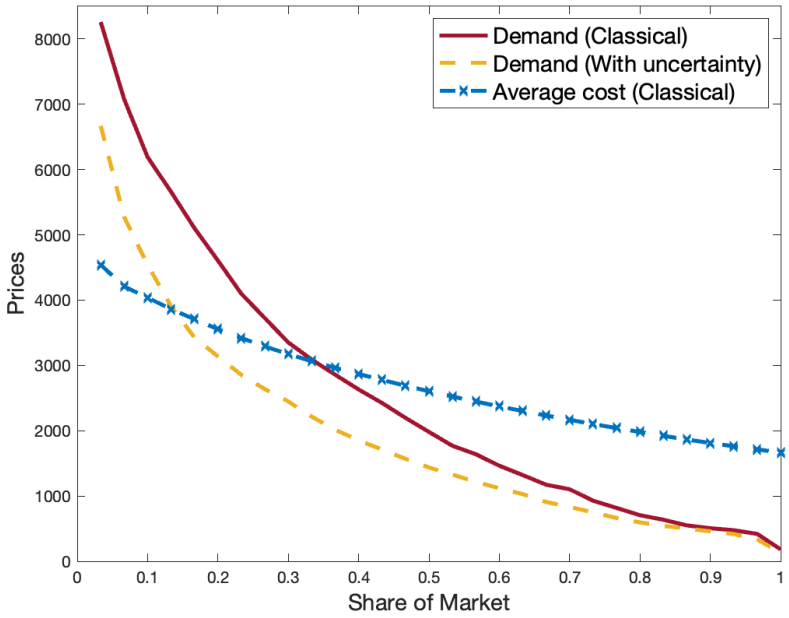
Table 2 reports the main results for baseline scenarios (risk aversion $\gamma = 2$ and consumption floor $\underline{c} = 5000$) for cases 1 to 4.[25] Relative to the classical case where consumers differ only in their medical risks, the introduction of heterogeneity in expected assets leads to a 2.32% 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 15.4%, accompanied by higher premiums of approximately \$226. Next, when earnings uncertainty is added to the model, the equilibrium take-up rate drops by a further 1.62%. In total, relative to the classical model, the equilibrium take-up decreases by 14.66%, and premiums increase by around \$116.

The socially optimal take-up rate declines significantly after introducing heterogeneity in earnings uncertainty. Specifically, incorporating heterogeneity in assets and expected earnings reduces the optimal take-up rate by 17.2%, while earnings uncertainty further lowers it by an additional 6.6%. These findings suggest that ignoring earnings dynamics in insurance demand models may lead to an overestimation of the optimal allocation of health insurance in the market.

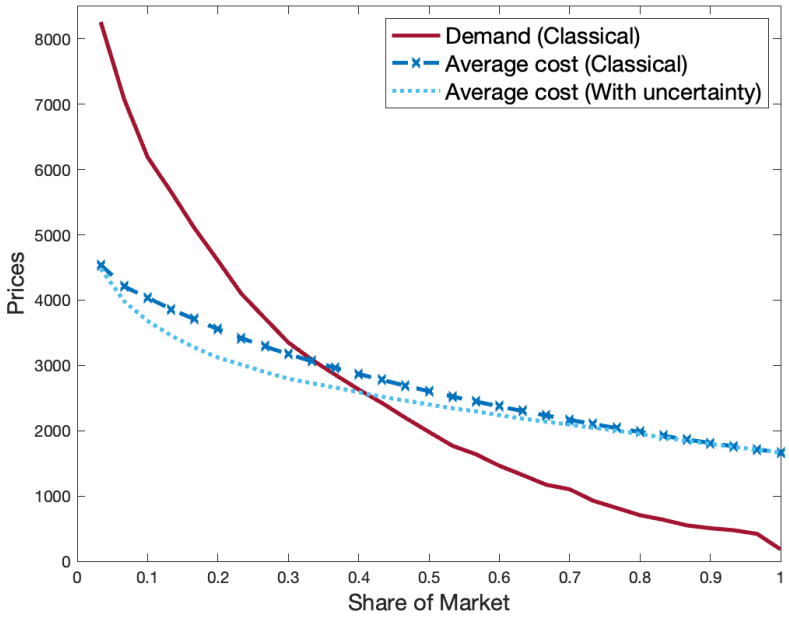
Since individuals have different WTP across these cases, deadweight loss (DWL) is not an ideal measure for assessing adverse selection. DWL can decrease either due to lower WTP, or because a more socially efficient allocation is achieved. Instead, I use an alternative measure to better capture whether allocations become more socially efficient: the share of optimal total surplus

[25] Appendix Table E1 shows the relative changes in each estimated statistics.

Figure 7: Effects of Earnings Dynamics on Demand and Average Cost Curves



(a) Demand curve shifts



(b) Average cost curve changes

Source: Model simulation. *Notes:* This graph compares the shifts in the demand and average cost curves between the Classical case (Case 1), where individuals differ only in medical risks, and Case 4, where individuals also differ in assets, expected earnings, and earnings uncertainty. Panel (a) illustrates the changes in the demand curve, while panel (b) depicts the changes in the average cost curve. The details of these models are provided in Section 5.

Table 2: Effects of Earnings Dynamics on Market Equilibrium and Social Efficiency

	Equilibrium Take-up			Efficient	Premium	Optimal TS
	Baseline	$\gamma = 3$	$\underline{c} = \$3000$	Take-up		Gained
	(1)	(2)	(3)	(4)	(5)	(6)
Case 1: Classical	0.3514	0.6188	0.4125	1	3067	0.7772
	(0.0096)	(0.0102)	(0.0101)	(0)	(40)	(0.0081)
Case 2: Add heterogeneous assets	0.3746	0.6431	0.4439	1	2991	0.7797
	(0.0092)	(0.0084)	(0.0100)	(0)	(40)	(0.0073)
Case 3: Add heterogeneous expected earnings	0.2210	0.4989	0.3159	0.8289	3217	0.6503
	(0.0076)	(0.0090)	(0.0078)	(0.0058)	(58)	(0.0116)
Case 4: Add uncertainty in earnings	0.2048	0.4707	0.3012	0.7632	3183	0.6320
	(0.0075)	(0.0086)	(0.0095)	(0.0067)	(55)	(0.0123)
Case 5: Allow ESI access to impact WTP	0.2113	0.4638	0.3051	0.7419	3107	0.6406
	(0.0080)	(0.0088)	(0.0092)	(0.0066)	(61)	(0.0133)
Case 6: Allow ESI access to impact insurers' costs	0.3928	0.5757	0.4669	0.8241	1905	0.8016
	(0.0113)	(0.0070)	(0.0099)	(0.0058)	(41)	(0.0091)

Source: Model simulation. *Notes:* This table shows the changes when adding earnings dynamics iteratively to the classical case (case 1), which only considers medical risks. More detailed introductions of the models are in Section 5. A detailed discussion of the model with ESI access and how I estimate the model can be found in Appendix F. 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 5.1. The share of optimal total surplus gained is calculated by dividing the equilibrium total surplus by the socially efficient total surplus. The standard deviations are generated using 50 bootstrap samples.

gained (reported in Table 2, column (6)). This measure is calculated by dividing the equilibrium total surplus by the socially efficient total surplus. The reported share of optimal total surplus gained declines step by step as heterogeneity in assets, expected earnings, and earnings uncertainty are introduced into the insurance demand model. This reflects that abstracting insurance model from earnings dynamics may lead to underestimation of how much socially efficient total surplus market equilibrium can achieve.

Robustness. — I begin by examining the robustness of my findings using a higher risk-aversion coefficient of 3, with the results presented in Table 2, column (2). Higher risk aversion increases WTP, leading to a higher take-up rate in the classical model. Next, I explore how the level of the consumption floor affects my results by adjusting it from \$5000 to \$3000 (column (3)). A lower consumption floor increases WTP for insurance. The overall pattern remains consistent with the baseline model in both alternative cases.

5.3 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. Additionally, 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 F.

Results. — Table 2 Case 5 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 Case 6, 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 18.8%, and premiums decrease by around \$1278.

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.[26] 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.

6 Implications for Subsidy Designs

Means-tested subsidy is often used in health insurance policies. The Congressional Budget Office projected the Federal government would spend 1.1 trillion dollars for the non-group marketplaces established under the ACA and the Basic Health Program over the 2024–2033 period (CBO, 2023). One main economic objective of premium subsidies is to reduce adverse selection and thus improve welfare.

Subsidies influence adverse selection through several channels. First, lower premiums increase uninsured individuals' WTP and thus directly increase insurance take-up. I follow Tebaldi (2024) to define the market equilibrium at this stage as "off-equilibrium". Second, average insurance costs change as some uninsured individuals transition to being insured. 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

[26] 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.

descriptions of how subsidies work can be found in Online Appendix G.

As shown in Section 5, incorporating heterogeneity in earnings dynamics into insurance demand models lead to changes in estimated WTP distribution. This has important theoretical implications for subsidy designs in private health insurance markets such as the ACA marketplace.

In the baseline case, where individuals differ only in medical risks, subsidies consistently incentivize healthier consumers to enroll, reducing equilibrium premiums and deadweight loss significantly. However, when heterogeneity in earnings dynamics are considered in the WTP estimation, 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. Thus, means-tested subsidies, which offer higher subsidies to lower-income individuals and often used in private health insurance markets, may not be as effective as implied by the classical case.

To shed light on this question, I first compare means-tested subsidies with a uniform subsidy that produces approximately the same costs for taxpayers.[27] The subsidies are applied to the case that allows individuals to differ in assets, expected earnings, and earnings uncertainty (Case 4). The details of the Case 4 can be found in Section 4.2.

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 another two component of social costs: (1) social cost of taxation to fund the health insurance, including subsidies and public insurance programs (2) social cost of taxation to fund the transfers from the consumption floor to the consumers.[28] Welfare per person is the difference between consumer surplus and the social costs. A detailed introduction of social costs and welfare calculation can be found in Online Appendix G.

Table 3 shows that a uniform subsidy, offered to all consumers at an equivalent cost, increases take-up by 5.11% more than a means-tested subsidy. Notably, the off-equilibrium take-up difference is only 1.81%, suggesting that the average cost reductions from previously uninsured individuals joining the insurance

[27] 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 D Table D1.

[28] One counterfactual analysis examines the combined effects of public insurance expansion for low-income individuals and subsidies for the rest in the private health insurance market. The social costs of covering these individuals under the expanded programs are incorporated into the first component of social costs.

pool are particularly effective under the uniform subsidy design. Additionally, uniform subsidies lead to higher total surplus and a greater reduction in deadweight loss (DWL). While the equilibrium premium is higher under the uniform subsidy, the reduction in premiums from off-equilibrium to market equilibrium is also significantly larger compared to the means-tested subsidy. These findings highlight potential room for improving the design of means-tested subsidies.

However, the public cost of funding the transfers from the consumption floor is 14% higher under the uniform subsidy compared to the means-tested subsidy. This reflects the potential spillover effects of uniform subsidies on other social programs and implicit insurances. As a result, total welfare under the two subsidy designs remains relatively similar. Moreover, under a uniform subsidy design, low-income individuals tend to receive fewer subsidies, raising concerns about inequality.

Motivated by the idea that subsidies granted to sicker consumers can reduce the effectiveness of subsidies in mitigating adverse selection, I explore the policy implications. 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. Second, ACA income-based subsidies are offered to the remaining eligible consumers.

As seen in Table 3, this policy would substantially increase the equilibrium take-up rate and reduce premiums, outperforming the other two subsidy types. Additionally, total surplus is approximately 34% higher than under the means-tested subsidy. While the reduction in deadweight loss (DWL) exceeds that of the means-tested subsidy, it remains slightly lower than that achieved by the uniform subsidy.

The public cost of implementing this policy—comprising the cost of expanded public insurance and private market subsidies—is about 13% higher than that of the means-tested subsidy. However, the public cost of funding transfers from the consumption floor decreases by 11%. Overall, total welfare increases by 38%, indicating a significant net welfare improvement.

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

Table 3: Counterfactual Subsidy Designs

	Off-equilibrium		Equilibrium		Total	DWL	Public cost		Welfare
	Take-up	Premium	Take-up	Premium	Surplus	Reduction	HI support	Consumption floor	Increases
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Means-tested	0.3874	2412	0.5774	2092	1213	129	194	191	827
	(0.0084)	(32)	(0.0091)	(29)	(25)	(7)	(5)	(11)	(20)
Uniform	0.4055	2601	0.6285	2142	1234	149	194	218	822
	(0.0118)	(42)	(0.0083)	(30)	(24)	(8)	(5)	(12)	(20)
Public HI expansion	0.5269	2336	0.7393	1901	1629	143	220	170	1144
	(0.0079)	(33)	(0.0067)	(28)	(28)	(8)	(6)	(8)	(23)

Source: Model simulation. *Notes:* This table compares three subsidy designs: means-tested, uniform, 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 (7) reports the social cost of taxation to fund the subsidies and public HI expansion. Column (8) reports the social cost of taxation to fund the transfers from consumption floor. See Appendix G for further details. Welfare per person is the difference between consumer surplus and the social costs of health insurance policy and transfers from consumption floor. Welfare changes column shows how the welfare changes after subsidy is implemented. The standard deviations are generated using 50 bootstrap samples.

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.

7 Conclusion

In this paper, I incorporate the joint dynamics of earnings and medical spending into a standard model of individuals' insurance choices. I develop a binary insurance choice model in which individuals decide between being uninsured and fully insured while facing uncertainty over *both* earnings and medical expenses.

Using unique datasets—the Utah All-Payer Claims Data and noise-infused earnings records—I empirically estimate individuals' willingness to pay (WTP) for health insurance. I then use a life-cycle model that accounts for earnings uncertainty to estimate asset accumulation, given the crucial role of wealth in insurance decisions. My analysis reveals significant heterogeneity in WTP distributions.

To examine how earnings dynamics affect adverse selection, I aggregate individuals' WTP to the market level. Unlike classical textbook models, WTP is no longer a straightforward predictor of medical costs. The inclusion of earnings dynamics weakens the correlation between WTP and expected medical costs, leading to *lower* equilibrium take-up rates and *higher* premiums. Additionally, ignoring earnings dynamics in insurance demand models may result in an overestimation of the socially efficient take-up rate.

The fact that employment dynamics *reduce* the correlation between WTP and expected medical costs has important implications 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 fully covers individuals below 100% of the federal poverty level (FPL)—as originally intended by the ACA—while subsidies are provided only to those above 100% FPL, equilibrium take-up increases, while premiums and 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, this paper does not separate

causes behind deviations from expected earnings, including unemployment, job mobility, and on-the-job variation in earnings. Future research can dig into separating these causes and revisit optimal grouping of workers in private health insurance markets based on their occupation and industry. Third, 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. Fourth, 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

Proof of Proposition 1. Recall that earnings and medical spending are jointly distributed and are independent:

$$\begin{pmatrix} w \\ m \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_w \\ \mu_m \end{pmatrix}, \begin{pmatrix} \sigma_w^2 & 0 \\ 0 & \sigma_m^2 \end{pmatrix} \right).$$

Denote the probability density function (PDF) for earnings and medical spending as $f(w)$ and $f(m)$, respectively. Individual's WTP p solves the following equation:

$$\int_w u(w-p)f(w)dw = \int_w \int_m u(w-m)f(w)f(m)dmdw \tag{10}$$

Apply Taylor expansion (2nd) for w on both sides, we get:

$$\begin{aligned} Left &= \int_w [u(w-\mu_m) + u'(w-\mu_m)(\mu_m - p)]f(w)dw \\ &= \int_w u(w-\mu_m)f(w)dw + (\mu_m - p)\int_w u'(w-\mu_m)f(w)dw \end{aligned} \tag{11}$$

$$\begin{aligned} Right = \int_w \int_m [u(w-\mu_m) + u'(w-\mu_m)(\mu_m - m) + \frac{1}{2}u''(w-\mu_m)(\mu_m - m)^2]f(w)f(m)dmdw \\ = \int_w u(w-\mu_m)f(w)dw + \frac{1}{2}\sigma_m^2 \int_w u''(w-\mu_m)f(w)dw \end{aligned} \tag{12}$$

Equate $Left$ and $Right$, we get WTP p

$$p = \mu_m - \frac{1}{2}\sigma_m^2 \frac{\int_w u''(w-\mu_m)f(w)dw}{\int_w u'(w-\mu_m)f(w)dw} \tag{13}$$

The WPT when there's no earnings volatility is

$$p_0 = \mu_m - \frac{1}{2}\sigma_m^2 \frac{u''(\mu_w - \mu_m)}{u'(\mu_w - \mu_m)} \tag{14}$$

Thus the WTP gap between the case when $\sigma_w > 0$ and when $\sigma_w = 0$ is:

$$p - p_0 = -\frac{1}{2}\sigma_m^2 [\frac{\int_w u''(w-\mu_m)f(w)dw}{\int_w u'(w-\mu_m)f(w)dw} - \frac{u''(\mu_w - \mu_m)}{u'(\mu_w - \mu_m)}] \tag{15}$$

Case 1: When utility function is CRRA:
Because $u''(.)$ is concave, $\int_w u''(w-\mu_m)f(w)dw < u''(\mu_w-\mu_m)$. Moreover, because $u'(.)$ is convex, $\int_w u'(w-\mu_m)f(w)dw > u'(\mu_w-\mu_m)$. Thus,

$$\frac{\int_w u''(w-\mu_m)f(w)dw}{\int_w u'(w-\mu_m)f(w)dw} - \frac{u''(\mu_w-\mu_m)}{u'(\mu_w-\mu_m)} < 0 \tag{16}$$

Thus, $p > p_0$.

Case 2: When utility function is CARA: $u(x) = -\frac{1}{\gamma}exp(-\gamma x)$.
Then $u'(x) = exp(-\gamma x)$ and $u''(x) = -\gamma exp(-\gamma x)$.

$$\frac{\int_w u''(w-\mu_m)f(w)dw}{\int_w u'(w-\mu_m)f(w)dw} = \frac{-\gamma\int_w exp(-\gamma(w-\mu_m))f(w)dw}{\int_w exp(-\gamma(w-\mu_m))f(w)dw} = -\gamma \tag{17}$$

$$\frac{u''(\mu_w-\mu_m)}{u'(\mu_w-\mu_m)} = -\gamma \tag{18}$$

Thus, $p = p_0$

Proof of Proposition 2. Recall that earnings w and medical spending m are jointly normal distributed. Thus, $z = w - m$ is also normally distributed, with $z \sim N(\mu_w - \mu_m, \sigma_w^2 + \sigma_m^2 - 2cov(w,m))$.

When w and m are negatively correlated, then $cov(w,m) < 0$, and $\sigma_z^2 = \sigma_w^2 + \sigma_m^2 - 2cov(w,m) > \sigma_w^2 + \sigma_m^2$, thus z is a mean preserving spread of the distribution when w and m are independent. Thus, for risk averse individuals with concave expected utility function, the WTP is higher than the case when earnings and medical spending are independent.

When w and m are positively correlated, then $cov(w,m) > 0$, and $\sigma_z^2 = \sigma_w^2 + \sigma_m^2 - 2cov(w,m) < \sigma_w^2 + \sigma_m^2$. Thus, for risk averse individuals with concave expected utility function, the WTP is lower than the case when earnings and medical spending are independent.

Supplemental Appendix

A. Data: Further Details

Defining Firm ID. — The file includes a variable that reports the average pay at the employer-quarter level for all workers whose primary employer was the given firm. Although this average pay variable is infused with white noise to protect privacy, it remains consistent at the firm-quarter level. For large firms, we observe many workers with identical sequences of quarterly firm average pay, an event with an extremely low probability due to the precision of the average pay data.

Based on this insight, we compute the statistical probabilities that different combinations of workers are coworkers within each quarter of the panel. Based on a simulated model, we estimate that in a sample of approximately 60,000 firms, the likelihood of two or more firms having the exact same average pay purely by statistical chance in a single quarter is less than 4%. The probability of this occurring by chance in two consecutive quarters is less than 0.001%. As a result, for firms that persist across multiple quarters—particularly those with five or more workers—the statistical estimation of firm boundaries is highly reliable. For workers with employer-sponsored health insurance, which is 81% of our analysis sample, we directly observe Firm IDs in the APCD. We further use these information from APCD to validate the statistical estimation procedure.

Sample Selection: Further Details. — Table A1 shows sample size changes with sample selection steps.

Table A1: 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 A2 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 4.1.

Table A2: 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 3. 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 A3 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 A1 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.

Health, Worker, and Firm Types. — Figure A2 shows the distribution of ACG scores. The distribution is highly skewed, which is consistent with other papers in the literature (Atal et al., 2025).

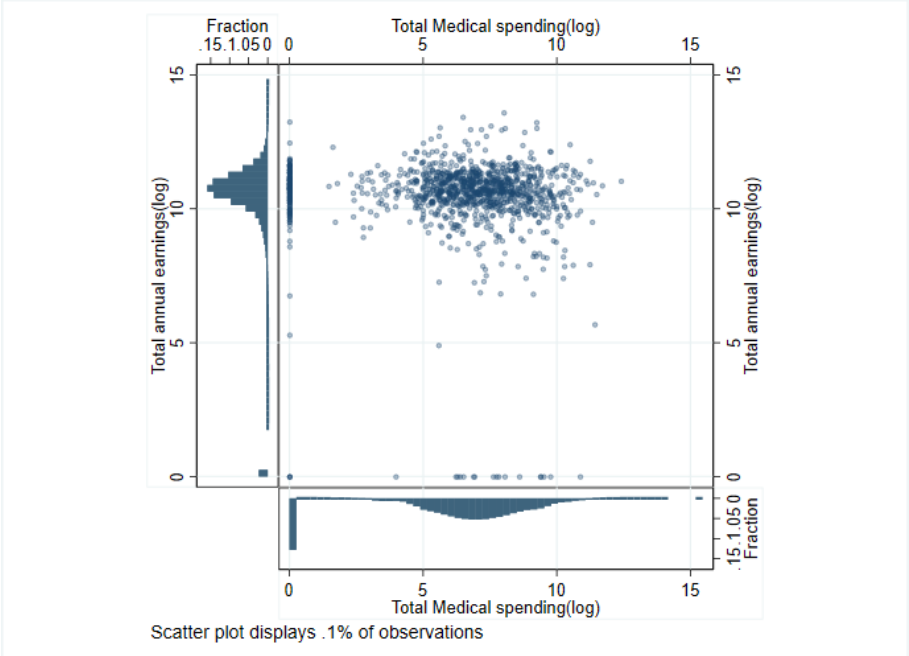
Figure A3 presents the distribution of estimated worker and firm fixed effects using two-way fixed effects model. Both worker and firm fixed effects are approximately normally distributed.

Table A3: 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	-

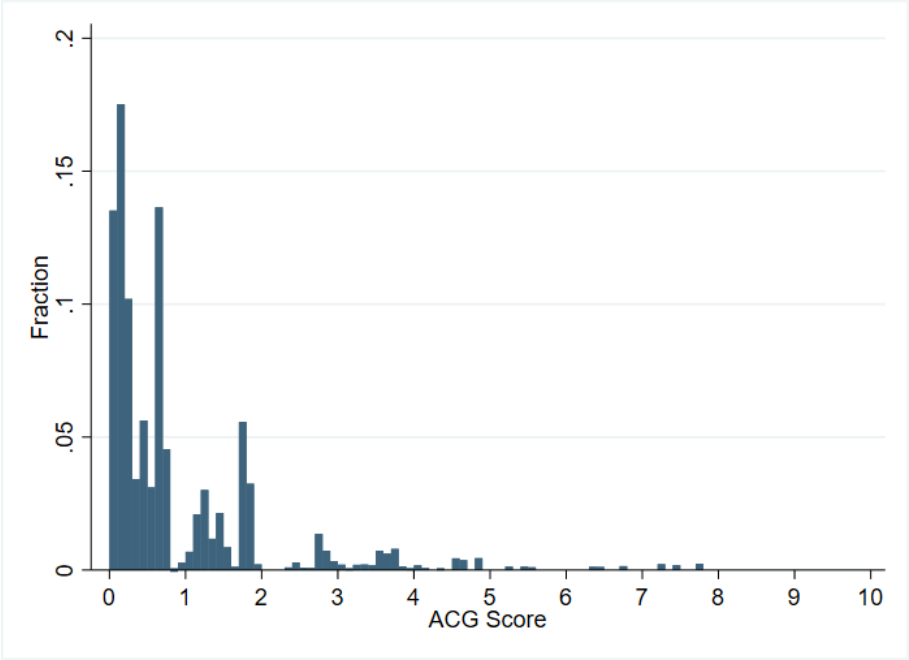
Source: 2013-2015 Utah All-payer Claims Data. *Notes:* The maximum value of ACG score and medical spending in all categories are omitted for privacy protection.

Figure A1: Joint Distribution of Earnings and Medical Spending



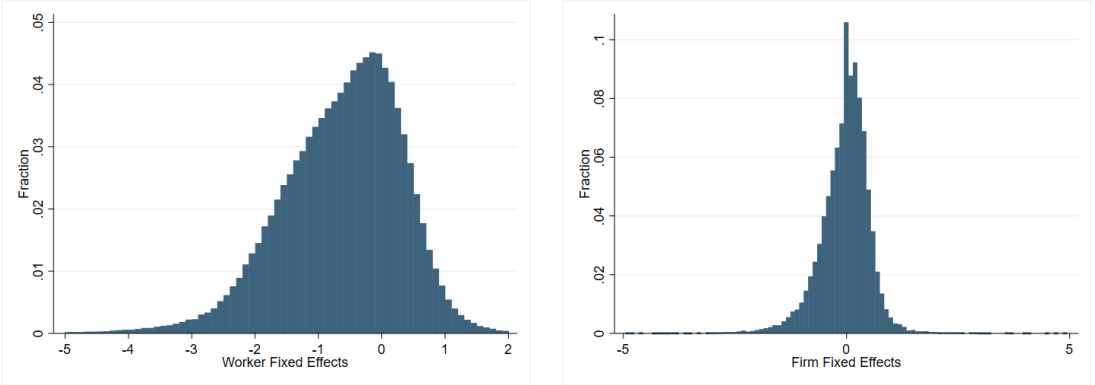
Notes: This figure shows the joint distribution of earnings and medical spending (in logs) (pooled years from 2013 to 2015).

Figure A2: 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 A3: 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 A4: 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.

B. 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 B1 presents the probability of realizing zero medical spending, while Table B2 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 B3 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 B1: 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 following logit regression:

$$Pr(I_{i,t+1}) = \gamma_0 + H_{i,t+1}\gamma_h + a_i\gamma_a + f(l_{it}, k_{it})\gamma_k + X_{i,t+1}\gamma_x + \epsilon^I_{i,t+1} \tag{19}$$

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

Table B2: 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.

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.

$$Pr(d_{i,t+1}) = \beta_0 + H_{i,t+1}\beta_h + a_i\beta_a + k_{it}\beta_k + X_{i,t+1}\beta_x + \epsilon^d_{i,t+1} \tag{20}$$

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

Table B3: 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 B4: 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 4.1.

using a multinomial logit model as follows:

$$Pr(k_{i,t+1}) = \omega_0 + H_{i,t+1}\omega_h + a_i\omega_a + f(I_{it}, k_{it})\omega_k + X_{i,t+1}\omega_x + \epsilon^k_{i,t+1} \qquad (21)$$

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 B5: 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 B6: 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 3.

Figure B1: Firm Transitions



Notes: Firm type transition matrices, evaluated at the means of control variables. Details of type construction can be found in Section 3.

C. Life-cycle Model: Further Details

This section offers more details about the life-cycle model used to estimate assets in Section 4.2.

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 4.1.[29] 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:

$$A_{t+1} = A_t + \tau_t(rA_t + w_t) - (1-\pi)m_t + b_t - c_t \tag{22}$$

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 $\underline{c}$.

$$b_t = \max\{0, \underline{c} - [A_t + \tau_t(rA_t + w_t) - (1-\pi)m_t]\} \tag{23}$$

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

[29] 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.

$$V_t(A_t, \delta_t, w_t, m_t) = \max_{c_t, A_{t+1}} \{u(c_t) + \beta s_t E_t V_{t+1}(A_{t+1}, \delta_{t+1}, w_{t+1}, m_{t+1})\} \quad (24)$$

subject to equations 22 and 23. 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:

$$V_t(x_t, \delta_t, w_t, m_t) = \max_{c_t, x_{t+1}} \{u(c_t) + \beta s_t E_t V_{t+1}(x_{t+1}, \delta_{t+1}, w_{t+1}, m_{t+1})\} \quad (25)$$

subject to:

$$x_t = A_t + \tau(rA_t + w_t) + b_t - (1-\pi)m_t \quad (26)$$

$$A_{t+1} = x_t - c_t \quad (27)$$

$$x_{t+1} = x_t - c_t + \tau(r(x_t - c_t) + w_{t+1}) + b_{t+1} - (1-\pi)m_{t+1} \quad (28)$$

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.[30]

[30] 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

D. 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 eligible individuals must pay for monthly 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 D1. 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 D1: 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.

E. Market Equilibrium: Further Details

In this section, I describe the details about how to estimate WTP for health insurance for each case in Section 5.

Case 1: Baseline.— Individual i holds assets at $\bar{A} = \frac{1}{N}\sum_i A_i$ and predicts that she will get earnings $\bar{\mu}_{wt}$ for next year as without any uncertainty. The expected earnings is calculated in equation 8.

She then predicts the health type for next year $t+1$ based on the transitions in Section 4.1.1 conditional on her health type, and other demographics observed in year t. For each possible realization of health type transitions $H_{iy(t+1)}$, she predicts the possible medical spending realizations using equation 6 and equation 7. The corresponding probability is determined by combining the likelihood of each health type transition, the probability of incurring medical expenses, and the probability of each transitory shock.

Individual i's WTP for health insurance plan is calculated by the following steps: First, I calculate the expected utility for individual i to choose no insurance option:

$$EU_{I_{i,t+1}=0} = \int_m u(\bar{A} + \bar{\mu}_{wt} - m_{t+1}, \underline{c}])f(m_{t+1})dm \tag{29}$$

Second, the expected utility to buy the insurance is a function of price p:

$$EU_{I_{t+1}=1}(p) = \int_m u(\bar{A} + \bar{\mu}_{wt} - (1-b)m_{t+1} - p), \underline{c}])f(m_{t+1})dm \tag{30}$$

with $b = 0.7$ standing for the coverage level of the insurance product.

Third, I search for the price g_{t+1} that solves $g_{t+1} = \max\{p : EU_{I_{t+1}=1}(p) \geq EU_{I_{t+1}=0}\}$.

Case 2: Heterogeneous Assets.— The process is very similar to the baseline case, but instead of holding assets at $\bar{A}$, she holds asset at A_i.

Case 3: Heterogeneous Expected Earnings.— The process is still very similar to the baseline case. Individuals however predicts the earnings at μ_{iwt} without any uncertainty.

Case 4: Uncertainty in Earnings.— Now individual i also predicts the possible realizations of earnings for year $t+1$. To do so, after she predicts the health

type, she predicts the employment type, including employed or not, changing employer or not, and which type of firm she works for. In total, she predicts employment types for the next four quarters. To reduce computation burden, I only consider the combinations without considering the permutations. The total employment types drop from 2401 to 210. For each employment type combination, she also predicts the corresponding probability.

Conditional on the predicted pair of health type and employment types, she predicts earnings and medical spending using equations 5, 6 and 7.

The steps to calculate WTP follow a similar logic to the baseline case. However, the expected utility of being uninsured is determined using equation 1, while the expected utility of purchasing insurance with premium p is given by equation 2. The WTP is therefore the price at which an individual is indifferent between these two options.

Table E1: Impact of Employment Dynamics on Market Equilibrium and Social Efficiency

	Equilibrium Take-up			Efficient	Premium	DWL	Optimal TS
	Baseline	$\gamma = 3$	$\underline{c} = \$3000$	Take-up			Gained
Case 1: Classical	0.3514	0.6188	0.4125	1	3067	253	0.7772
	(0.0096)	(0.0102)	(0.0101)	(0)	(40)	(6)	(0.0081)
Case 2: Add heterogeneous assets	+0.0232	+0.0243	+0.0314	0	-77	-7	+0.0025
	(0.0050)	(0.0056)	(0.0056)	(0)	(17)	(6)	(0.0070)
Case 3: Add heterogeneous expected earnings	-0.1536	-0.1442	-0.1280	-0.1711	+227	-14	-0.1294
	(0.0077)	(0.0075)	(0.0087)	(0.0058)	(34)	(6)	(0.0096)
Case 4: Add uncertainty in earnings	-0.0162	-0.0282	-0.0147	-0.0657	-35	-12	-0.0182
	(0.0051)	(0.0045)	(0.0071)	(0.0037)	(25)	(5)	(0.0083)
Total	-0.1466	-0.1482	-0.1113	-0.2368	+115	-33	-0.1451
	(0.0082)	(0.0079)	(0.0089)	(0.0067)	(35)	(7)	(0.01183)
Case 5: Allow ESI access to impact WTP	+0.0065	-0.0069	+0.0040	-0.0214	-75	-6	+0.0086
	(0.0038)	(0.0022)	(0.0041)	(0.0022)	(21)	(4)	(0.0081)
Case 6: Allow ESI access to impact insurers' costs	+0.1815	+0.1119	+0.1618	+0.0823	-1202	-32	+0.1610
	(0.01083)	(0.0062)	(0.0092)	(0.0043)	(52)	(9)	(0.0141)

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 5. 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 5.1. The standard deviations are generated using 50 bootstrap samples.

F. 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 b 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 b^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:

$$EU_{I_{it}=0} = \int_{w_t} \int_{m_t} u(\max[A_t + w_t - (1 - \frac{q^E b^E}{4})m_t - q^E p^E, \underline{c}])f(w_t, m_t)dmdw \tag{31}$$

Where, $\frac{q^E b^E}{4}$ 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:

$$EU_{I_t=1}(p) = \int_{w_t} \int_{m_t} u(\max[c_t, \underline{c}])f(w_t, m_t)dmdw \tag{32}$$

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

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

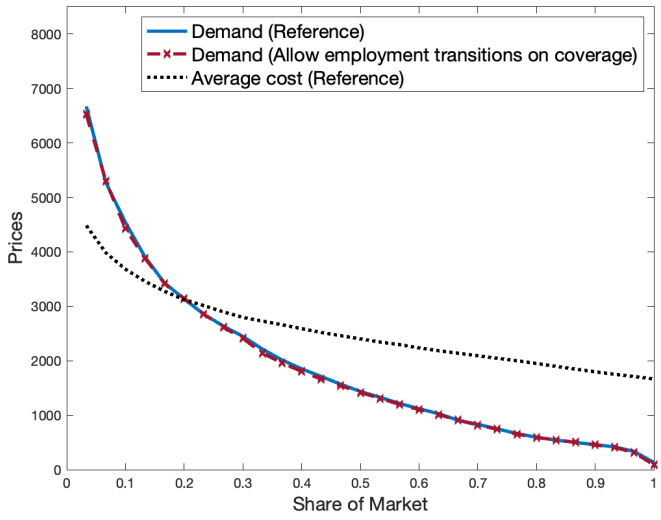
premium for private insurance for the entire year, unlike in a model excluding ESI access. Consequently, individuals may accept a higher quarterly price.

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.

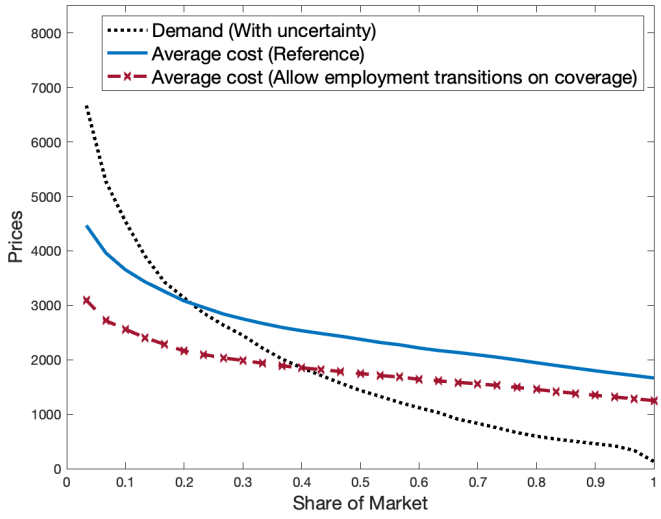
In the empirical analysis b is set at 70%, which is the actuarial value of the Silver plan in the ACA market. All employers offer the same employer-sponsored insurance that covers $b^E = 77.8\%$ of the total medical costs at a price of $p^E = \$162.45$ per quarter. [31]

[31] 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 F1: ESI Access and Market Equilibrium



(a)



(b)

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

G. 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:

$$\Delta q = \underbrace{\frac{1}{N}\sum_i \mathbf{1}(g_i \geq \hat{p}^*_{i,after})}_{\text{Equilibrium take-up after subsidies}(q_{after})} - \underbrace{\frac{1}{N}\sum_i \mathbf{1}(g_i \geq p^*)}_{\text{Equilibrium take-up before subsidies}(q_{before})} \tag{33}$$

The changes in consumer surplus are:

$$\Delta CS = \underbrace{\frac{1}{N}\sum_i (g_i - \hat{p}^*_{i,after})\mathbf{1}(g_i \geq \hat{p}^*_{i,after})}_{\text{Consumer surplus after subsidies}(CS_{after})} - \underbrace{\frac{1}{N}\sum_i (g_i - p^*)\mathbf{1}(g_i \geq p^*)}_{\text{Consumer surplus before subsidies}(CS_{before})} \tag{34}$$

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

$$DWL_{before} = \frac{1}{N}\sum_i (g_i - z_i)\mathbf{1}(g_i \geq z_i) - \frac{1}{N}\sum_i (g_i - z_i)\mathbf{1}(g_i \geq p^*) \tag{35}$$

The deadweight loss after subsidies is:

$$DWL_{after} = \frac{1}{N}\sum_i (g_i - z_i)\mathbf{1}(g_i \geq z_i) - \frac{1}{N}\sum_i (g_i - z_i)\mathbf{1}(g_i \geq \hat{p}^*_{i,after}) \tag{36}$$

Social costs of supporting HI policy.— 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:

$$\lambda \frac{1}{N}\sum_i (p^*_{after} - \hat{p}^*_{i,after})\mathbf{1}(g_i \geq \hat{p}^*_{i,after}) \tag{37}$$

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.

For the counterfactual subsidy policy that combines public insurance expansion with a means-tested subsidy, an additional source of social cost arises: the cost of covering individuals under the expanded public health insurance program. Since the policy provides the same type of insurance as the private market—covering 70% of expected medical costs—it is straightforward to calculate the total expected medical costs for these individuals and multiply by 70%. Finally, I apply $\lambda = 0.3$ to account for the social cost of taxation required to fund coverage for these low-income individuals.

Social costs of supporting transfers by consumption floor.— Transfers from consumption floor represent another source of social costs. If individual i is uninsured, her expected transfers from consumption floor is:

$$T_i^U = \int_w \int_m \max(\underline{c} - (A_i + w_{it} - m_{it}), 0) f(w_{it}, m_{it}) dw_{it} dm_{it} \tag{38}$$

If she is insured, expected transfers is:

$$T_i^I = \int_w \int_m \max(\underline{c} - (A_i + w_{it} - (1-b)m_{it} - p^*), 0) f(w_{it}, m_{it}) dw_{it} dm_{it} \tag{39}$$

The average total welfare in a market with equilibrium price of p^* is thus:

$$T = \lambda \frac{1}{N} \sum_i (T_i^U 1(g_i \leq p^*) + T_i^I 1(g_i > p^*)) \tag{40}$$

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).

Note that individuals covered under the expanded public health insurance program are treated as if they have a plan with a premium of zero in this calculation.