Earnings Dynamics and Selection in Health Insurance Markets

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Abstract

This paper investigates how earnings dynamics affect adverse selection in health insurance markets. I model how individuals predict the joint distribution of quarterly earnings and medical spending by incorporating health status transitions, employment status, and employer transitions. I empirically estimate the model by combining Utah UI records and Utah All-Payer Claims Dataset, which allows me to observe individuals' quarterly medical spending, earnings, and their employers from 2013 to 2015. Finally, I apply the model estimates and find that the average willingness to pay in models with earnings dynamics is lower, especially for individuals with higher expected medical costs. Incorporating earning uncertainties causes a weaker relationship between willingness to pay for insurance and expected medical costs. By reducing the influence of private information about medical risks, earnings dynamics reduce deadweight loss by 40%. The equilibrium take-up is 5.2% higher, and premiums are 17.2% lower. Moreover, counterfactual analysis shows that implementing a uniform subsidy in models with earnings dynamics reduces a lower share of deadweight loss. These results suggest that the evaluation of public policies to reduce adverse selection can be improved by considering the joint dynamics of health and earnings.

1 Introduction

Many health policies to reduce welfare loss from adverse selection are often designed based on earnings. For example, the Affordable Care Act (ACA) subsidy eligibility depends on households' income. However, we still do not fully understand how the joint earning and medical spending dynamics affect adverse selection is understood. In contrast to many textbook models of insurance demand, real-world insurance demand does not only depend on medical risk. When making health insurance decisions, individuals face considerable earning uncertainties and are often exposed to economic risk after bad health shocks (Dobkin et.al., 2018).

Knowledge about how earnings dynamics affect adverse selection is essential for designing policies like subsidies. In the textbook Akerlof adverse selection model, the expected medical costs of the uninsured are always lower than the insured (Akerlof, 1970). However, when earnings dynamics are considered, some unhealthy individuals may remain uninsured. As a result, subsidy may not be as efficient as predicted in the textbook model because it can potentially motivate high-cost individuals to purchase the plans.

In this paper, I investigate the impact of joint earning and medical spending dynamics on adverse selection in the health insurance markets. Besides earning levels, earning uncertainty and its correlation with medical spending can also influence individuals' willingness to pay for health insurance. Motivated by the potential correlation between earnings and medical risks, I first model the predictions of joint earnings and medical spending dynamics. Health shocks affect both earnings and medical spending. Moreover, health shocks are allowed to have a persistent impact on earnings via influencing the probability of being not employed[1] or transiting to firms with different levels of wage compensation. I empirically estimate the model using novel datasets that combine Utah UI records and the All-Payer Claims Dataset, allowing me to track individuals' earnings and medical spending from 2013 to 2015. I find that incorporating earning uncertainties in the model causes a weaker relationship between willingness to pay for insurance and expected medical costs. By reducing the influence of private information about medical risks in insurance markets, earnings dynamics (along with their connection to medical risks) tend to attenuate deadweight loss from adverse selection, relative to models that abstract from earnings dynamics. Finally, counterfactual simulations reveal evidence that subsidies are less effective in reducing deadweight loss in models with earnings dynamics. This evidence suggests that incorporating joint earnings and medical spending dynamics could improve policy evaluations.

This paper first discusses how earnings dynamics affect individuals' decisions between being fully insured or uninsured. I stress the importance of considering earning uncertainty and the correlation between earning and medical spending. As predicted in the textbook model, individuals with higher medical costs are unambiguously more willing to buy the plan. How-

[1] I only observe how much individuals earn and the employers they match to if they earn a positive amount in a quarter. Why individuals are not employed is unobserved. They could take days off but are still considered as employees in the firm last quarter. They could be unemployed or leave the labor force. For accuracy, I defined the state as not employed instead of unemployed.

ever, the impact of earning on willingness to pay differs from medical risks, for it is a net impact of two opposing forces. Higher earning uncertainty or lower expected earning level increases individuals' willingness to pay because they derive lower utility from being uninsured. At the same time, a fixed nominal insurance premium reduces consumption utility by a greater amount when consumers have lower baseline consumption levels. Individuals with lower expected earnings or earning uncertainty are more likely to face states with lower baseline consumption levels, therefore causing reductions in their incentive to purchase insurance.

Furthermore, motivated by the evidence in the literature on the dependence between earning and medical spending, I discuss how the correlation matters for the willingness to pay for insurance. (e.g., Dobkin et.al., 2018; Cochrane, 1991; Charles, 2003; Chung, 2013; Meyer and Mok, 2013; Poterba, Venti, and Wise, 2017; Lockwood, 2022). When earnings and medical spending are negatively correlated, the willingness to pay is larger than when they are independent. The intuition is that the negative correlation reallocates resources from a bad state to a good one, undesired by risk-averse individuals. However, the positive correlation can reduce the willingness to pay because it works as implicit insurance by reallocating consumption from good to bad states.

Heterogeneity in earnings dynamics can further cause wealth inequality. Differences in assets should be incorporated in insurance decisions because protecting assets is one important reason to purchase health insurance. To incorporate the impacts of safety nets, I also assume a consumption floor. The literature has provided evidence for the impact of the consumption floor on demand for health insurance, including protection from bankruptcy (Mahoney, 2015) and uncompensated care (Garthwaite et al., 2015). Building on this insight, this model points out that people with different earnings dynamics receive different amounts of protection from the consumption floor. For example, an individual with higher earning uncertainty expects a higher probability of receiving transfers from the consumption floor, implicitly increasing the incentive to stay uninsured.

I then present a model on how individuals jointly predict earnings and medical spending for the next quarter. My model of earning prediction is motivated by the literature that models earnings dynamics using employer-employee-matched databases (Abowd et al., 1999; Addario et al., 2022; Bonhomme et al., 2019). I assume that people predict earnings using deterministic information, such as age, gender, and a fixed person earning type. The fixed person earning types represent general skills or human capital levels that are rewarded equally across employers. Individuals predict earnings following three steps. First, individuals are uncertain about the health status of the next period. Second, conditional on each possible realization of health type, individuals predict their job mobility status and the destination firm types if they change employers. Finally, conditional on each possible type of realization, individuals are uncertain about the transitory earning errors. Individuals predict their medical spending using past medical spending, health type transition, and whether they have chronic conditions such as diabetes and hypertension. The correlation between earnings and medical spending is embedded because health-type transition affects medical spending and earnings. My paper is closely related to Blundell et al. (2020), which model the household's health and income as transitory-permanent processes and allow the health and income shocks to be correlated. Because the earning data in this paper is an employer-employee-matched database, I can model the permanent component of earning as changes in employment status or employers with different compensation levels. The health status can thus have a permanent effect on earnings by causing unemployment or job mobility.

I empirically estimate this model by combining Utah All-payer Claims Data and Utah UI records. Utah All-payer Claims data include detailed information about medical utilization and insurance coverage of people in Utah. One unique feature of the Utah UI records database is that I observe how employers and employees are linked each quarter. I can link individuals' earnings and medical utilizations across these panel datasets. The model estimates show a negative correlation between earnings and medical spending. Conditional on type realizations, transiting to worse health status leads to higher medical spending and lower earnings. Moreover, people with bad health face difficulty in transiting out of the state of not being employed, revealing the potential negative impact of health on employment status.

I apply these model estimates to study how heterogeneity in earning dynamics influences adverse selection. I find that models that abstract from differences in earnings dynamics on average overestimate willingness to pay, especially for individuals with higher medical risk. Because earnings and medical spending tend to be negatively correlated, individuals with higher medical costs are more likely to be those who earn expected lower earnings and higher earning uncertainties. They also tend to face difficulty in accumulating assets. Thus they are more likely to hit the consumption floor, and the protection from the consumption floor significantly reduces their willingness to pay.

I find downward shifts in demand curves after incorporating earnings dynamics, which cause a lower equilibrium take-up rate and a higher premium. Moreover, marginal cost curves are no longer monotonic. The individuals with higher incentives to buy insurance are not necessarily those more costly to cover. Thus average cost curves in models that incorporate earnings dynamics are steeper, which results in increases in the equilibrium take-up rate and reductions in the equilibrium premiums. On the net, the effect of changes in average cost curves dominates. Moreover, the socially efficient take-up rate is lower in models with earnings dynamics. Therefore, it implies that mandating everyone to enroll may cause welfare loss.

Finally, I investigate how the efficiency of subsidies changes if incorporating earnings dynamics. When applying a uniform subsidy, deadweight loss reduction is lower in models with earnings dynamics. Moreover, counterfactual simulations show that more subsidies to the lower-earning group cannot effectively reduce deadweight loss as uniform subsidies. These results reveal the importance of incorporating earnings dynamics in subsidy designs.

Related literature. — My work shows the importance of considering the joint dynamics of earnings and medical spending. However, obtaining data on earnings and medical utilization for a sample with a wide range of heterogeneity in earnings is difficult. The literature has found ways to reduce the potential negative impact of the under-modeled joint distribution of earnings and medical spending. For example, some studies exclude the income effect by assuming the CARA utility function and incorporate a limited degree of income heterogeneity in risk preferences (e.g., Einav et.al., 2013; Handel, 2013; Marone and Sabety, 2022). Some other studies follow Einav, Finkelstein, and Cullen (2010) to use price variations to estimate the willingness to pay for insurance. One advantage of this method is that it does not require the researcher to make assumptions about consumer preferences or ex-ante information. Thus the distribution of earnings is not necessary when applying this method. However, these methods limit our ability to investigate how earnings dynamics affect adverse selection.

This paper also contributes to the literature on how actual insurance markets differ from the textbook adverse selection models. The multidimensional private information can cause advantageous selection (Finkelstein and McGarry, 2006; Fang et al., 2008). Other factors considered include administrative costs of providing insurance and preference heterogeneity (Einav and Finkelstein, 2011), uninsurable background risk (Doherty and Schlesinger, 1983), consumer inertia (Handel, 2013), selection on moral hazard (Einav et.al., 2013), and hospital networks (Ho and Lee, 2017). My paper discusses how earning dynamics may cause adverse selection to deviate from the prediction of the textbook model. Furthermore, understanding the impact of earning dynamics is uniquely essential. First, it helps to improve the design of many policies that target people based on income levels, such as subsidies and individual mandates in ACA. Second, modeling earnings dynamics enables us to discuss the spillovers of safety nets or labor market shocks in the health insurance market. For example, individuals' earnings dynamics might be unevenly affected by a financial crisis. How policymakers modify health insurance policies when a financial crisis occurs requires knowledge of the impact of earnings dynamics on adverse selection.

2 Theoretical Framework

This section presents a theoretical discussion on how earning dynamics affect adverse selection. First, I begin by introducing the model environment and the market equilibrium. Second, I discuss how earnings dynamics affect individuals' willingness to pay for health insurance.

2.1 Model environment

Setup and Notation. — Individuals face uncertainty about joint earnings and medical spending dynamics. Individuals have two options to cover the potential medical risks: purchasing full insurance at a price of p and no insurance. I take the characteristics of the insurance contracts as given. Therefore, my analysis follows Akerlof (1970) rather than Rothschild and Stiglitz (1976), in which the health insurance plan coverage is determined endogenously.

I define the population by a distribution $Z(\xi)$, where ξ is a vector of consumer characteristics. Examples of consumer characteristics include gender, age, health, and employment status. The individuals are assumed to be risk averse and have homogenous concave utility function $u(.)$.

Earning uncertainty. — In my model, the individuals face two layers of earning uncertainty. First, given the current information at time t, individual i is uncertain about the probability of the type $\theta_{i,t+1} \in \Theta$ realized next period. I denote the probability to transit to $\theta_{i,t+1}$ as $Pr(\theta_{i,t+1})$. For example, individuals are uncertain about their health status or employment status. Second, conditional on realized $\theta_{i,t+1}$, individuals are also uncertain about the transitory log earning errors $\sigma(\theta_{i,t+1})$. I assume the log earning errors follow a normal distribution, with CDF as $F(\sigma)$.

Individuals calculate the expected earnings in two steps. First, conditional on realizing type $\theta_{i,t+1}$ and log earning errors $\sigma(\theta_{i,t+1})$, the earning is given as

$$w(\theta_{i,t+1}) = e^{f_W(\theta_{i,t+1})+\sigma(\theta_{i,t+1})} \tag{1}$$

where $f_W(\theta_{i,t+1})$ is the part of the log earning predicted by the type $\theta_{i,t+1}$ and other permanent individual characteristics. Second, individuals take expectations over the error terms.

$$\bar{w}(\theta_{i,t+1}) = \int w(\theta_{i,t+1}) dF(\sigma) \tag{2}$$

We can also interpret it as the expected earning conditional on realizing type $\theta_{i,t+1}$. Finally, individuals take expectations over all possible types that could realize next period.

$$E(\bar{w}(\theta_{i,t+1})) = \sum_{\theta_{i,t+1} \in \Theta} Pr(\theta_{i,t+1}) \bar{w}(\theta_{i,t+1}) \tag{3}$$

It is important to notice that $E(\bar{w}(\theta_{i,t+1}))$ is influenced by the degree of earning uncertainty individual i faces. If an individual i faces a higher probability of transiting to a low earning type, he also calculates a lower expected earning.

Medical spending uncertainty. — The individuals also face two layers of medical spending uncertainty. I assume there is no income effect on medical spending and moral hazard. Thus, individuals will not adjust the utilization of medical services with increases in earnings or insurance enrollment status.

First, individuals are uncertain about which type will realize in the next quarter $t + 1$. If individual i draws type $\theta_{i,t+1} \in \Theta$, he predicts mean of log medical spending as $f_M(\theta_{i,t+1})$. Second, individuals are also uncertain about the log medical spending errors $\nu(\theta_{i,t+1})$. I assume log medical spending errors follow a normal distribution, with CDF as $F(\nu)$.

Individuals also calculate expected medical spending in two steps. First, conditional on drawing log medical spending $\nu(\theta_{i,t+1})$, and realizing type $\theta_{i,t+1}$, the medical spending is given by

$$m(\theta_{i,t+1}) = e^{f_M(\theta_{i,t+1}) + \nu(\theta_{i,t+1})} \tag{4}$$

Second, individuals take expectations over the log medical spending error draws.

$$\bar{m}(\theta_{i,t+1}) = \sum_{\theta_{i,t+1} \in \Theta} Pr(\theta_{i,t+1}) \bar{m}(\theta_{i,t+1}) \tag{5}$$

The final step is to take expectations over all possible types.

$$E(\bar{m}(\theta_{i,t+1})) = \sum_{\theta_{i,t+1} \in \Theta} Pr(\theta_{i,t+1}) \bar{m}(\theta_{i,t+1}) \tag{6}$$

Joint distribution of earning and medical spending. — Individual i earns $w(\theta_{i,t+1})$ and spends $m(\theta_{i,t+1})$ for medical needs. I assume that $(w(\theta_{i,t+1}), m(\theta_{i,t+1}))$ follows a joint distribution, with CDF as $G(w, m)$. I denote the CDF of distribution of earnings and medical spending as $G(w)$ and $G(m)$, respectively. I assume that the parameter ρ_i summarizes the correlation between earnings and medical spending. When $\rho_i = 0$, earnings and medical spending are uncorrelated. If $-1 < \rho_i < 0$, then earnings and medical spending are negatively correlated, which means earning level is more likely to be low when medical spending is high. If $0 < \rho_i < 1$, earnings and medical spending are positively correlated.

Willingness to pay. — I assume that firms cannot price discriminate against individuals because of private information. Therefore, all consumers in the market, who are assumed to be price takers, would be offered the full insurance plan at the same premium. For individual i, the expected utility of being uninsured is $V_i^N = \int \int u(w - m)dG(w, m)$. The expected utility of purchasing full insurance is a function of possible prices of the plan p: $V_i^B(p) = \int u(w - p)dF(w)$. Individual i chooses to buy the insurance at a price p if and only if the expected utility of purchasing the plan exceeds the expected utility of being uninsured: $V_i^B(p) \geq V_i^N$. I define the maximum price individual i is willing to pay for health insurance as $g(\xi_i) = max\{p : V_i^B(p) \geq V_i^N\}$.

Market Demand. — The market demand reflects the proportion of people willing to pay for the plan at each possible market price p. Market demand is given as follows:

$$D(p) = Pr(g(\xi_i) \geq p) = \int 1(g(\xi) \geq p)dZ(\xi) \tag{7}$$

Market supply. — I assume perfect competition on the supply side. There are $N > 2$ identical insurers who set prices following the Nash equilibrium. The insurers would set the same price, and the individuals would choose to purchase from a random firm. The expected cost of providing full insurance to individual i is $E(M(\xi_i))$.

The marginal cost reflects the expected medical cost of the marginal buyer whose willingness to pay is the price p. Therefore, the marginal cost curve is as follows:

$$MC(p) = E(M(\xi)|g(\xi) = p) \tag{8}$$

The average cost curve in the market is determined by the costs of the individuals who choose to be fully insured. It is given by

$$AC(p) = E(M(\xi)|g(\xi) > p) = \frac{1}{D(p)} \int M(\xi)1(g(\xi) \geq p)dZ(\xi) \tag{9}$$

Market equilibrium. — The competitive equilibrium price of the plan is determined by the market demand curve and the average cost curve. The equilibrium market price is the break-even price:

$$p^{eqm} = \{p : D(p) = AC(p)\} \tag{10}$$

2.2 Earnings dynamics influence willingness to pay

In this section, I discuss how people with different earning dynamics value health insurance differently. I will discuss expected earnings, earning uncertainty, and the correlation between earnings and medical spending. It is tempting to think that people with higher earning uncertainty are willing to pay more for health insurance because they face more consumption uncertainty. However, the impact of earning uncertainty on the willingness to pay for health insurance is ambiguous, even when individuals face independent earnings and medical spending, and their consumption levels never fall under the consumption floor. I explore two opposing forces: changes in (1) the expected utility of being uninsured and (2) the expected utility cost of premium payment.

2.2.1 Earning uncertainty

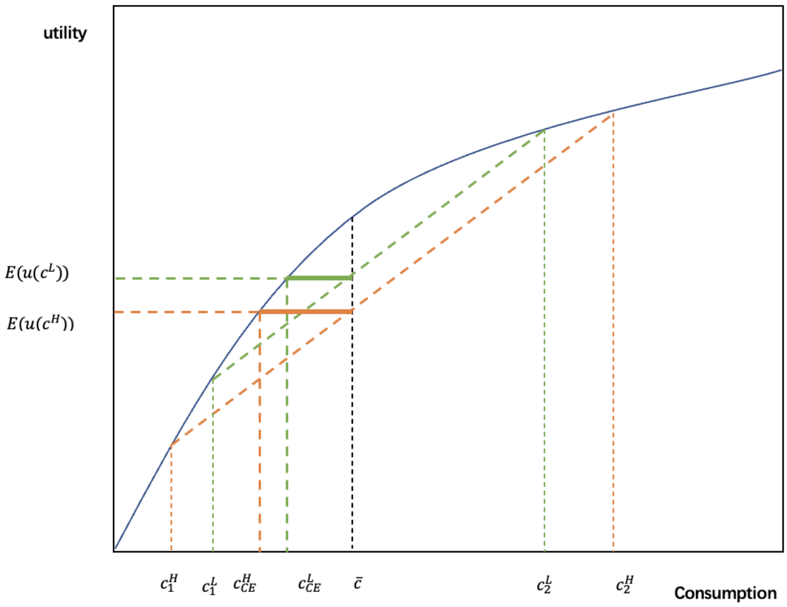
1. *Higher earning uncertainty leads to higher consumption risk*
   Higher earning uncertainty leads to higher consumption volatility.[2] Risk-averse individuals derive lower expected utility from volatile consumption. Figure 1 helps to illustrate the first channel. Individuals face two consumption realizations, c_1^H and c_2^H, with equal probability when earning uncertainty is higher. When earning uncertainty is lower, the possible consumption realizations change to c_1^L and c_2^L. For both cases, the average consumption is $\bar{c}$. When consumption is more volatile, the expected utility is lower: $E(u(c^H)) < E(u(c^L))$. Therefore, individuals with higher earning uncertainty are worse off if choosing to be uninsured, making them more willing to purchase health insurance.

2. *Higher earning uncertainty leads to higher expected utility cost of premium payment*

[2] To see this, the variance of consumption when choosing to be uninsured is $\sigma^2_{W-M} = \sigma^2_W + \sigma^2_M$, which increases with the variance of earning σ^2_W. This is under the assumption that both earnings and medical spending are independent and normally distributed.

A fixed nominal insurance premium reduces the consumption utility by a greater amount when individuals face lower baseline consumption levels. Individuals with higher earning uncertainty are more likely to be in the low-earning state. On average, they must give up more utility for the same premium. The more "expensive" insurance in terms of utility drives down the incentive to purchase health insurance, leading to lower willingness to pay.[3]

Figure 1: Higher earning uncertainty leads to higher consumption volatility



Note: This figure illustrates how consumption volatility changes with earning uncertainty. Individuals face two consumption realizations, c_1^H and c_2^H, with equal probability when earning uncertainty is higher. When earning uncertainty is lower, the possible consumption realizations change to c_1^L and c_2^L. For both cases, the average consumption is $\bar{c}$. When consumption is more volatile, the expected utility is lower: $E(u(c^H)) < E(u(c^L))$.

2.2.2 Expected earning

How expected earning changes affect the willingness to pay can also be explained as the net impact of the two forces. First, individuals with lower expected earnings derive lower expected utility from the uninsured choice. Therefore, they have a higher incentive to purchase health

[3]When the utility function is differentiable, the utility given up to pay an additional unit of money for insurance when the earning is W can be represented by $u'(W)$. Because individuals are risk averse, utility function $u(.)$ is concave, and the marginal utility $u'(.)$ is convex. Thus, $E((u'(W^H)) > E((u'(W^L))$ holds, where W^H is the case that earning uncertainty is higher.

insurance. [4] Second, individuals with lower expected earnings consider insurance more expensive in terms of utility. [5]

2.2.3 The correlation between medical spending and earning

If earnings and medical spending are not independent, what would happen to the willingness to pay for health insurance? The answer to this question is important because the literature has provided evidence of the dependence between them (Dobkin et al., 2018; Cochrane, 1991; Charles, 2003; Chung, 2013; Meyer and Mok, 2013; Poterba, Venti, and Wise, 2017).

Consumption volatility increases when earnings and medical spending are negatively correlated and decreases when the correlation is positive.[6] Moreover, this correlation does not affect the utility cost of premium payment. Therefore, a negative correlation between earnings and medical spending unambiguously increases the willingness to pay.

The negative correlation serves as reallocating resources from low-resource states to high-resource states, which risk-averse individuals do not favor. However, the positive correlation is implicit insurance that reallocates resources from high-resource states to low-resource states, increasing individuals' expected utility.

2.3 Precautionary Saving

In this section, I introduce precautionary saving to the model. Wealth affects the demand for health insurance. Individuals buy insurance to protect assets by reducing out-of-pocket medical spending and medical debt (Finkelstein et al., 2018). Earnings dynamics affect the wealth accumulated. First, it changes the saving motivations. Second, negative earning shocks can reduce wealth levels. Moreover, individuals are harder to accumulate wealth after persistent shocks, such as unemployment.

2.4 Consumption floor

In this section, I relax the assumption that individuals' consumption never falls under the consumption floor. The consumption floor works by transferring wealth to individuals when

[4] As illustrated in Figure A.1 in Appendix A, facing the same level of earning uncertainty, if the average consumption equals $\bar{c}_L$, the expected utility is $E(u(c^L)$, which is lower than $E(u(c^H))$, which is the expected utility when the average consumption is $\bar{c}_H$.

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

[6] The consumption volatility $\sigma^2_{W-M} = \sigma^2_W + \sigma^2_M - \rho\sigma_W\sigma_M$ increases if earning and medical spending are negatively correlated ($\rho < 0$), and decreases if the correlation is positive ($\rho > 0$).

they face extremely bad states. The ability to claim bankruptcy policy is one example.

The consumption floor affects the willingness to pay because it is implicit insurance for uninsured individuals. Moreover, individuals with different earnings dynamics differ in how much protection they obtain from the consumption floor. For example, individuals with lower expected earnings or higher earning uncertainty are more likely to hit the consumption floor. Therefore, their willingness to pay is hugely affected by the consumption floor. In addition, the negative correlation between earnings and medical spending further increases the amount of protection from the consumption floor. Individuals face worse low-resource states. Thus, they are more likely to be protected by the consumption floor.

3 Empirical Model

I now specify a model of how individuals predict earnings and medical spending in period $t+1$, given their information in period t. I first discuss the prediction of earnings and medical expenditures separately. Second, I discuss how my model incorporates their correlations.

3.1 Earnings

My model of individual earnings follows the literature pioneered by Abowd et al. (1999) — AKM model. In the AKM framework, the log earnings depend on observed characteristics, unobservable worker-level components, and unobservable employer-specific components. However, the massive number of heterogenous workers and employers can make predicting job mobility challenging. Therefore, I follow Abowd et al. (2019) and Bonhomme et al. (2018) using a latent-type framework. The workers and employers are associated with latent heterogeneity types that affect earnings and job mobility. Moreover, the number of job movers per firm tends to be small, which creates small-sample biases. This concern can be alleviated by reducing the number of types (Bonhomme et al., 2018).

3.1.1 Population heterogeneity

I consider an economy composed of workers, indexed by $i \in \{1, ..., I\}$ and firms, indexed by $j \in \{1, ..., J\}$. I denote the type of worker i as α_i. I assume that workers with the same person type α_i are rewarded equally across employers due to reasons like skills and human capital. In addition to their unobserved types, workers may also differ in terms of their observable characteristics X_{it}. I interpret it as factors that affect workers' pay at all jobs. I denote the health type for worker i in time t as h_{it}, and denote the health type transition from $h_{i,t-1}$ to h_{it} as H_{it}.

Employers are also heterogeneous. I consider two dimensions of time-invariant heterogeneity: earning level and earning risk. The firm j has a firm type of $(k_j^{\mu}, k_j^{\sigma})$. k_j^{μ} captures the firm component of log wage. I assume that all employees in the firms with type k_j^{μ} receive the same pay premium due to reasons such as efficiency wage. k_j^{σ} captures its' workers' earning uncertainty.

At the beginning of period t, the workers will first choose insurance. After the insurance choice, the earnings and medical spending are realized. The workers may separate from the job and transit to not being employed. I consider four types of job transition between $t-1$ and t.

- $Q_{it} = 1$ means this worker stays in the same firm between $t-1$ and t.
- $Q_{it} = 2$ stands for that the worker changes employer between $t-1$ and t. I allow the probability that the workers move to a firm with the same type as the original firm.
- $Q_{it} = 3$ means the worker changes from not employed in $t-1$ to employed in t.
- $Q_{it} = 4$ means the worker is not employed in t.

Worker i receives earning W_{it} at time t. I denote the earning level type and the earning risk type of the firm j that the worker i works for at time t as $k_{j(it)}^{\mu}$ and $k_{j(it)}^{\sigma}$ respectively.

3.1.2 Earning determination

I assume that the workers believe that their log of earnings evolves according to the following equation if they are employed at time t, that is, $Q_{it} \neq 4$.

$$lnW_{it} = a\alpha_i + bQ_{it} \times k_{jit}^{\mu} + dk_{j(it)}^{\sigma} + eH_{it} + fX_{it} + \epsilon_{it} \tag{11}$$

The vector X_{it} includes observable time-varying characteristics. In practice, it includes age, gender, and year-quarter dummies. Q_{it} stands for the job mobility type transitions. I allow the destination firm earning level type $k_{j(it)}^{\mu}$ to interact with mobility types. $k_{i(it)}^{\sigma}$ is the firm earning risk type. H_{it} describes how the health type transit between $t-1$ and t. The error term ϵ_{it} captures the uncertainty about the log earnings. I assume that the volatility of the error term is determined by firm earning volatility type: $Var(\epsilon_{it}) = f(k_{j(it)}^{\sigma})$.

In this model, I assume exogenous mobility. Therefore, ϵ_{it} is uncorrelated with earning conditional on employment and mobility status Q_{it}, time-varying covariates X_{it}, health type transitions H_{it}, and firm classes. No matching component is allowed to affect the earnings.

3.1.3 Mobility Model

Health type transition. — I assume that the health risk type of individual i at time t depends on the risk category $h_{i,t-1}$ and his age group $X^{age}_{i,t-1}$ at $t-1$ (in 5-year bin, from 26 to 60 and 61 to 64). That is, $Pr(h_{i,t}) = f_h(h_{i,t-1}, X^{age}_{i,t-1})$.

Job mobility type transition. — I assume that job mobility type depend on the gender, person fixed earning type (α_i), realized health type at t (h_{it}), and past job mobility type ($Q_{i,t-1}$). That is, $Pr(Q_{it}) = f_Q(\alpha_i, Q_{i,t-1}, h_{it}, X^{gender})$.

Firm type transition. — I consider the firm-type transition conditional on job mobility types.

1. If the worker remains in the same firm from $t-1$ to t, the firm type does not change.

2. If the worker changes employer, the firm type depends on the person fixed earning type α_i, realized health type h_{it}, and past firm types. That is, $Pr(k^{\mu}_{j(it)}) = f_{k^{\mu}}(k^{\mu}_{j(i,t-1)}, \alpha_i, h_{it})$ and $Pr(k^{\sigma}_{j(it)}) = f_{k^{\sigma}}(k^{\sigma}_{j(i,t-1)}, \alpha_i, h_{it})$.

3. If the worker changes from not employed to employed, the firm type depends on the person fixed earning types α_i and realized health type h_{it}. That is, $Pr(k^{\mu}_{j(it)}) = f_{k^{\mu}}(\alpha_i, h_{it})$ and $Pr(k^{\sigma}_{j(it)}) = f_{k^{\sigma}}(\alpha_i, h_{it})$.

3.2 Medical spending

I assume that workers first predict the annual medical spending of the year y that consists of the quarter of interest t. The medical spending predicted for the quarter of interest would be 25% of the predicted annual medical spending. I avoid directly predicting quarterly medical spending because I constructed health types based on annual ACG scores. The health type is the primary determinant of the medical spending prediction. Therefore, predicting annual medical spending is more accurate.

$$lnM_{iy} = \rho lnM_{i,y-1} + AX_{iy} + BH_{iy} + C\phi_i + Gr_{iy} + \nu_{iy} \tag{12}$$

M_{iy} and $M_{i,y-1}$ represent annual log total medical spending in year y and the past year $y-1$. X_{iy} is time-varying observables, including gender, age groups, and year dummies. The health type transition from year $y-1$ to y is H_{iy}. r_{iy} is the average health insurance coverage of the year y. I further include ϕ_i, which documents whether the worker has chronic conditions or not. The error term ν_{iy} stands for the uncertainty of log medical spending. I assume it to be independent of the log medial spending last year $lnM_{i,y-1}$ conditional on person-fixed component ϕ_i, and the time-varying health status H_{iy}, other covariates X_{iy}, and plan characteristics r_{iy}. The volatility of the error term is determined by realized health type at time t: $Var(\nu_{iy}) = f(h_{iy})$.

3.3 Correlation between earnings and medical spendings

Health-type transitions affect the prediction of earnings in two different ways. First, the health transition indicator H_{it} determines the log earning mean prediction conditional on employment and job mobility status. Second, health type transition H_{it} also indirectly determines wage realization because it influences individuals' job mobility status and their destination firm types. I assume that ϵ_{it} and ν_{iy} are independent. However, earnings and medical spending are still correlated because health-type transitions affect earnings and medical spending simultaneously.

4 Data

Estimating the model requires data on both medical spending and employee earning records. I combine two pieces of data for this analysis: Utah UI records and 2013-2015 All-Payer Claims Data (APCD). Utah UI records contain information on the quarterly earnings of workers and which employers hire them in each quarter. All-Payer Claims Data (APCD) provides information on medical spending and service utilization of Utah residents from 2013-2015, including insurance coverage, diagnosis of patients, and medical utilization records for inpatient, outpatient, physician office visits, and prescription drug consumption. Moreover, the Johns Hopkins ACG System is applied to calculate the annual health risk score. Researchers widely use health risk scores to describe or predict patients' healthcare costs. Finally, I can track everyone across the various files and link their earnings and medical records over time. This combined data set is suitable for this research because it is a quarterly panel data with observations of labor market dynamics and medical spending simultaneously.

This section will first discuss how I use the data to construct the types mentioned in the empirical model section. The types include person earning level types α_i, firm earning level types k^{μ}_j and risk types k^{σ}_j, and health types h_{it}. Second, I will talk about the sample selection and the summary statistics of the selected sample.

4.1 Type constructions

4.1.1 Health types (h_{it})

I group the employees into four health-type categories based on the Annual Health risk score from 2013-2015. Health type takes values of 1, 2, 3, and 4, representing the people with risk scores below 1, between 1 to 1.5, between 1.5 and 2.5, and above 2.5, respectively. Because the distribution of risk scores is high right-skewed, grouping observations into health types can fit the data better than true quartiles. Moreover, because only annual risk scores are observed, I consider the health type of an individual does not change in a year. The health type transitions H_{it} represent how an individual i's health type transiting to t from four quarters ago.

4.1.2 Person earning types (α_i) and firm fixed earning level types (k_i^{μ})

As described in Section 3, workers with the same person earning type (α_i) are assumed to be rewarded equally across employers, and workers work in the firms with the same earning level type (k_j^{μ}) receive the same pay premium. To construct them, I first follow Abowd, Kramarz, and Margolis (1999, also known as AKM) by estimating a linear model with additive person and firm fixed effects. Then, I run the following regression on the sample of workers from the year 2011 to 2017.

$$ln(W_{ijt}) = \gamma_i + \Phi_{j(it)} + \beta X_{it} + \eta_{ijt} \tag{13}$$

W_{ijt} stands for the observed earning of individual i who works for employer j in period t. γ_i is the person fixed effects. $\Phi_{j(it)}$ is the firm fixed effects. X_{it} is the year-quarter fixed effects.

Second, because the two-way fixed effects model is estimated on a short-term panel from 2011 to 2017, the person fixed effects γ_i also reflect the impact of age on the pay premium. To adjust the age effect, I first regress γ_i on eight age groups in 5-year bins.[7] I estimate the residuals $\hat{\gamma}_i$ and divide the workers into six groups based on this adjusted person fixed effects, with 1 standing for the lowest earning type and 6 standing for the highest earning type. I also divide the firms into four groups based on the firm fixed effects $\Phi_{j(it)}$, with type 1 standing for the lowest firm earning type and type 4 standing for the highest firm earning type.

[7] The 8 age groups are as follows: group 1: 26-30, group 2: 31-35, group 3: 36-40, group 4: 41-45, group 5: 46-50, group 6: 51-55, group 7: 56-60, group 8: 61-64

4.1.3 Firm earning uncertainty types (k_i^σ)

I use firm earning uncertainty type k_j^σ as a proxy for the degree of earning uncertainty an average employee faces inside firm j. I first calculate the log earning difference between subsequent quarters t and $t-1$ for each employee in each firm.

$$\Delta ln(W_{i(t-1,t)}) = ln(W_{it}) - ln(W_{i,t-1}) \tag{14}$$

Second, I calculate the standard deviation of the log earning difference for each firm j as $SD(F_j) = SD(\Delta ln(W_{i(t-1,t)}))$ and group the firms into four categories with equally amount of firms based on $SD(F_j)$. I only keep the firms with at least 20 log earning differences during 2013-2015 to reduce the inaccuracy of standard deviation. The firm earning uncertainty types can take values from 1 to 4, with 1 standing for the lowest uncertainty type and 4 standing for the highest uncertainty type.

4.2 Sample selection and summary statistics

This paper focuses on individuals aged between 26 and 64 from the year 2013 to 2015. I restrict the sample to individuals under 65 because most people above 65 are retired and are eligible for Medicare. Because the Utah UI records do not include hours of work and full-time or part-time status, I cannot calculate workers' wages. Furthermore, I restrict to the sample that is enrolled in plans with a large enough number of enrollees because only for these plans can we estimate the plan actuarial value, which is the percentage of total costs that insurers cover on average.[8] I also restrict them to be linked to firms so that I can construct firm types. Moreover, I focus on people who earn a positive amount for at least one quarter from 2014-2015 because people who have never earned anything from 2014-2015 may have exited the labor force after 2013. Table 1 reports how the sample size change when I step by step select the sample based on (1) age, (2) whether covered by insurance or not, (3) whether enrolled in plans with estimated plan actuarial value, (4) whether the worker is working in the firms with constructed types, (5) whether the worker is employed for at least one quarter from 2014-2015. How the detailed summary statistics change with different sample selection criteria is given in Table B1 in Appendix B.

Table 2 reports descriptive statistics on the person-quarter observations with missing earnings filled as zero.[9]The summary statistics show a potential negative correlation between earnings

[8]The plan actuarial value is defined for every person who is in a plan that pays out a positive number of claims to someone else (the focal person is left out).

[9]The reason for the reported number of person-quarter observations different from Row 6 in Table 1 is that Table 1 is only reporting the observed person-quarter pair when positive earning is observed. In Table

and medical spending. Individuals who are predicted to spend more on medical spending are also those who earn less per quarter and experience a higher probability of not being employed or changing employers.

In Figure 2, I plot the mean log earnings of each person type by firm earning level types and firm earning risk types. Both Figure 2 (a) and (b) reveal that lower-type workers earn less on average than higher-type workers. Moreover, on average, individuals who work in firms with higher earning levels type tend to earn more. However, workers in firms with higher earning risk tend to earn less. Figure 3 shows that lower-earning type firms contain a higher share of higher-risk firms. This negative correlation between earning level and risk type reveals that workers who are working in lower-earning firms also tend to face higher risks.

2, I filled the quarters with missing earnings with zero earnings.

Table 1: Number of observations change with sample selection criterions

	Person observation	Person-quarter observation
Starting Sample	1,283,539	14,118,929
Age (26-65)	788,655	8,675,205
Insured	783,104	7,008,764
With plan characteristics	382,122	4,203,342
No missing types	348,146	3,829,606
Potential stayers in labor force	314,685	3,461,535

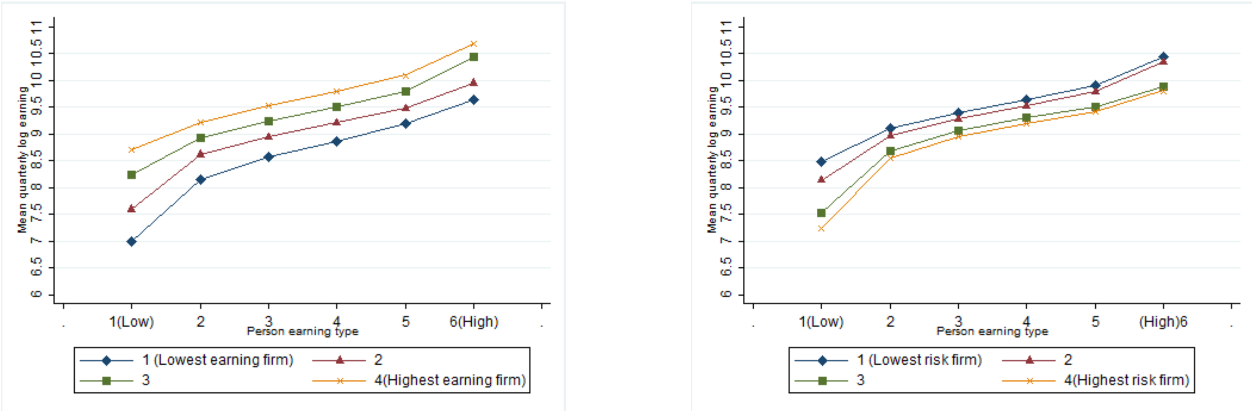
Notes: This table shows how the number of observations, including the number of unique persons observed, and the number of person-quarter observations change by sample selection criterions. I begin with the whole sample in Row 1. In Row 2, I restrict the sample to people between 26 to 64. In Row 3, I restrict to people who are insured in all quarters in 2013-2015. In Row 4, I restrict to people who are enrolled in plans with large enough number of enrollees. in Row 5, I restrict the sample to people who are linked to employers that we could construct firm earning level type and volatility types. in Row 6, I consider the sample size change if we focus on the people who are employed from 2014-2015, so that we could limit the impact of including people who have exited the labor force after 2013.

Table 2: Summary Statistics by current health type from 2013 to 2015

	(1) All mean	(2) Health type = 1 (Lowest Spending) mean	(3) Health type = 2 mean	(4) Health type = 3 mean	(5) Health type = 4(Highest Spending) mean
Age	43.5	41.2	47.2	47.4	47.7
Male	0.5	0.6	0.4	0.4	0.4
Quarterly Earning	15875.4	16188.4	15940.9	15465.3	14282.9
Quarterly Earning(Imputed)	14762.2	15123.8	14839.7	14304.4	12959.9
Not Employed	7.0	6.6	6.9	7.5	9.3
Stay in the same firm	96.5	96.6	96.6	96.4	95.8
Change employer	1.9	1.9	1.7	1.8	1.8
Change to earn zero amount	1.6	1.4	1.7	1.8	2.4
Change to earn positive amount	23.5	24.1	23.5	22.6	21.5
Continue to earn zero amount	76.5	75.9	76.5	77.4	78.5
Inpatient Spending(Quarterly)	178.3	3.8	54.2	123.8	1483.4
Outpatient Spending(Quarterly)	294.3	32.0	192.2	441.4	1876.5
Office Visits Spending(Quarterly)	372.5	98.6	340.3	545.4	1896.1
Pharmacy Spending(Quarterly)	217.8	27.5	164.0	377.1	1277.5
Total Medical Spending(Quarterly)	1062.8	161.9	750.7	1487.7	6533.5
Total Medical Spending(Annually)	4251.4	647.7	3002.8	5950.8	26134.1
Acg risk score	1.2	0.5	1.2	1.9	4.8
Has Diabetes	5.7	1.7	7.4	13.8	19.0
Has Hypertension	14.4	4.9	24.2	31.6	38.5
Health Plan Actuarial Value	79.5	79.0	80.0	80.6	81.2
N	3776220	2382740	562828	440348	390304

Notes: This table reports descriptive statistics on the person-quarter observations in the whole sample. Column 1 is the whole sample of interest, with including potential part-time workers. Column 2 to Column 5 report the summary statistics with health types equal to 1,2,3,4 respectively. Quarterly Earning(Imputed)" means the quarters with missing earning is imputed as zero."

Figure 2: Mean log earning of each person type by firm earning level type and risk type



(a) By earning level types **(b)** By earning risk types

Note: This figure presents the mean log earning by person type and firm type. In the left graph, I plot the mean log earnings, by person type and firm earning level type. It indicates that firms of higher earning levels type tend to pay more for workers with the same person types. Moreover, people with higher earning types also tend to earn more conditional on the firm type. In the right graph, I plot the mean log earnings, by person type and firm risk type. Conditional on person type, high-risk types tend to pay less.

Figure 3: Fraction of firms by earning risk type conditional on firm earning type

Note: This figure shows the fraction of firms by earning risk type and level type. It reveals negative correlation between earning level type and risk type: low earning type firms contain a higher share of high risk firms than higher-earning firm groups

5 Model Estimates

In this section, I empirically estimate the model that predicts the joint distribution of earnings and medical spending proposed in Section 3 using the data and sample selected in Section 4. I present estimates for the earning determination equation (equation 11) and the medical spending prediction equation (equation 12). Moreover, I show the transition matrices estimated for health type and job mobility status transitions.

5.1 Earning and medical spending predictions

I begin by presenting the estimates for the parameters of the earning determination equation (equation 11) and medial spending equation (equation 12). Individuals in the model are assumed to predict the log earnings and medical spending conditional on the realized types, including health, job mobility, or employer firm types.

The first column of Table 3 reports part of the parameter estimates of the log earning equation. The reference group is females whose ages range from 26 to 30 and whose health type transits from 1 to 1. They are also stayers in firms with firm earning levels as type 1 — the firm type with the lowest compensation level. Moreover, their person earning level is type 1 (the lowest person earning type), and they work in firms with risk type 1 (the firms with the lowest risk). The estimates reveal that workers with higher person pay premiums are predicted to earn more on average. Moreover, age group dummies, gender, and firm risk types are also important predictors for log earnings.

The second column of Table 3 shows how age, medical spending of last year, plan characteristics, and whether the worker has diabetes or hypertension help predict the annual log medical spending. On average, people with chronic conditions like diabetes or hypertension are predicted to pay more for medical services. Lagged medical spending is also a good predictor of this year's medical spending, reflecting the persistence of medical spending. On average, individuals enrolled in plans with higher medical coverage are also predicted to spend more for medical services.

Figure 4 reveals a negative correlation between earnings and medical spending. Panel (a) reports the parameters of health-type transitions in the earning equation. Moreover, conditional on transiting into firms of the same earning type, stayers are predicted to earn more than movers, and workers begin to be employed this quarter. Figure 5 panel (b) shows how health type transition influences medical spending prediction. Individuals with worse health type realized are expected to face higher medical bills on average. Moreover, last year's health type is also an important predictor of this year's medical spending.

Figure 5 reports the impact of job transitions on the mean of log earnings. On average, conditional on the same job transitions, the workers who end up transiting into firms with a higher earning level type earn more. Moreover, conditional on transiting into firms with the same earning type, stayers are predicted to earn more than movers and newly-employed workers this quarter. One potential reason is that the movers and the newly employed do not work the entire job transition quarter. Another reason is that the movers and the newly-employed workers are new to the destination firm. Thus, they earn less because of their shorter tenure in the firm. Unfortunately, I cannot distinguish between the two reasons because hours of working or separation reasons are unobservable in the dataset.

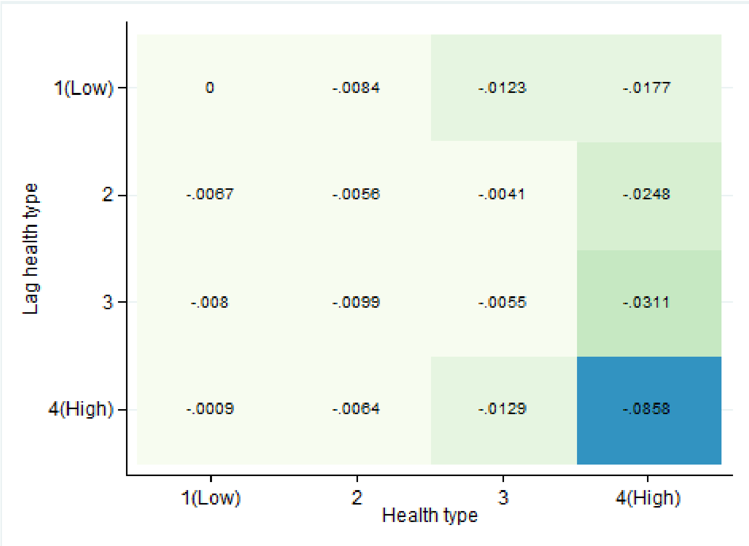
Table 4 reports the sample standard deviation of the log earning errors. The standard deviation of the log earning error is higher for firms with higher risk types. The log medical spending error standard deviation is stable across health types except health type 1. It shows that the uncertainty over the log medical spending is exceptionally high for the lowest medical spending group. One reason could be high spending accidents occur on healthy people, which is hard to predict with past information.

Table 3: Parameter estimates for earning and medical spending equation

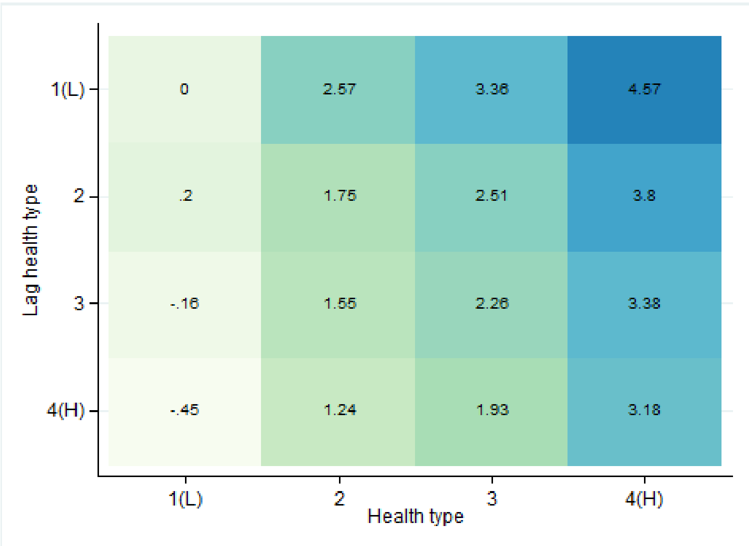
	Log Quarterly Earning	Log Annual Medical Spending
Person type 2	0.795*	
	[0.002]	
Person type 3	1.112*	
	[0.001]	
Person type 4	1.385*	
	[0.001]	
Person type 5	1.682*	
	[0.002]	
Person type 6	2.219*	
	[0.002]	
Male	0.050*	–0.431*
	[0.001]	[0.005]
Age 31-35	0.109*	0.022*
	[0.001]	[0.011]
Age 36-40	0.230*	0.051*
	[0.001]	[0.011]
Age 41-45	0.311*	0.064*
	[0.001]	[0.011]
Age 46-50	0.349*	0.048*
	[0.001]	[0.011]
Age 51-55	0.365*	–0.017
	[0.001]	[0.011]
Age 56-60	0.357*	–0.068*
	[0.001]	[0.011]
Age 61-64	0.314*	–0.030*
	[0.002]	[0.013]
Firm risk type 2	0.025*	
	[0.001]	
Firm risk type 3	–0.005*	
	[0.001]	
Firm risk type 4	–0.033*	
	[0.001]	
Last year medical spending		0.340*
		[0.002]
Plan characteristics		0.604*
		[0.026]
Has Diabetes		0.214*
		[0.006]
Has Hypertension		0.199*
		[0.004]
Constant	7.074*	2.879*
	[0.002]	[0.024]
N	3,224,032	629,370
R-Sq	0.724	0.520

Notes: Column 1 reports part of the parameter estimates of the log earning equation. The reference group is females whose ages range from 26 to 30 and whose health type transits from 1 to 1. They are also stayers in firms with firm earning level as type 1 — the firm type with lowest compensation level. Moreover, their person earning level is type 1 (the lowest person earning type), and they work in firms with risk type 1 (the firms with the lowest risk). Column 2 shows how age, medical spending of last year, plan characteristics, and whether the worker has diabetes or hypertension help predict the annual log medical spending.

Figure 4: Impact of health type transition on the mean of log earning and medical spending



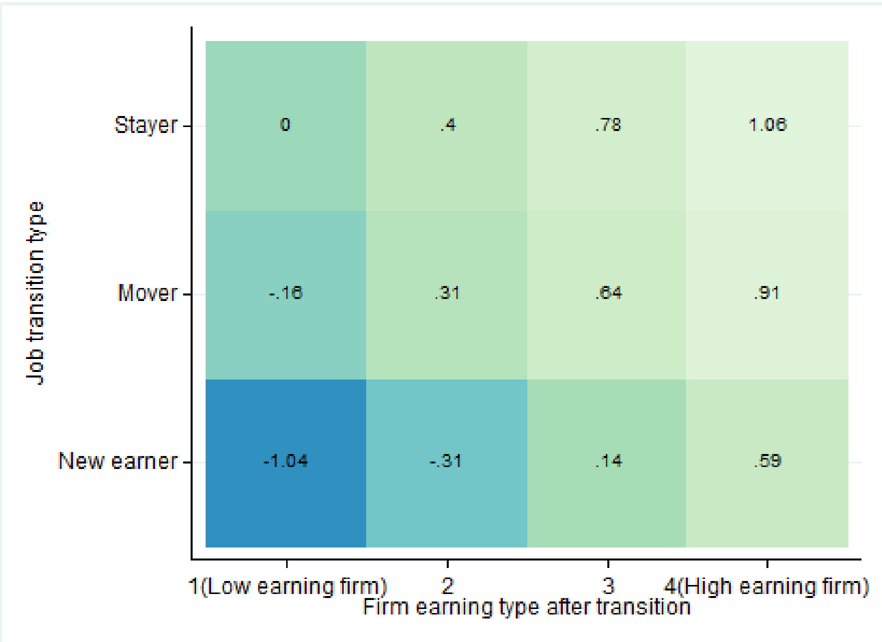
(a) Log quarterly earning



(b) Log annual medical spending

Note: This figure reports the parameters of health type transitions in the earning equation (equation 11) and medical spending equation (equation 12). Panel (a) reports the parameters of health-type transitions in the log earning equation. Panel (b) shows how health type transition influences the prediction of log annual medical spending.

Figure 5: Impact of Job transition type on the mean of log quarterly earning



Note: This figure reports the parameters of the correlation term between job mobility transitions from t to $t+1$ and destination firm earning level types in $t+1$ ($Q_{i,t+1} \times k^{\mu}_{ji,t+1}$) in equation 11. There are three job mobility types. Stayers are those who do not switch employer from t to $t+1$. Movers are those who change employers. New earners are those who are not employed in t and get payment in $t+1$. Firm earning level types reflect the firm compensation, which is estimated in Section 4. The firm earning level types take values of 1 to 4, with 1 standing for the lowest earning level type and 4 standing for the highest earning level type.

Table 4: Sample standard deviation of the log earning and medical spending prediction error

Firm earning risk type	1(lowest risk)	2	3	4(Highest risk)	Average
std(earning error)	0.35	0.46	0.58	0.75	0.49
Health type	1(Healthiest)	2	3	4(Sickiest)	Average
std(medical error)	2.36	0.91	0.87	1.0	1.95

Notes: This table reports the sample standard deviation of the log earning errors ($SD(\hat{\epsilon}_{it})$ in equation 12) by firm earning risk type $k^{\sigma}_{j(it)}$ and log medical spending errors ($SD(\hat{\nu}_{iy})$ in equation 13) by health type h_{it}.

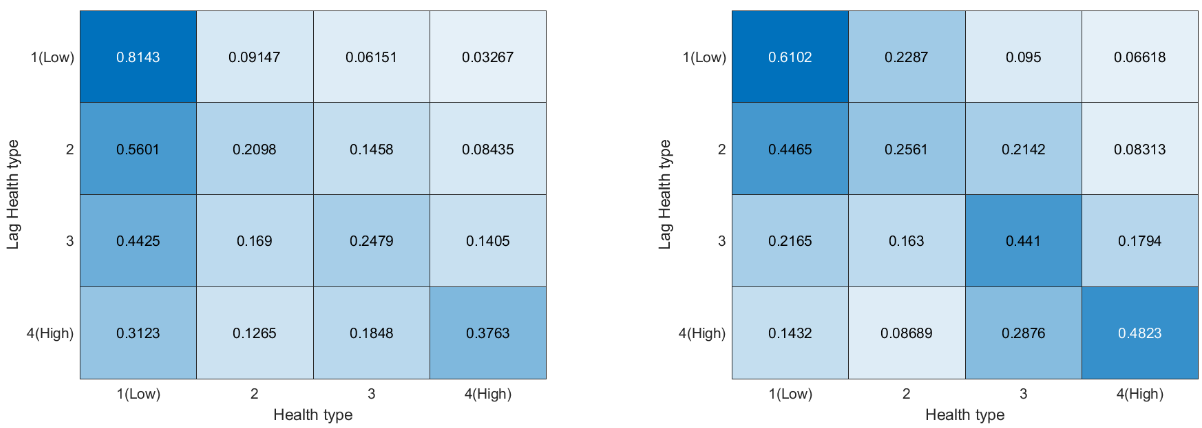
5.2 Transition matrices

This section shows the estimation of the transition matrices of health types, job mobility types, and firm types. Individuals are assumed to follow these transition matrices to predict each possible type's probability to realize in the next period.

5.2.1 Health type transitions

I allow the transition probabilities for health to depend on health type four quarters ago, gender and age group (in 5-year bins). I estimate it by fitting the transitions observed in the data from 2013-2015 into a multinomial logit model. Figure 6 presents the health type transition matrices from $t-1$ to t for females from 26-30 and 61-64. Two facts emerge from Figure 6. First, the health risk is highly persistent. If an individual transits into the worst health type, he faces a low probability of transiting out of the bad health status. Second, transition rates are highly dependent on age. Older individuals are harder to remain in the healthier type and transit back to the healthier type.

Figure 6: Health type transitions by age group



(a) Age: 26-30 **(b)** Age: 61-64

Note: This figure presents the health type transitions for females in two age groups: 26-30 and 61-64. The health types are constructed using ACG risk scores. People with higher risk scores are predicted to have higher medical spending. Health type takes values of 1, 2, 3, and 4, representing the people with risk scores below 1, between 1 to 1.5, between 1.5 and 2.5, and above 2.5 respectively. The health transitions for males and other age groups can be found in Appendix F.

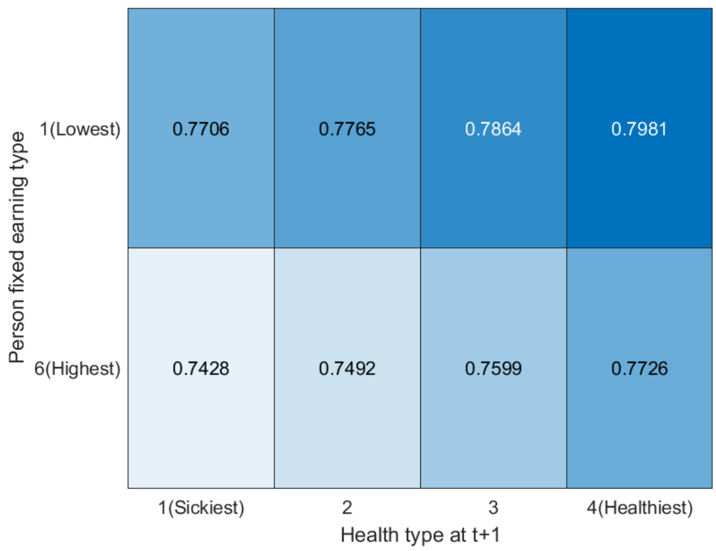
5.2.2 Job mobility transitions

I allow the transition probabilities to depend on current health types $h_{i,t+1}$, past job mobility types Q_{it}, person types α_i, age groups, and gender. The transitions are estimated using a multinomial logit model. Figure 7 shows the probability of remaining unemployed in $t+1$

if the individual is currently not employed in t. I show the probabilities for females with age 26-30. The probabilities for males, other age groups, and person types can be found in Appendix E. Figure 7 reveals that individuals with a higher person earning type are more likely to transit out of the not-employed state. Moreover, sicker individuals are more likely to remain not employed, revealing the negative impact of health shocks on the probability of getting out of the state of not being employed.

Figure 8 shows the job mobility type transitions if individuals are currently employed in t. Comparing panels (a) and (c) (or panels (b) and (d)), individuals with a higher person earning level type are more likely to stay in the firm and less likely to transit to not employed state. Comparing panels (a) and (b) (or (c) and (d)), we can see that a sicker health state decreases the probability of staying in the old firm and increases the probability of not being employed.

Figure 7: Probability to remain not employed



Note: This figure presents the probability to remain not employed in $t+1$ if currently not employed in t. This figure focuses on females whose ages are from 26 to 30. The health types are constructed using ACG risk scores. People with higher risk scores are predicted to have higher medical spending. Health type takes values of 1, 2, 3, and 4, representing the people with risk scores below 1, between 1 to 1.5, between 1.5 and 2.5, and above 2.5 respectively. Person fixed earning types α_i are constructed from a two-way fixed effects model as explained in Section 4. The probabilities for males, other age groups, and person types can be found in Appendix F.

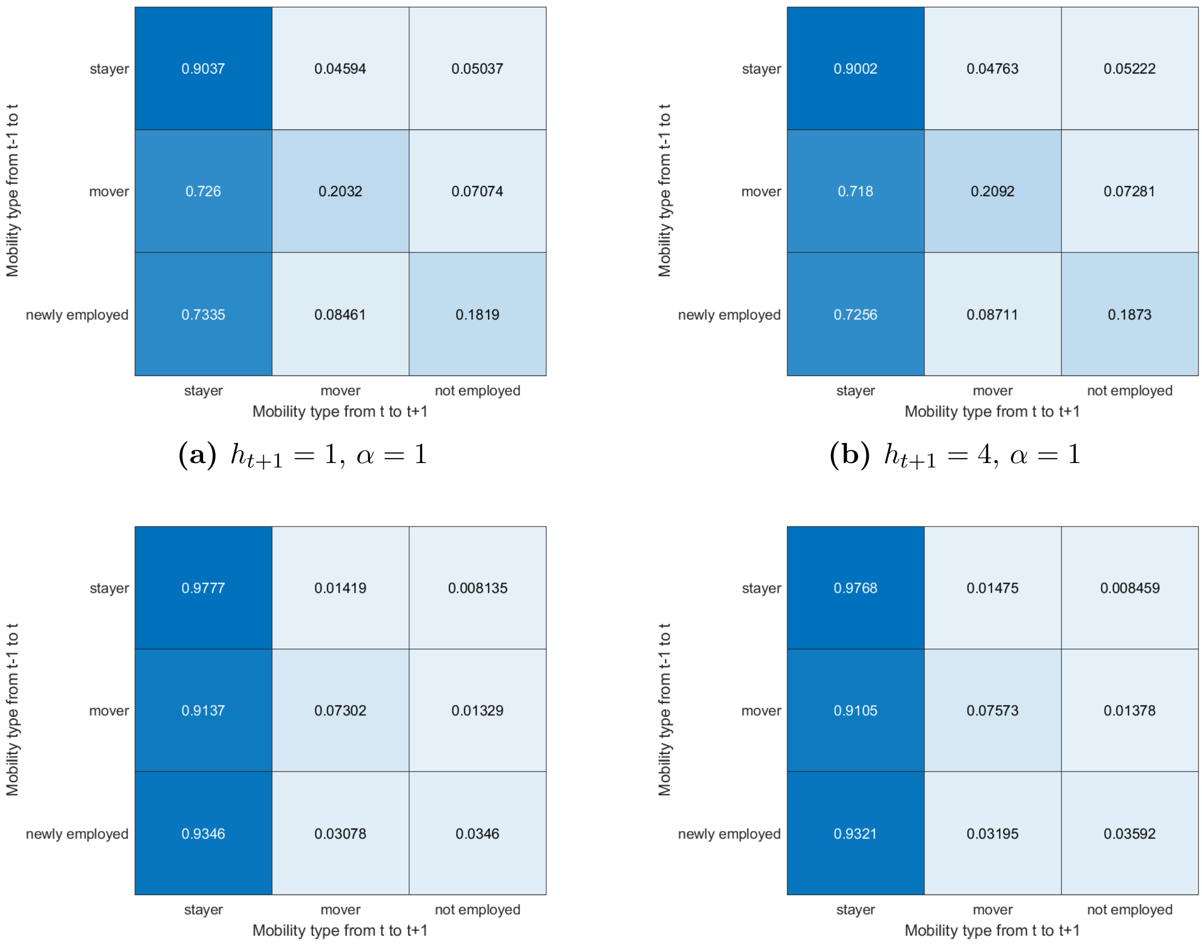
5.2.3 Firm type transitions

I first estimate the probability of transiting to different types of firms if the individuals are newly-employed at $t+1$. Figure 9 shows the case for females aged from 26 to 30. Individuals with a higher person earning level type are more likely to move to firms with higher earning levels and lower earning risk.

Second, I consider the firm-type transitions for the movers. Movers that those who are continuously employed but change employers. I allow the transition probabilities to depend on gender, the person type, age group, health type, past firm earning level, and risk type. Figure 10 shows the estimated probability of destination firm earning level types for females from 26 to 30. First, workers in firms with a high earning level type are more likely to work in firms with high compensation levels after moving. Second, when we compare panel (a) and (c) or (b) and (d), we can conclude that the probability of moving to higher compensation firms are higher for individuals with a higher person earning type. Third, comparing panels (a) and (b), or (c) and (d), we see that sicker individuals face a higher probability of moving to firms with lower compensations.

Figure 11 presents the estimated firm earning risk type transitions for movers. Comparing panels (a) and (c) or (b) and (d), individuals with a higher person earning type tend to move to firms with lower risks. Moreover, if we compare panels (a) and (b) or (c) and (d), we see that sicker individuals are more likely to transit to firms with higher risks.

Figure 8: Job mobility type transitions for the currently employed



(a) $h_{t+1} = 1,\ \alpha = 1$

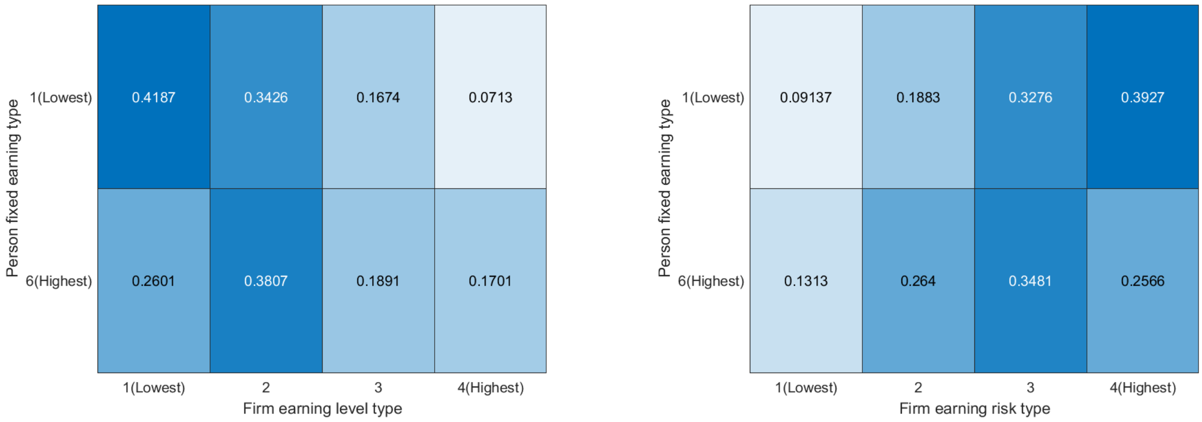
(b) $h_{t+1} = 4,\ \alpha = 1$

(c) $h_{t+1} = 1,\ \alpha = 6$

(d) $h_{t+1} = 4,\ \alpha = 6$

Note: This figure presents the job mobility type transitions from t to $t-1$ by health type if currently employed in t. The focus is females whose ages are from 26 to 30 and person earning types of 1 (lowest earning type). The stayers are those who stay in the same firm. Movers are those who are continuously employed but change employers. Newly employed means not employed last quarter. The health types are constructed using ACG risk scores. People with higher risk scores are predicted to have higher medical spending. Health type takes values of 1, 2, 3, and 4, representing the people with risk scores below 1, between 1 to 1.5, between 1.5 and 2.5, and above 2.5 respectively. Person fixed earning types are constructed from a two-way fixed effects model as explained in Section 4. The probabilities for males, other age groups, and person types can be found in Appendix F.

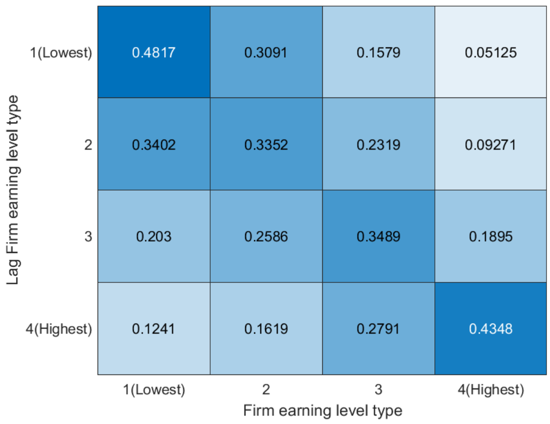
Figure 9: Firm type transitions if newly employed



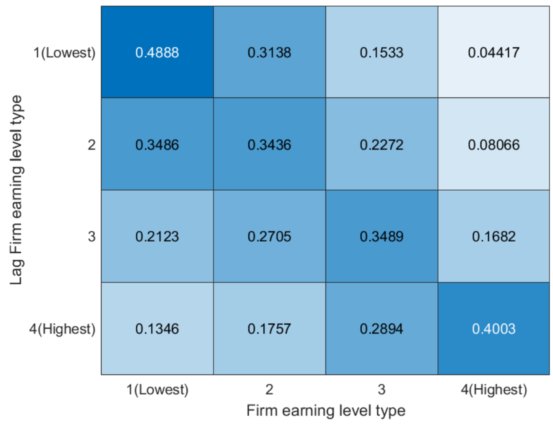
(a) Firm earning level type **(b)** Firm earning risk type

Note: This figure presents the probability of transiting into different firm-level type k_j^μ and firm risk type k_j^σ in time $t+1$ if newly employed from t to $t+1$. The focus is females whose ages are from 26 to 30. Newly employed means not employed last quarter. The health types are constructed using ACG risk scores. People with higher risk scores are predicted to have higher medical spending. Health type takes values of 1, 2, 3, 4, representing the people with risk scores below 1, between 1 to 1.5, between 1.5 and 2.5, and above 2.5 respectively. Person-fixed earning types are constructed from a two-way fixed effects model as explained in Section 4. The probabilities for males, other age groups, and person types can be found in Appendix F.

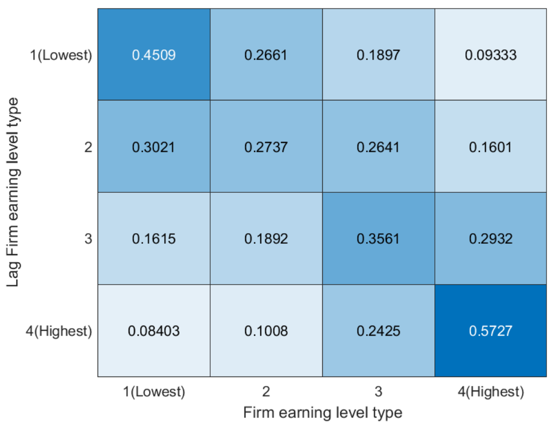
Figure 10: Firm earning level type transitions for movers



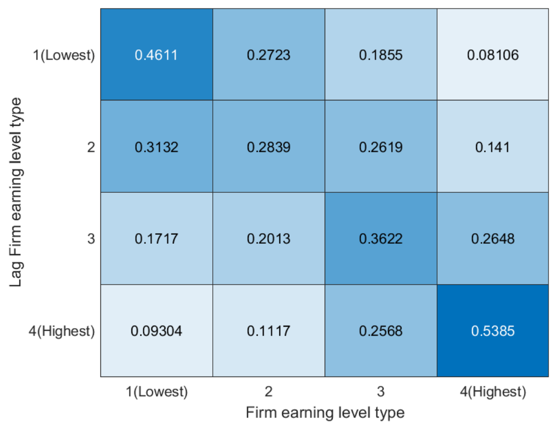
(a) $h_{t+1} = 1$, $\alpha = 1$



(b) $h_{t+1} = 4$, $\alpha = 1$



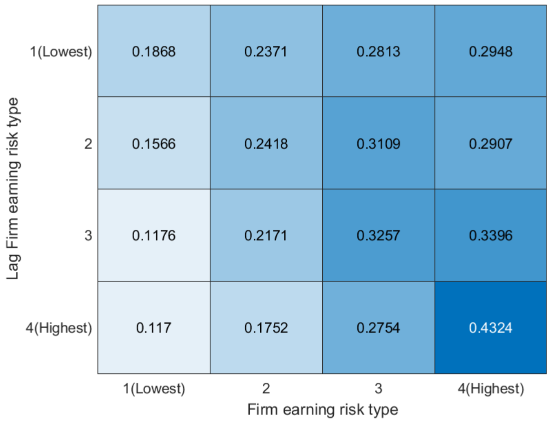
(c) $h_{t+1} = 1$, $\alpha = 6$



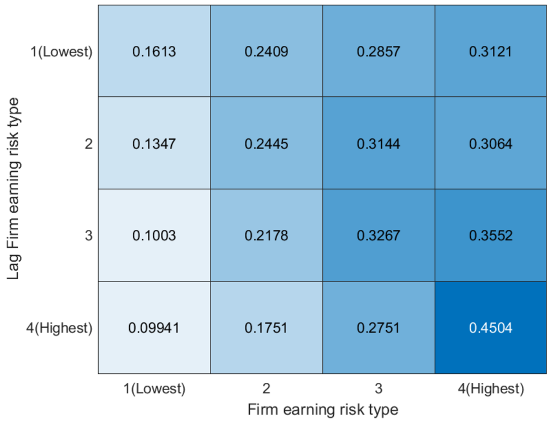
(d) $h_{t+1} = 4$, $\alpha = 6$

Note: This figure presents the probability of transiting into different firm-level type k_j^{μ} in time $t+1$ if change employer from t to $t+1$. The focus is females whose ages are from 26 to 30. The health types h_{t+1} are constructed using ACG risk scores. People with higher risk scores are predicted to have higher medical spending. Health type takes values of 1, 2, 3, and 4, representing the people with risk scores below 1, between 1 to 1.5, between 1.5 and 2.5, and above 2.5 respectively. Person fixed earning types α are constructed from a two-way fixed effects model as explained in Section 4, with 1 standing for the lowest earning type and 6 standing for the highest earning type. The probabilities for males, other age groups, and person types can be found in the Appendix F.

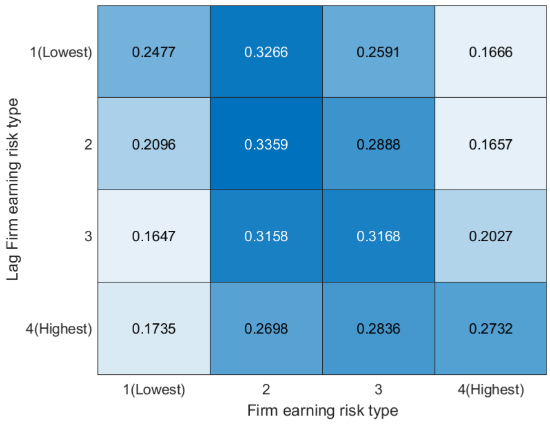
Figure 11: Firm earning risk type transitions for movers



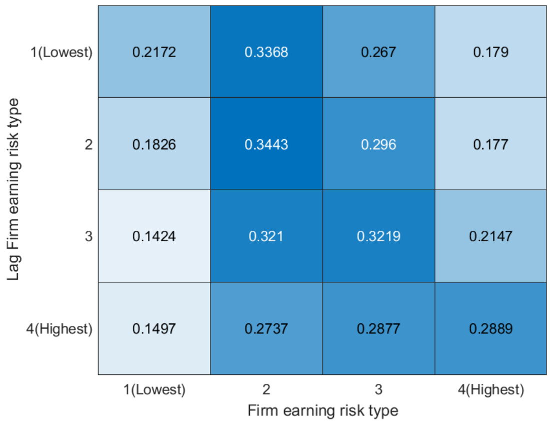
(a) $h_{t+1} = 1$, $\alpha = 1$



(b) $h_{t+1} = 4$, $\alpha = 1$



(c) $h_{t+1} = 1$, $\alpha = 6$



(d) $h_{t+1} = 4$, $\alpha = 6$

Note: This figure presents the probability of transiting into different firm risk type k_j^{σ} in time $t+1$ if change employer from t to $t+1$. The focus is females whose ages are from 26 to 30. The health types h_{t+1} are constructed using ACG risk scores. People with higher risk scores are predicted to have higher medical spending. Health type takes values of 1, 2, 3, 4, representing the people with risk scores below 1, between 1 to 1.5, between 1.5 and 2.5, and above 2.5 respectively. Person fixed earning types α are constructed from a two-way fixed effects model as explained in Section 4, with 1 standing for the lowest earning type and 6 standing for the highest earning type. The probabilities for males, other age groups, and person types can be found in the Appendix F.

6 Precautionary Saving

This section introduces how I estimate the implied unequal asset holding caused by heterogenous earning dynamics. Wealth level influences the demand for health insurance. Health insurance protects assets by reducing out-of-pocket medical spending and medical debt, motivating individuals to purchase plans (Finkelstein, Mahoney, and Notowidigdo, 2018). Moreover, individuals with lower wealth are more likely to receive a transfer from the consumption floor.

Earnings dynamics can cause wealth-holding inequality (De Nardi and Fella, 2017). Higher earning uncertainty may motivate people to save more to smooth consumption between today and tomorrow. However, on the other hand, negative earning shocks can also lead to wealth reduction. In particular, the persistent attribute of negative earning shocks makes it even harder to accumulate wealth afterward.

6.1 Life-cycle saving model

Individual i seeks to maximize his expected lifetime utility at tth quarter of his life after birth until the last quarter of age 100. The individuals maximize the lifetime expected utility by choosing consumption c. Each quarter, the individual's utility depends only on consumption — the flow utility from consumption is $u(c)$. [10]

One empirical difficulty is that I do not observe assets directly in the data. Therefore, I assume individuals save according to a life-cycle model and enter the labor market at age 26 with zero assets. All individuals die at age 100 and derive no utility from left-over assets after death. Therefore, there is no bequest motive in this saving model. All individuals retire at the first quarter of age 65 and begin to receive constant paychecks from social security each quarter until death. Moreover, I assume individuals do not adjust their earnings prediction model during the life cycle. [11] I further assume individuals save as if they face no medical risk. Under these assumptions, the different saving incentives only arise from individuals' differences in earnings dynamics.

[10]Individuals' utility doesn't depend on health status, which is often assumed in the literature. For example, De Nardi, French, and Jones, 2010 allow the utility to be dependent on health status.

[11]This assumption indicates that people make current saving decisions without adjusting their belief of the following over time: (1) the person fixed earning level type, and the firm's earning level and volatility type (2) the transition matrixes of job mobility and health status remain unchanged.

The next period's assets are given by:

$$A_{t+1} = \tau_t(rA_t + W_t) + b_t - c_t \tag{15}$$

Where W_t stands for earning at period t, and A_t is the asset holding at the beginning of period t. $\tau_t(rA_t + W_t)$ denotes the posttax income, with $\tau_t(.)$ standing for a function that maps pretax income with posttax income. Assets have to satisfy a borrowing constraint: $A_t \geq 0$. b_t denotes government transfers.

I also assume that government transfers b_t to individuals to provide a consumption floor at $\underline{c}$.

$$b_t = \max\{0, \underline{c} - \tau_t(rA_t + W_t)\} \tag{16}$$

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

$$V_t(A_t, \delta_t, W_t) = \max_{c_t, A_{t+1}} \{u(c_t) + \beta s_t E_t V_{t+1}(A_{t+1}, \delta_{t+1}, W_{t+1})\} \tag{17}$$

subject to equation 15 and 16. s_t stands for the probability that an individual is alive at period $t+1$, conditional on gender and being alive at period t.

When estimating, the problem is redefined in terms of cash on hand x_t to save on state variables. The problem is re-written as following.
The value function for a single agent is given by

$$V_t(x_t, \delta_t, W_t) = \max_{c_t, x_{t+1}} \{u(c_t) + \beta s_t E_t V_{t+1}(x_{t+1}, \delta_{t+1}, W_{t+1})\} \tag{18}$$

subject to:

$$x_t = A_t + \tau(rA_t + W_t) + b_t \tag{19}$$

$$A_{t+1} = x_t - c_t \tag{20}$$

$$x_{t+1} = x_t - c_t + \tau(r(x_t - c_t) + W_t) + b_{t+1} \tag{21}$$

To enforce the consumption floor, I impose that for all t:

$$x_t \geq \underline{c} \tag{22}$$

The nonnegative assets require that:

$$c_t \leq x_t \tag{23}$$

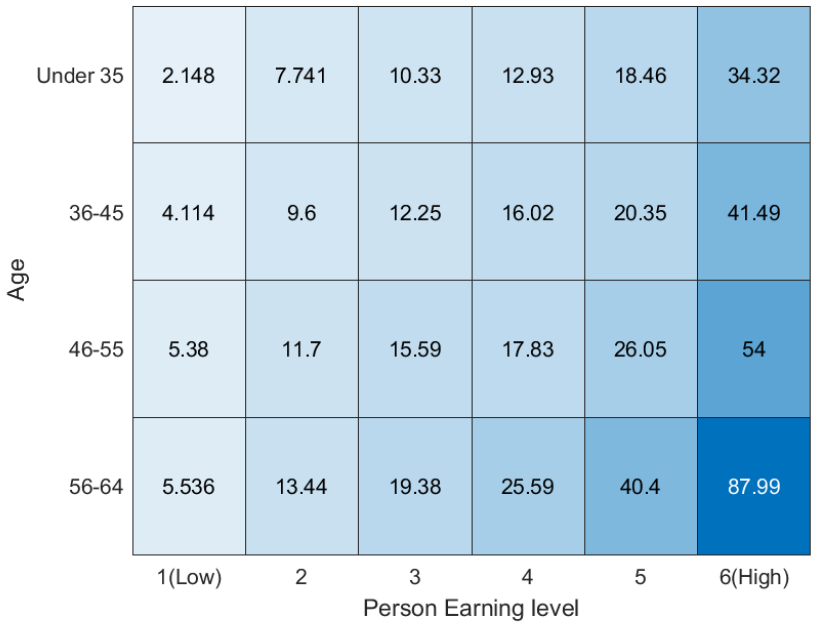
The estimation of assets for each person in the sample follows two steps. First, I simulate the potential past path of type realizations for each person in the sample. Second, I simulate the assets by combining the consumption-saving strategies estimated from life-cycle models and their simulated past life path.

6.2 Estimated wealth distribution

Figure 12 reports the mean asset holding by the person earning level type and age groups. On average, people tend to accumulate more assets if they have a higher person earning level. Moreover, the assets accumulated tend to grow with age. It is consistent with the pattern observed in actual US wealth distribution that higher-income people and older people tend to accumulate more assets.

Several reasons explain why the estimated wealth distribution differs from the observed net worth data in the US. First, the saving model does not allow borrowing or intergeneration transfers from parents, making it hard for individuals in the model to own homes. However, equity in home ownership is a huge component of net worth in US data. Second, this is a single-agent saving model. Therefore, this model does not capture the effect of marriage and children on wealth. Third, to reduce the heterogenous medical expense impact on saving modeling, medical expenses are not modeled in the saving model. However, medical expenses can motivate high-income people to save (De Nardi, French, and Jones, 2010). At the same time, a huge medical bill can also destroy accumulated wealth.

Figure 12: Mean asset(000s of 2013 dollars) by the person earning level type and age group



Note: This figure reports the mean asset simulated by the person earning level types and age groups. The statistics are bootstrapped 50 times with replacement and re-simulation of assets for the randomly selected 1 percent of the original sample.

7 How earning dynamics affect adverse selection

In this section, I study how the degree of heterogeneity in earning dynamics among potential buyers in a health insurance market affects adverse selection. I start with the baseline model that the only heterogeneity between the consumers is the medical spending risk. I then sequentially add in different sources of heterogeneity among consumers and document the effect on the equilibrium take-up rate, premium of the full coverage plan, and total surplus. I focus on a randomly selected approximated 1% subsample of the estimation sample and end up with 3219 individuals. Finally, the assets are simulated by applying the consumption-saving strategy estimated in Section 6.

This section begins by introducing the different models with different levels of heterogenous earnings dynamics. Second, I will introduce how the willingness to pay is calculated. Third, I introduce the key statistics of interest, including market equilibrium take-up, prices, consumer surplus, and two measures of socially efficient outcomes. Finally, I discuss the results and potential mechanisms. I also discuss how incorporating earnings dynamics may influence subsidy efficiency.

7.1 Models of different degrees of heterogeneity

I consider heterogeneity in expected earnings, earning uncertainty, and wealth levels. Before introducing the details of each model, we first recall how earning is predicted.

If the realized type of individual i in the next period $t+1$ is $\theta_{i,t+1}$ and the log-earning error is drawn as $\epsilon(\theta_{i,t+1})$, the log-earning is given as:

$$log(w(\theta_{i,t+1})) = \underbrace{f_W(\theta_{i,t+1})}_{\text{mean log earning}} + \underbrace{\epsilon(\theta_{i,t+1})}_{\text{log earning error}} \tag{24}$$

The expected earning conditional on realizing $\theta_{i,t+1}$ is calculated by taking expectation over log earning errors $\epsilon(\theta_{i,t+1})$ as

$$\bar{w}(\theta_{it}) = \int w(\theta_{i,t+1})dF(\epsilon) \tag{25}$$

with $F(\epsilon)$ as the CDF of the distribution of log earning errors.

The individual i further takes expectation over possible types of realizations:

$$E(\bar{w}(\theta_{i,t+1})) = \sum_{\theta_{i,t+1}\in\Theta} Pr(\theta_{i,t+1})\bar{w}(\theta_{i,t+1}) \tag{26}$$

where $Pr(\theta_{i,t+1})$ denotes the probability for individual i to transit to type $\theta_{i,t+1}$.

The average expected earning for the sample is calculated as the mean of the individual expected earnings:

$$E(\bar{w}) = \frac{1}{N}\sum_{i=1,2,...,N} E(\bar{w}(\theta_{i,t+1})) \tag{27}$$

The individual are certain about their assets A_i at the time of the insurance decision, and the average asset of the sample is

$$\bar{A} = \frac{1}{N}\sum_{i=1,2,...,N} A_i \tag{28}$$

To understand how different levels of heterogeneity in earning dynamics affect the adverse selection, I keep the medical risk people face constant across models. I begin with Model 1—the "no-heterogeneity" model. In this model, I keep only the heterogeneity in medical risk among consumers. I assume that everyone is currently holding the average assets of this sample at $\bar{A}$ and is certain about receiving average expected earning $E(\bar{w})$ next quarter.

Because I incorporate the consumption floor in Model 1, we can also consider Model 1 as the textbook Akerlof selection model with the consumption floor. In Model 2, I add in the heterogeneity in assets. I assume that Individual i is certain about his/her asset level at A_i before making decisions on insurance. The different assets in this model represent the long-term outcomes of individuals' different earning dynamics. In Model 3, I further allow individuals to hold different expected earnings for next quarter. The individual i is expecting to receive $E(\bar{w}(\theta_{i,t+1}))$ for sure in time $t+1$. There is no uncertainty over possible types to realize or transitory log earning errors. Model 4 is the "full-heterogeneity" model, in which I assume people are uncertain over both types of realization, the log earning errors, and the correlation between earning and medical spending. One possible realization of earning for individual i is $w(\theta_{i,t+1})$.

7.2 Willingness to pay

This section introduces how the willingness to pay for the full-coverage plan is calculated. Individuals have homogenous expected utility preferences over wealth. Individual i faces uncertainty over the joint distribution of earning and medical spending denoted as $F(w,m)$. The marginal earning distribution and marginal medical spending distributions are denoted as $F(w)$ and $F(m)$, respectively. Model timing proceeds as follows: (1) individual i decides whether to purchase health insurance or not (2) individual i's medical spending m_i and earning w_i are realized. Individual i is certain about the wealth A_i he carried from the end of the last period to this quarter. Moreover, individual i understands that government will transfer money to make sure his consumption will not be lower than the consumption floor $\underline{c}$ in any possible state of the world. The expected medical cost $z(\xi_i)$ when choosing to be uninsured is calculated as $z(\xi_i) = \int m_i dF(m)$.

The willingness to pay for the full-coverage plan is the monetary payment that makes consumers indifferent between (1) losing this monetary amount for sure if they buy the insurance and (2) facing risky medical risk if choosing to be uninsured. I denote the willingness to pay for individual i as $g(\xi_i)$. Individual i calculates first the expected utility of staying uninsured as

$$V_i^u = \int u(\max(A_i + w_i - m_i, \underline{c}))dF(w,m) \tag{29}$$

The expected utility of being insured with the full-coverage plan of premium p is given as

$$V_i^i(p) = \int u(\max(A_i + w_i - p, \underline{c}))dF(w) \tag{30}$$

The willingness to pay $g(\xi_i)$ is thus the maximum price that solves: $V_i^i(g(\xi_i)) = V_i^u$.

In the following simulations, I assume that individuals have constant relative risk aversion (CRRA) utility with a risk aversion of 2. The consumption floor is assumed to equal $2000.

7.3 Equilibrium and social efficiency

I compare models' equilibrium and socially efficient outcomes. The statistics of interest include take-up rate, insurance premiums, consumer surplus, and deadweight loss.

7.3.1 Market equilibrium

I assume perfect competition among insurers. The equilibrium premium p^* is thus the price that insurers earn zero expected profits. The equilibrium take-up rate is the share of the people enrolled in the full-coverage plans at the market equilibrium. The equilibrium take-up rate is thus given as

$$s^* = \int [1(g(\xi) \geq p^*)dG(\xi) \tag{31}$$

I measure the consumer surplus by the certainty equivalent. Because in this model, there is only one full-coverage insurance for choice, we can also call this monetary payment the willingness to pay for the full insurance. The consumer surplus at the equilibrium is

$$CS^* = \int [(g(\xi) - p^*)1(g(\xi) \geq p^*)]dG(\xi) \tag{32}$$

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

7.3.2 Social efficiency

The textbook Akerlof selection model calculates the socially efficient take-up rate and premiums by finding the intersection between demand and marginal cost curves. However, when earnings dynamics are considered, the marginal cost curves may not be monotonic. This non-monotonicity creates difficulty in accurately finding the intersection. I introduce two measures of socially efficient outcomes.

Measure 1

In the first measure, it is socially efficient to cover individuals whose willingness to pay is above the expected medical cost. No socially efficient price can be calculated. The socially efficient take-up rate is given as

$$s^o = \int [1(g(\xi) \geq z(\xi))dG(\xi) \tag{33}$$

The socially efficient level of consumer surplus is given as

$$CS^o = \int [(g(\xi) - z(\xi))1(g(\xi) \geq z(\xi))]dG(\xi) \tag{34}$$

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

$$DWL^o = \int [(g(\xi) - z(\xi))1(g(\xi) \geq z(\xi), g(\xi) < p^*)]dG(\xi) \tag{35}$$

Measure 2
In the second measure, I smooth the non-monotonic marginal cost curves and consider the intersection between the smoothed marginal cost curve with the demand curve as the socially efficient premium and take-up rate under measure 2. I denote the socially efficient premium as p^{mo} and the take-up rate as s^{mo}.

The consumer surplus under this measure is thus

$$CS^{mo} = \int [(g(\xi) - z(\xi))1(g(\xi) \geq p^{mo})]dG(\xi) \tag{36}$$

The deadweight loss under this measure is thus the consumer surplus of those whose willingness to pay above p^{mo} but below p^*.

$$DWL^{so} = \int [(g(\xi) - z(\xi))1(g(\xi) \geq p^{mo}, g(\xi) < p^*)]dG(\xi) \tag{37}$$

7.4 Results

Equilibrium. — Table 5 Panel A reports the changes in the market equilibrium relative to the baseline "No-heterogeneity" Model. When I sequentially add differences in wealth, expected earnings, and earning uncertainty, the equilibrium take-up rate rises, and the price of the insurance drops. Compared with the "No-heterogeneity model", 5.2% more individuals enroll in the full-insurance plans, and the equilibrium premiums decrease by around \$333. Moreover, the consumer surplus per person estimated for models with earnings dynamics decreases dramatically.

Social efficiency — Significant changes happen to the estimated socially optimal outcomes. Table 5 Panel B reports the changes in socially efficient outcomes under measure 1. Measure 1 defines individuals whose willingness to pay above their expected medical cost as those that should be socially efficient to cover. The socially efficient take-up rate in the "Full-heterogeneity" Model (Model 4) is 17% lower than the "No-heterogeneity" Model (Model 1). Abstracting from earnings dynamics causes overestimation of socially optimal consumer surplus and deadweight loss.

The changes in the outcomes are the net impact of both changes in the demand curves and average cost curves. Figure 13 shows how demand and average cost curves change when shifting from the "No-heterogeneity" model to the "Full heterogeneity" model. In Panel (a), I compare the changes in the demand curve while keeping the average cost curve unchanged. The demand curve shifts downward when earning dynamic heterogeneity is considered. The equilibrium take-up rate decreases by around 5.5%, and the price increases by $148. Panel (b) shows that the average cost curve is steeper when incorporating earnings dynamics. The equilibrium take-up increases by 10.6%, and the premium goes down by $481. The impact of the changes in the average cost curve on the market equilibrium dominates the shifts in demand curves.

7.5 Discussion

Heterogeneous changes in WTP. — The changes in willingness to pay are the key reasons that cause changes in the marginal cost curve. Individuals with higher expected medical costs may not still be the ones with a higher willingness to pay. In Figure 14, I plot the smoothed changes in the willingness to pay when earning dynamics are incorporated.[12] In Panel (a), individuals are ranked by their willingness to pay in the "No-heterogeneity" Model. From Panel (b) to (d), I sequentially add differences in assets, expected earnings, and earning uncertainty. I find that, on average, ignoring earnings dynamics overestimates willingness to pay.

Figure 14 also reveals heterogeneous changes in WTP. Panel (a) reports that for the people who are ranked at around the first 20% of the willingness to pay distribution, their willingness to pay tends to drop after allowing different earnings dynamics. However, the willingness to pay tends to increase for people ranked in the middle — ranked from around 20% to 40%. Finally, the changes in the willingness to pay are small for people with a low incentive (ranked after around 60%) to enroll in plans in the "No-heterogeneity" Model. Notice the willingness to pay ranking approximates the expected cost ranking well in the "No-heterogeneity"

[12]The curves are smoothed with robust linear regression over each window of 20 points.

model — textbook Akerlof selection model with consumption floor.[13] Therefore, Figure 14 (a) provides evidence that the willingness to pay changes could be correlated with expected medical costs.

One potential channel is that individuals with higher medical costs tend to receive more protection from the consumption floor, significantly reducing their willingness to pay. The negative correlation between earnings and medical risks causes some unhealthy people to earn less. Moreover, they face higher difficulty in accumulating assets because bad earning shocks can destroy their wealth. The persistent earning shocks like unemployment makes it difficult for them to re-accumulate assets. Given their bad financial situation, they are more likely to hit the consumption floor than healthier individuals who can successfully accumulate assets.

The differences between Model 3 and Model 4 ("Full-heterogeneity" model). — Compared with the "No-heterogeneity" Model, Model 3 adds the heterogeneity in assets and expected medical spending. How does this model approximate Model 4 — the "Full-heterogeneity" Model? The critical difference between Model 3 and Model 4 is that individuals are certain about the earnings in all states of the world in Model 3, while in Model 4, people face volatile earnings. In Figure 14 (d), I plot the changes in willingness to pay for people ranked by their willingness to pay estimated in Model 3. First, ignoring the earnings uncertainty could overestimate the willingness to pay of people who have a high willingness to pay in Model 3. Because higher earning uncertainties increase their probability of receiving transfers from the consumption floor, their protection from the consumption floor could be underestimated. Second, we could underestimate the willingness to pay for those who are considered very unwilling to purchase the plan in Model 3 (ranked after around 95%). These are people who have extremely low expected earnings and almost zero wealth. In model 3, health insurance is of almost zero value because the probability of obtaining resources above the consumption floor is extremely low. However, in model 4, they face a positive probability of earning enough to have enough resources above the consumption floor. Therefore, they consider health insurance valuable in these states with positive earning shocks.

Non-monotonic marginal cost curve — Adverse selection implied by the textbook Akerlof selection model is severe because the willingness to pay is a perfect predictor of individuals' medical risks. Though insurers cannot distinguish among the buyers, they understand that those with a higher willingness to pay are always more expensive to cover. However,

[13]Because the "No-heterogeneity" Model allows the consumption floor, people in extremely high medical spending state could receive transfers from consumption floor. Thus, individuals with higher medical spending uncertainty could receive more protection from the consumption floor, causing expected medical cost not the only predictor for willingness to pay.

incorporating earnings dynamics changes people's willingness to pay, making those who have higher incentives to enroll no longer always more costly. As a result, the marginal cost curve is no longer monotonically decreasing as predicted in the textbook Akerlof selection model.

Steeper average cost curves. — The non-monotonically decreasing marginal cost curves affect the average cost curves insurers use to price the plans. At each possible price, insurers face a group of relatively healthier consumers, leading to a steeper average cost curve. Steeper average cost curves can result in a higher equilibrium take-up rate and a lower price.

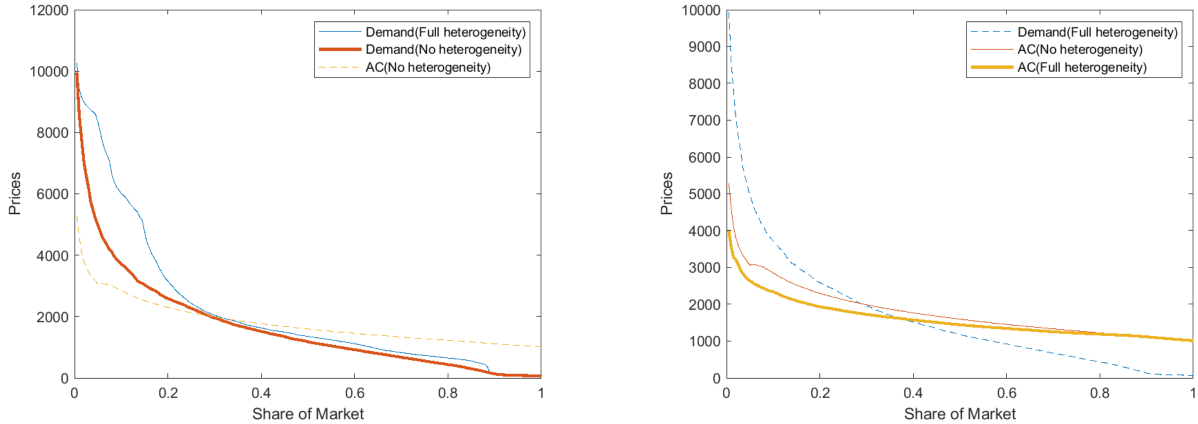
Socially efficient outcomes are hard to achieve with a single price. —In the textbook Akerlof selection model, the intersection between the demand and marginal cost curve gives the price that can achieve socially efficient allocations. Individuals with a willingness to pay above it are socially efficient to cover. However, it is hard to achieve a socially efficient outcome with a single price when the marginal cost curve is not monotonically decreasing. Table 5 Panel C reports the socially efficient outcomes under measure 2 — socially efficient price p^{mo} is the intersection price between smoothed marginal cost curves and demand curves. People willing to pay more than p^{mo} enroll in health insurance. However, this approximation causes inaccurate estimation of the socially efficient take-up rate, consumer surplus, and deadweight loss. Therefore, it may be important to individualize the premiums when marginal cost curves are non-monotonic.

Table 5: Impact of earnings dynamics on equilibrium and social efficient outcomes

Panel A: Equilibrium					
Model	Description	Take-up	Price	Consumer surplus	
1	**Only differ in medical risk**	**0.320**	**1941.8**	**944.9**	
	No-heterogeneity	**(0.02)**	**(51.22)**	**(26.84)**	
2	Add different assets	+0.172	-346.8	-106.0	
		(0.01)	(37.38)	(25.24)	
3	Add different expected earning	+0.082	-359.6	-266.1	
		(0.02)	(40.06)	(23.59)	
4	Add earning uncertainty	+0.052	-333.1	-343.5	
	Full-heterogeneity	(0.01)	(38.64)	(22.99)	
Panel B: socially efficiency (measure 1)					
Model	Description	Take-up	Price	Consumer surplus	Deadweight loss
1	**Only differ in medical risk**	**1.000**		**1190.9**	**246.0**
	No-heterogeneity	**(0.00)**		**(27.88)**	**(12.29)**
2	Add different assets	+0.000		-200.0	-94.1
		(0.00)		(21.49)	(11.97)
3	Add different expected earning	-0.136		-370.9	-104.8
		(0.01)		(20.70)	(12.14)
4	Add earning uncertainty	-0.170		-442.5	-99.0
	Full-heterogeneity	(0.01)		(21.86)	(10.59)
Panel C: socially efficiency (measure 2)					
Model	Description	Take-up	Price	Consumer surplus	Deadweight loss
1	**Only differ in medical risk**	**0.905**	**172.0**	**1189.8**	**244.8**
	No-heterogeneity	**(0.01)**	**(102.01)**	**(27.96)**	**(12.37)**
2	Add different assets	+0.095	-119.6	-199.0	-93.0
		(0.01)	(102.27)	(21.72)	(12.05)
3	Add different expected earning	-0.021	-48.9	-417.2	-151.1
		(0.04)	(120.32)	(22.69)	(12.58)
4	Add earning uncertainty	-0.088	+224.7	-534.6	-191.1
	Full-heterogeneity	(0.06)	(173.51)	(27.12)	(15.64)

Notes: This table compares Model 2 to 4 with the Model 1 — no-heterogeneity model. Model 1 is the model that allows only heterogeneity in medical risk. Individuals are holding the average asset level of the sample $\bar{A}$ and expect to earn the average expected earning $E(\bar{w})$. Model 2 add heterogeneity in asset, and individual i holds assets at A_i. Model 3 adds the heterogeneity in expected earning based on Model 3. Individual i gets the expected earning at $E(\bar{w}(\theta_{i,t+1}))$ in all possible states. Model 4 is the full-heterogeneity model, in which people are uncertain about earning and the connection between earning and medical spending is allowed. The medical risk distribution are kept unchanged in all models. All individuals are assumed to have homogenous constant relative risk aversion utility function with risk aversion at 2. The consumption floor are set at $2000 in all models. Panel A reports equilibrium take-up rate, premiums and consumer surplus. To calculate the equilibrium outcomes, I assume that insurers obtain zero expected profits. Column 4 in Panel A reports the cost of public funds to raise taxes to pay for the wealth transfers when consumption hits consumption floor. Panel B reports the socially efficient take-up rate, consumer surplus and deadweight loss under measure 1—people with higher willingness to pay than expected medical cost are considered as those who should be socially optimal to cover. It is impossible to calculate the premiums under measure 1. Panel C reports the socially efficient outcomes under measure 2 by smoothing non-monotonic marginal cost curves. The marginal cost curves are smoothed with robust linear regression over each window of 20 points. The socially optimal allocation under measure 2 is given by the intersection point between demand and smoothed marginal cost curves. More details can be found in Section 7.3.

Figure 13: Compare Full-heterogeneity and No-heterogeneity models



(a) Demand:
s^*: -0.055[0.015]]
p^*: +148[44.2]

(b) Average cost:
s^*: +0.106[0.015]]
p^*: -481[56.5]

Note: This figure shows how demand and average cost curve changes when we compare the "No-heterogeneity" model that individuals only differ in medical risk, and the "Full-heterogeneity" model which considers full heterogeneity in earning dynamics. Panel (a) compares the changes in Demand curves. Panel (b) shows the changes in average cost curves. The changes in equilibrium take-up and premiums are reported for each step.

7.6 Subsidy

This section discusses how incorporating earnings dynamics may influence subsidy efficiency and the potential mechanisms. When the equilibrium price in the market is p^*, an individual's price is adjusted to $\hat{p}_i^* = \max(p^* - k_i, 0)$ if he receives a subsidy of k_i. Table 6 reports the different impacts of two uniform subsidies on adverse selection across the models. The changes in equilibrium take-up rate, premiums, and consumer surplus are lower in models with earnings dynamics. Moreover, the share of deadweight loss reduced when everyone receives the same subsidy is also lower.

Uniform subsidies can attract high medical risk consumers. — A uniform subsidy works in several steps in the textbook Akerlof selection model:

1. Some uninsured individuals switch to buying the plan given the status quo equilibrium premium (equilibrium premium before a subsidy is implemented).

2. The average insurance cost goes down because the switchers are always cheaper to cover than those insured at the status quo.

3. The lower average cost causes the premium to drop further and attracts more consumers with the updated premium.

4. The process stops at a new equilibrium when insurers earn zero expected profits.

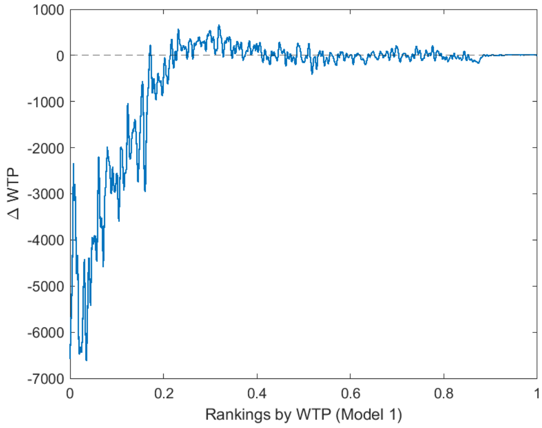
However, non-monotonic marginal cost curves can attract high medical-risk consumers when a uniform subsidy is implemented. As shown in Table 7, approximately 7% of the switchers have higher expected medical costs than the status quo average cost. This feature suggests the importance of considering the non-monotonic marginal cost curves when designing subsidies.

More subsidies for low-earning individuals may not be the most efficient design. — In Table 8, I compare three subsidy designs on the "Full-heterogeneity" Model. The three subsidies offer the same average subsidy to the sample. Individuals are divided into three groups by their expected earnings: high-earning, median-earning, and low-earning. The first subsidy design offers \$300 to everyone. The second subsidy design offers zero subsidies to the highest-earning group and increases the subsidy to the low-earning group to \$900. The third subsidy keeps the subsidy to the low-earning group at \$300 but increases the subsidy to the median-earning group to \$900.

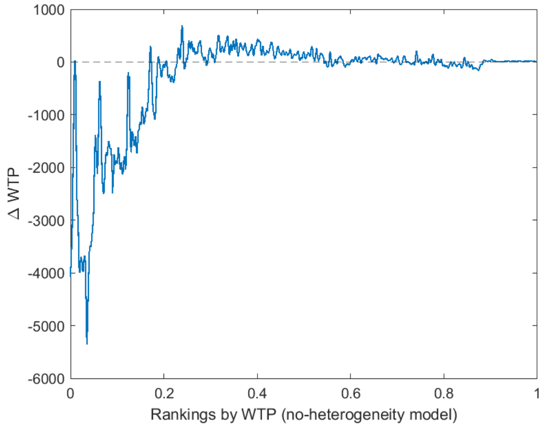
When the equilibrium price is not adjusted, we see similar changes in the subsidies' take-up rates that target low-earning and median-earning groups. Moreover, the take-up changes in the uniform subsidy design are significantly lower than the subsidies that target groups with different earnings. However, the average cost of the insured is significantly lower if the subsidy targets the median-earning group. After the price is adjusted at the equilibrium, we see that the subsidy targets the median-earning group covers more people. It also reduces premium and deadweight loss more than the other two subsidies. Moreover, the subsidy that targets the low-earning group does not significantly affect the deadweight loss.

The negative correlation between earnings and medical spending is one potential cause for this uneven performance of the three subsidies. Individuals who face higher earning uncertainty and lower expected earnings tend to receive more protection from the consumption floor, significantly reducing their willingness to pay. They are also more costly to cover. If more subsidies are given to the lower-earning group, the switchers are more likely to be higher-cost individuals. Therefore, it is hard to lower the average cost before price adjustment, which further influences how much lowering average cost could reduce adverse selection.

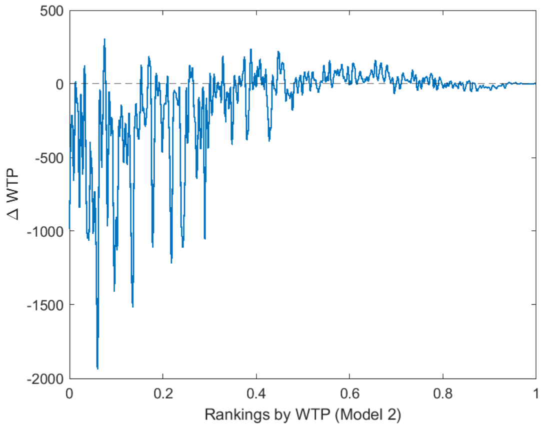
Figure 14: Willingness to pay changes across models



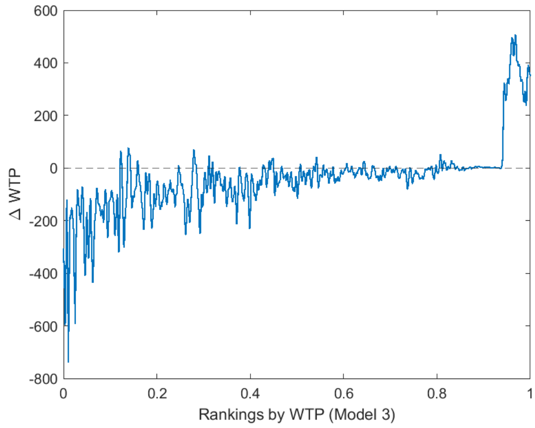
(a) Model 1 to Model 4: mean(ΔWTP)= -553



(b) Model 1 to Model 2: mean(ΔWTP)= -200



(c) Model 2 to Model 3: mean(ΔWTP)= -293



(d) Model 3 to Model 4: mean(ΔWTP)= -61

Note: This figure compares how the willingness to pay changes across models with different levels of heterogeneity in earning dynamics. Panel (a) plots the differences in willingness to pay estimated in Model 1 ("No-heterogeneity" Model) and Model 4("Full-heterogeneity" Model). In the "No-heterogeneity" model, individuals only differ in medical risk, and the "Full-heterogeneity" model considers full heterogeneity in earning dynamics. People are ranked from high to low willingness to pay based on estimations in Model 1. Panel (b) to Panel (c), differences in assets, expected earnings, and earning uncertainties are added.

Table 6: Impact of uniform subsidies

Subsidy	Model	Description	ΔTake -up	ΔPremium	ΔConsumer surplus	Subsidy welfare cost	ΔWelfare	Share changes in Deadweight loss
$400	1	Only differ in medical risk No-heterogeneity	0.306	-521	422	75	347	−69.5%
	2	Add different assets	0.181	-237	369	81	288	−66.2%
	3	Add different expected earning	0.198	-250	321	72	249	−57.2%
	4	Add earning uncertainty Full-heterogeneity	0.200	-241	297	68	228	−46.2%
$800	1	Only differ in medical risk No-heterogeneity	0.558	-804	946	211	735	−99.2%
	2	Add different assets	0.371	-440	836	207	629	−96.5%
	3	Add different expected earning	0.393	-440	736	191	546	−71.3%
	4	Add earning uncertainty Full-heterogeneity	0.447	-430	705	196	509	−34.6%

Notes: This table reports the changes in equilibrium outcomes with two levels of uniform subsidies: $400 and $800 for Models that differ in earnings dynamics. When the equilibrium price in the market is p^*, an individual's price is adjusted to $\hat{p}_i^* = \max(p^* - k_i, 0)$ if he receives a subsidy of k_i. The consumer surplus per person for the status quo (before the subsidy) is calculated as $\frac{1}{N}\sum_i (g_i - p^*)$, where g_i is the willingness to pay for the plan. The consumer surplus per person after the subsidy is calculated as $\frac{1}{N}\sum_i (g_i - \hat{p}_i^*)$. Public funds cost for subsidy is calculated using 0.3 as the estimate of the marginal cost of public funds, which is the average subsidy payment per person times 0.3. The welfare is the difference between consumer surplus and the public fund's cost for subsidy. Deadweight loss for the status quo (before subsidy) is calculated as $DWL_{before} = \frac{1}{N}\sum_i [g_i - z_i | g_i \geq z_i, g_i < p^*]$, where z_i is the expected medical costs. The deadweight loss after the subsidy is calculated as $DWL_{after} = \frac{1}{N}\sum_i [g_i - z_i | g_i \geq z_i, g_i < \hat{p}_i^*]$. The changes in deadweight loss due to subsidy is: $\Delta DWL = DWL_{after} - DWL_{before}$. The share of deadweight loss change is thus defined as $\frac{\Delta DWL}{DWL_{before}}$.

Table 7: Share of newly insured with higher than average medical costs

		Subsidy (dollars)			
Model	Description	400	800	1000	1200
1	Only differ in medical risk	0	0	0	0
	No-heterogeneity	(0)	(0)	(0)	(0)
2	Add different assets	0	0	0	0
		(0)	(0)	(0)	(0)
3	Add different expected earning	0.046	0.031	0.031	0.032
		(0.012)	(0.006)	(0.006)	(0.006)
4	Add earning uncertainty	0.076	0.078	0.078	0.079
	Full-heterogeneity	(0.014)	(0.010)	(0.010)	(0.009)

Notes: This table reports the share of switchers after uniform subsidy that have higher expected cost than the average cost in the status quo (before subsidy). When the equilibrium price in the market is p^*, an individual's price is adjusted to $\hat{p}_i^* = \max(p^* - k_i, 0)$ if he receives a subsidy of k_i. The switchers are those whose willingness to pay is lower than the status quo equilibrium premium but would be willing to buy the insurance facing the same premium after each uniform subsidy. The average cost in the status quo is estimated as the mean of those insured without subsidy.

Table 8: Subsidy design Targeted by earnings

Panel A: Equilibrium Price not Adjusted			
	Uniform	Low-earning	Median-earning
Take-up	0.454	0.500	0.501
Average cost	1498	1514	1413
Panel B: Equilibrium Price adjusted			
	Uniform	Low-earning	Median-earning
Take-up	0.509	0.559	0.602
Premium	1432	1453	1304
Consumer surplus per person	810	845	962
Public funds cost for subsidy	46	74	88
Welfare per person	764	770	874
Δ Deadweight loss	-56	5	-67

Notes: This table reports the comparisons of three counterfactual subsidy design on the Model 4 — "Full-heterogeneity" Model. When the equilibrium price in the market is p^*, the price is adjusted to $\hat{p}_i^* = \max(p^* - k_i, 0)$ for an individual who receives a subsidy of k_i. Individuals are divided into three groups by their expected earnings: high-earning, median-earning and low-earning. Column 1 reports results for a uniform subsidy design at $300. Column 2 reports the results for a subsidy that targets the low-earning group with subsidy at $900, and offers subsidy to the median-earning group at $300. Column 3 reports the results for a subsidy that targets the median-earning group with subsidy at $900, and offers subsidy to the low-earning group at $300. Panel (A) reports the off-equilibrium outcomes, when the equilibrium price is not adjusted with subsidy. Panel (B) reports the equilibrium outcomes. The consumer surplus per person is calculated as $\frac{1}{N}\sum_i(g_i - \hat{p}_i^*)$, where g_i is the willingness to pay for the plan. Public funds cost for subsidy is calculated using 0.3 as the estimate of marginal cost of public funds, which is the average subsidy payment per person times 0.3. The welfare is the difference between consumer surplus and the public funds cost for subsidy. Deadweight loss for the status quo (before subsidy) is calculated as $DWL_{before} = \frac{1}{N}\sum_i[g_i - z_i | g_i \geq z_i, g_i < p^*]$, where z_i is the expected medical costs. The deadweight loss after the subsidy is calculated as $DWL_{after} = \frac{1}{N}\sum_i[g_i - z_i | g_i \geq z_i, g_i < \hat{p}_i^*]$. The changes in deadweight loss due to subsidy is: $\Delta DWL = DWL_{after} - DWL_{before}$. The reported values are the mean of 50 bootstrapped samples.

8 Conclusion

In this paper, I incorporate the heterogeneous earning uncertainty and its correlation with medical risk into modeling individuals' insurance choices. I model the prediction of joint earnings and medical spending by health status to affect them simultaneously. I empirically estimate the model using a novel dataset that combines Utah UI records and All-Payer Claims Dataset. One unique feature of this dataset is that I can link individuals' earnings and medical spending quarterly from 2013 to 2015.

I document that incorporating earnings dynamics result in significant changes in the willingness to pay distribution and its correlation with expected medical cost. Marginal cost curves are no longer monotonically decreasing, and average cost curves are steeper. The influence of private information about medical risks is reduced because insurers can attract healthier consumers when they decrease prices. Models incorporating earnings dynamics tend to predict higher equilibrium take-up rates, lower equilibrium premiums, and lower deadweight loss.

Moreover, when a uniform subsidy is implemented, the changes in equilibrium take-up rate, premiums, and consumer surplus are lower in models with earnings dynamics. Moreover, the share of deadweight loss reduced is also lower. Counterfactual simulations also show that more subsidies to the lower-earning group cannot effectively reduce deadweight loss as uniform subsidies.

My findings point to several directions for future research. The first is to incorporate marriage into the model. The impact of including marriage and family in the model is theoretically ambiguous. Marriage is one form of implicit insurance for some people. However, the assortative mating feature of the marriage market may also cause increases in earnings dynamics heterogeneity. Second, my paper focuses on the extensive margins (choices between uninsured and insured). Allowing choices among plans with different levels of coverage could deliver interesting and important results. Third, more research needs to be done on incorporating earnings dynamics in subsidy designs. Finally, studies can be done on the optimal adjustment of health insurance policies when we face financial crisis, industry-specific shocks, or changes in other labor market policies.

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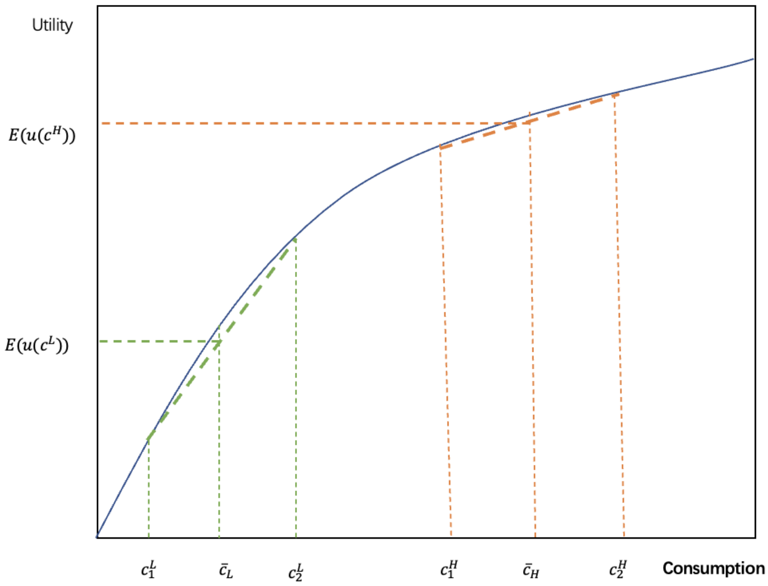
Appendix

A. More theoretical discussion

Figure A1 Lower earning mean leads to lower expected utility of uninsured



Note: This figure illustrates that people with lower expected earning tend to have lower expected utility of being uninsured. Facing the same level of earning uncertainty, if the average consumption equals $\bar{c}_L$, the expected utility is $E(u(c^L)$. This is lower than $E(u(c^H))$, which is the expected utility when the average consumption is $\bar{c}_H$.

B. Sample selection Details

In this section, I present the details in the summary statistics change of the sample when I apply sample selection criteria in Table 1.

When I restrict the sample to people insured in relatively large plans with estimated plan actuarial value, the average earning increases, and the probability of not being employed or changing employers decreases. This evidence reveals that people with higher earnings may be more likely to access health insurance. The potential full-time workers also earn more quarterly and are less liked not to be employed or change employers.

B1.Summary Statistics by Sample section criterions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Starting Sample	1. Age(25-64)	2. Insured	3. With plan characteristics	4. no missing types	5. potential stayers in labor force	6. potential full-time workers
	mean	mean	mean	mean	mean	mean	mean
Age	35.88	42.45	42.98	43.62	43.59	43.61	43.80
Male	0.52	0.53	0.52	0.52	0.52	0.54	0.60
Quarterly Earning	11591.71	13947.54	14650.62	15792.11	15917.53	15946.03	18025.77
Quarterly Earning(Imputed)	7661.68	10576.08	11917.18	13264.50	13458.91	14851.94	17542.20
Not employed	33.90	24.17	18.66	16.01	15.45	6.86	2.68
Stay in the same firm	88.05	91.54	93.56	95.61	96.24	96.52	97.98
Change employer	6.18	4.29	3.39	2.10	1.86	1.86	1.32
Change to earn zero amount	5.77	4.17	3.05	2.29	1.90	1.62	0.70
Newly hired	12.43	13.09	14.18	11.69	9.92	23.48	25.61
Continue to earn zero amount	87.57	86.91	85.82	88.31	90.08	76.52	74.39
Inpatient Spending	161.41	183.80	209.84	190.73	192.00	180.41	145.76
Outpatient Spending	214.73	252.55	308.26	306.76	307.59	299.06	273.85
Office visits spending	273.18	308.90	375.01	388.09	391.41	375.91	324.12
Pharmacy spending	151.85	181.68	221.54	229.45	231.05	221.50	211.27
Total quarterly medical spending	801.17	926.93	1114.66	1115.03	1122.05	1076.88	955.00
Total yearly medical spending	3191.25	3690.89	4354.66	4432.45	4460.77	4281.73	3796.54
Acg risk score	1.04	1.17	1.21	1.25	1.25	1.23	1.16
Number of chronic conditions	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Has Diabetes	4.35	5.30	5.47	5.72	5.80	5.77	5.63
Has hypertension	10.50	12.89	13.34	14.30	14.39	14.41	14.54
N	14118929	8675205	7008764	4203342	3829606	3461535	2778325

Notes: This table reports the summary statistics for the sample with sample selection criteria, and is a detailed version of Table 1. I begin with the whole sample in Column 1. In Column 2, I restrict the sample to people between 26 to 64. In Column 3, I restrict to people who are insured in all quarters in 2013-2015. In Column 4, I restrict to people who are enrolled in plans with a large enough number of enrollees. in Column 5, I restrict the sample to people who are linked to employers so that we could construct firm earning level types and volatility types. in Column 6, I consider the sample size change if we focus on the people who were employed from 2014-2015 so that we could limit the impact of including people who have exited the labor force after 2013. In Column 7, I consider the changes if people who are potentially part-time workers are excluded. I consider workers whose quarterly earnings are above $3480 to be more likely to be full-time workers. $3480 is the quarterly total earning if the individual works at the minimum wage $7.25 for 8 hours a day, 5 days a week, 48 weeks annually.

C. Compare Demand and cost curves with the textbook model

C1. The impact of Demand curves changes relative to the "Full-heterogeneity" model
Conditional on textbook cost curve

Panel A: Equilibrium					
Model	Description	Take-up	Price	Consumer surplus	Deadweight loss
4	**Full-heterogeneity**	+0.259	2123.4	441.4	
		(0.02)	(78.36)	(27.51)	
1	Only differ in medical risk	+0.057	-161.3	+497.1	
		(0.02)	(51.86)	(29.49)	
2	Add different assets	+0.222	-489.6	+378.7	
		(0.01)	(58.19)	(16.09)	
3	Add different expected earning	+0.051	-146.6	+97.9	
		(0.01)	(35.45)	(10.39)	
Panel B: socially efficiency (measure 1)					
Model	Description	Take-up	Price	Consumer surplus	Deadweight loss
4	**Full-heterogeneity**	0.995		637.7	196.3
		(0.01)		(24.05)	(14.29)
1	Only differ in medical risk	0.005		+553.2	+56.1
		(0.01)		(25.22)	(12.19)
2	Add different assets	0.005		+353.1	-25.6
		(0.01)		(10.76)	(11.42)
3	Add different expected earning	-0.180		+74.8	-23.1
		(0.01)		(5.93)	(7.87)
Panel C: socially efficiency (measure 2: smooth MC)					
Model	Description	Take-up	Price	Consumer surplus	Deadweight loss
4	**Full-heterogeneity**	0.965	105.0	637.2	195.8
		(0.06)	(101.46)	(24.07)	(14.41)
1	Only differ in medical risk	+0.035	-53.9	+553.8	+56.7
		(0.06)	(101.31)	(25.13)	(12.36)
2	Add different assets	+0.035	-52.7	+353.6	-25.1
		(0.06)	(101.26)	(10.73)	(11.59)
3	Add different expected earning	-0.174	+280.1	+75.3	-22.7
		(0.06)	(99.35)	(6.21)	(8.04)

Notes: This table aims to compare how the demand curves change across models with different degrees of heterogeneity. The table compares the equilibrium take-up, prices, consumer surplus, and deadweight loss with Model 4—the "Full-heterogeneity" model. All models differ in terms of the demand curves while keeping the marginal cost curve and average cost curves in the textbook version. The textbook version's marginal cost curve is ordering consumers by their expected medical costs. The textbook version's average cost curve is calculated based on the textbook version's marginal cost curves. Take-up rate, prices, consumer surplus, and deadweight loss are reported in Panel A to B, respectively. Column 3 shows the take-up rate, prices, and consumer surplus at the market equilibrium, which is calculated by assuming insurers obtain zero expected profits. Two versions of social efficiency are considered. The first version considers that individuals who have a higher willingness to pay than the expected medical cost are those socially efficient to cover. Column 4 shows the take-up rate, consumer surplus, and deadweight loss calculated using the first version of social efficiency. The second version first calculates the price at the intersection point between the demand curve and the marginal cost curves. The socially efficient people to cover are those whose willingness to pay is higher than the price. Column 5 shows the take-up rate, price, consumer surplus, and deadweight loss defined by the second version of social efficiency.

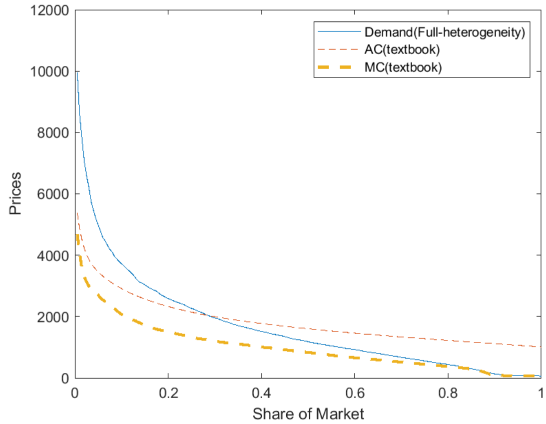
C2. The impact of deviation from textbook marginal cost curve

Conditional on "Full-heterogeneity" Model Demand curve

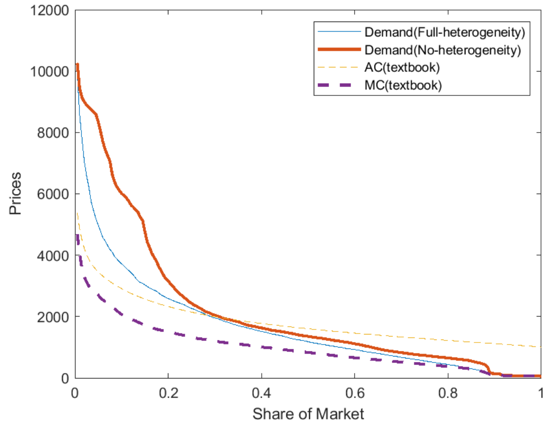
Model	Description	Take-up	Price	Consumer surplus	Deadweight loss
Panel A: Equilibrium					
1	Only differ in medical risk	+0.006	-33.8	+8.7	
		(0.00)	(12.41)	(2.85)	
2	Add different assets	+0.030	-158.0	+42.9	
		(0.01)	(30.75)	(6.65)	
3	Add different expected earning	+0.105	-483.2	+148.4	
		(0.01)	(62.49)	(14.58)	
4	Full-heterogeneity	+0.112	-514.7	+160.0	
		(0.02)	(63.69)	(15.03)	
Panel B: socially efficiency (measure 1)					
Model	Description	Take-up	Price	Consumer surplus	Deadweight loss
1	Only differ in medical risk	-0.020		+1.6	-7.1
		(0.01)		(0.27)	(2.95)
2	Add different assets	-0.075		+3.7	-39.3
		(0.01)		(0.80)	(6.58)
3	Add different expected earning	-0.133		+118.5	-30.0
		(0.01)		(6.89)	(12.31)
4	Full-heterogeneity	-0.165		+110.7	-49.3
		(0.01)		(5.92)	(12.69)
Panel C: socially efficiency (measure 2: smooth MC)					
Model	Description	Take-up	Price	Consumer surplus	Deadweight loss
1	Only differ in medical risk	+0.005	-28.5	+0.1	-8.7
		(0.07)	(106.94)	(1.21)	(3.25)
2	Add different assets	-0.053	+77.2	-0.7	-43.6
		(0.08)	(135.73)	(1.35)	(7.05)
3	Add different expected earning	-0.043	-5.9	+69.3	-79.2
		(0.06)	(99.92)	(5.93)	(14.04)
4	Full-heterogeneity	-0.148	+291.7	+18.0	-142.0
		(0.07)	(148.15)	(10.23)	(18.74)

Notes: This table aims to compare how the average cost curves and marginal cost curves deviate from the textbook cost curves across models. The demand curve is kept at the demand curve of model 4 across all models. The textbook version's marginal cost curve is ordering consumers by their expected medical costs. The textbook version's average cost curve is calculated based on the textbook version's marginal cost curves. The statistics are calculated in two steps. First, I calculate the statistics with the textbook cost curves and demand curve of model 4 — the "Full-heterogeneity" Model. Second, I calculate the statistics using the cost curves of each model and retain the demand curve of model 4. I get the final reported statistics by subtracting the second-step statistics from the first-step statistics. Take-up rate, prices, consumer surplus, and deadweight loss are reported in Panel A to B, respectively. Column 3 shows the take-up rate, prices, and consumer surplus at the market equilibrium, which is calculated by assuming insurers obtain zero expected profits. Two versions of social efficiency are considered. The first version considers that individuals who have a higher willingness to pay than the expected medical cost are those socially efficient to cover. Column 4 shows the take-up rate, consumer surplus, and deadweight loss calculated using the first version of social efficiency. The second version first calculates the price at the intersection point between the demand curve and the marginal cost curves. The socially efficient people to cover are those whose willingness to pay is higher than the price. Column 5 shows the take-up rate, price, consumer surplus, and deadweight loss defined by the second version of social efficiency.

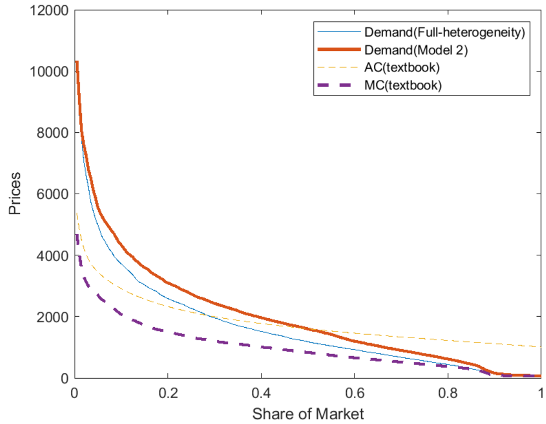
Figure D1. Compare Demand curves with the Full-heterogeneity model



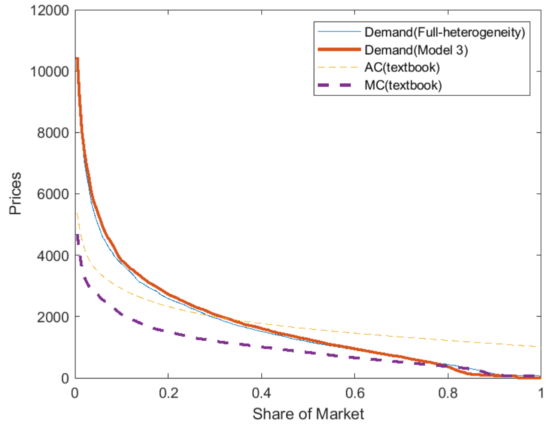
(a) Full-heterogeneity Model
s^*: 0.259[0.018]
s^o: 0.995[0.006]



(b) Model 1: only differ in medical risk
Δs^*: +0.057[0.015]
Δs^o: +0.0052[0.006]



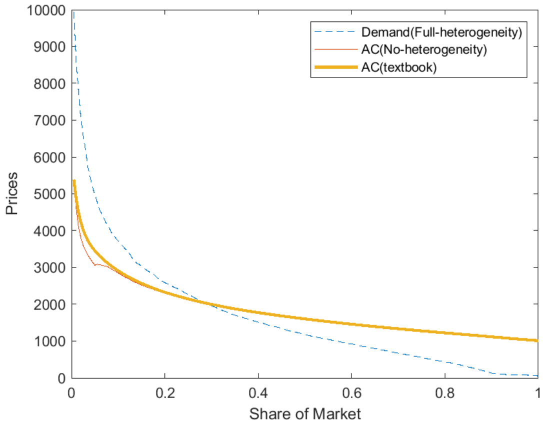
(c) Model 2: add different asset
Δs^*: +0.222[0.014]
Δs^o: +0.0052[0.06]



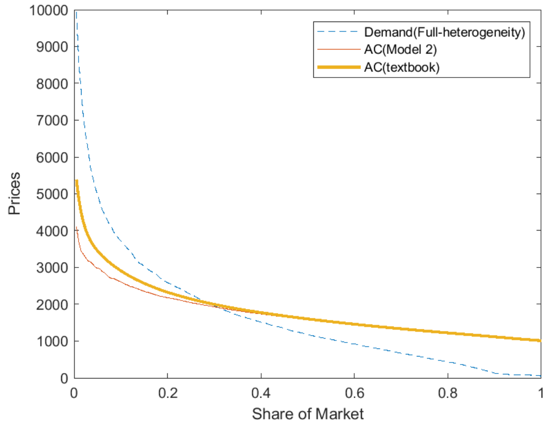
(d) Model 3: add different expected earning
Δs^*: +0.051[0.010]
Δs^o: -0.18[0.012]

Note: This figure compares how the demand curve change across models with different level of heterogeneity in earning dynamics.

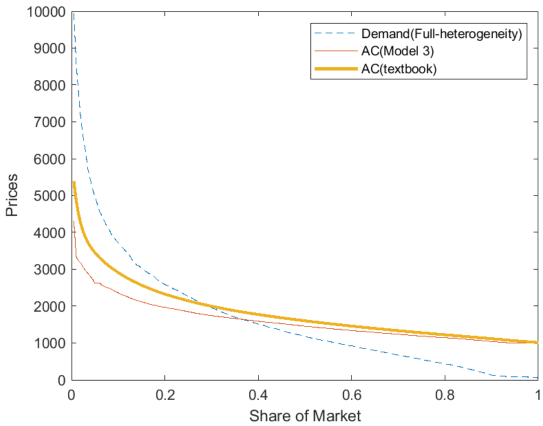
Figure D2. Compare the deviation of average cost curves from the textbook model



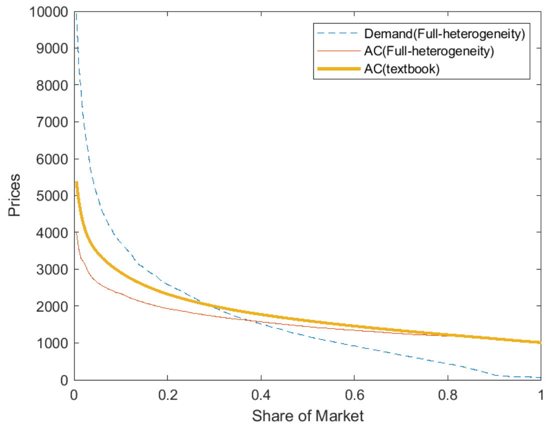
(a) Model 1: Only differ in Medical cost
Δs^*: +0.006[0.003]



(b) Model 2: add different asset
Δs^*: +0.03[0.007]



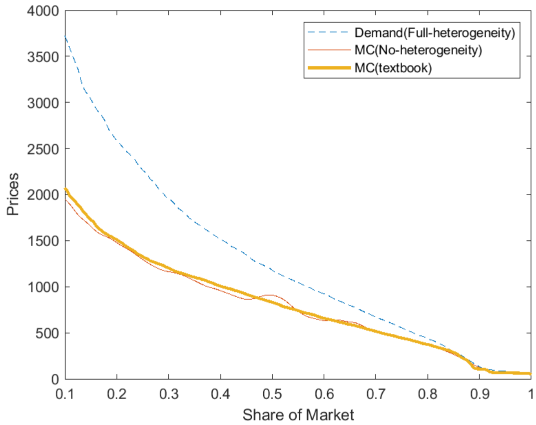
(c) Model 3: add different expected earning
Δs^*: +0.104[0.015]



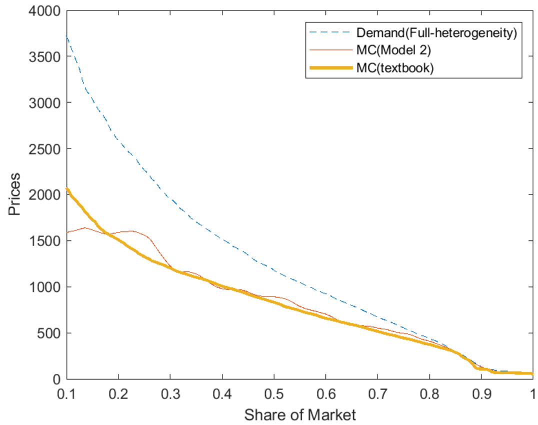
(d) Model 4: add earning uncertainty
Δs^*: +0.112[0.016]

Note: This figure compares how the average curve change across models with different level of heterogeneity in earning dynamics.

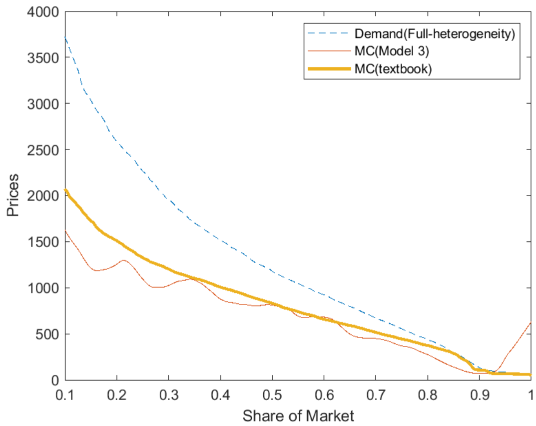
Figure D3. Compare the deviation of marginal cost curves from the textbook model



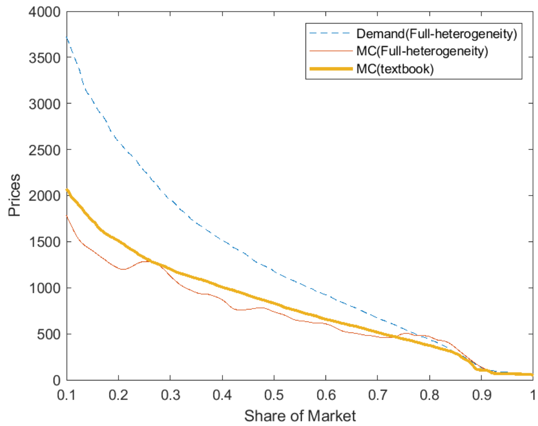
(a) Model 1: Only differ in Medical cost
Δs^{o}: -0.020[0.005]
Δs^{mo}:+0.005[0.07]



(b) Model 2: add different asset
Δs^{o}: -0.075[0.009]
Δs^{mo}:-0.053[0.08]



(c) Model 3: add different expected earning
Δs^{o}: -0.133[0.007]
Δs^{mo}:-0.043[0.06]



(d) Model 4: add earning uncertainty
Δs^{o}: -0.165[0.007]
Δs^{mo}:-0.148[0.07]

Note: This figure compares how the marginal curve change across models with different level of heterogeneity in earning dynamics.

D. ACA subsidy summary

This section summarizes the subsidy (Premium Tax Credit) in ACA. The Affordable Care Act caps the amount that individuals eligible for the tax credit to lower the monthly insurance payment in the Health Insurance Marketplace. How much tax credit to receive is based on income and household information. The eligibility and generosity of this subsidy in 2017 is given in Table D1. The final amount of the tax credit each person receives is based on the final yearly income. They will get the refund when they file the federal income tax return.

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 poverty. This person's percentage of income 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 $\$4,485 - \$2,485 = \$2,000$ tax credit annually.

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.

D1. Affordable Care Act Tax Credit Premium Cap for single individuals, by income in 2017

Income %Poverty	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

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. Source: Kaiser Family Foundation

E. Logged earning retransformation

It is common practice to use a log-transformed dependent variable when dealing with dependent variables that are badly skewed. Thus, in the earning prediction equations, individuals are assumed to predict log earnings instead of directly predicting earning levels. However, according to Manning (1998), a term that captures the heteroscedasticity in the log error term will need to be added if the interest is the variable, not the logged variable.

Individuals first predict the mean of log earning following equation 11 if they are earning a positive amount of money in period t as follows:

$$E(ln(W_{it})|\alpha_i, Q_{it}, k_{it}^{\mu}, k_{it}^{\sigma}, H_{it}, X_{it}) = \underbrace{a\alpha_i + bQ_{it} \times k_{it}^{\mu} + dk_{it}^{\sigma} + eH_{it} + fX_{it}}_{G_{it}} \tag{38}$$

When predicting W_{it}, the error term on the log scale ϵ_{it} needs to be considered. ϵ_{it} is normally distributed: $\epsilon_{it} \sim N(0, \sigma_\epsilon(k_\sigma)^2)$. Then,

$$\begin{aligned} E(W_{it}|\alpha_i, Q_{it}, k_{it}^{\mu}, k_{it}^{\sigma}, H_{it}, X_{it}) &= exp(G_{it})E(exp(\epsilon_{it})) \\ &= exp(G_{it} + 0.5\sigma_\epsilon(k_\sigma)^2) \\ &> exp(G_{it}) \end{aligned} \tag{39}$$

From equation 11, we notice that the mean of the earning level is partly affected by the error variance. I assume that people do not make systematic mistakes when predicting the arithmetic mean of earnings, thus some adjustment is needed so that heterogeneity in log error doesn't affect the prediction of earning arithmetic mean.

First, I assume that people compute the mean of the log errors with respect to different firm risk types:

$$\bar{\sigma_\epsilon} = E(\sigma_\epsilon(k_\sigma)) \tag{40}$$

Second, people predict the mean of the earning level using $\bar{\sigma_\epsilon}$:

$$E(W_{it}|\alpha_i, Q_{it}, k_{it}^{\mu}, k_{it}^{\sigma}, H_{it}, X_{it}) = exp(G_{it} + 0.5\bar{\sigma_\epsilon}^2) \tag{41}$$

Third, the error term of the earning level when the log error term is ϵ_{it} is given by:

$$\hat{\eta_{it}} = exp(G_{it} + \epsilon_{it}) - exp(G_{it} + 0.5\sigma_\epsilon(k_\sigma)^2) \tag{42}$$

Final, the predicted earning level is:

$$\hat{W}_{it} = exp(G_{it} + 0.5\bar{\sigma_{\epsilon}}^2) + \hat{\eta_{it}} \tag{43}$$