Earnings Dynamics and Selection in Health Insurance Markets*

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Abstract

This paper investigates how incorporating earnings dynamics affects adverse selection in health insurance markets. Using a novel dataset that links Utah All-payer Claims Data to the earnings records, I empirically estimate a structural demand model that jointly considers earnings dynamics and medical risk. I show that incorporating earnings dynamics causes a weaker relationship between willingness to pay for insurance and expected medical costs. Deadweight loss is reduced by 40%, due to reduced private information about medical risks. The equilibrium take-up of insurance is 5.2% higher, and premiums are 17.2% lower. Counterfactual analysis shows that a uniform subsidy is less effective at reducing deadweight loss than in models without earning dynamics. Targeting low earners is less efficient than uniform subsidies or targeting median earners. 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.

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I Introduction

Since 2014, the Federal government has spent around $40 billion per year to provide health insurance subsidies under the premium tax credit program, which was introduced by the 2010 US healthcare reform (Tebaldi, 2022). One rationale for spending this enormous amount of money is that subsidies are a textbook policy response to adverse selection (Einav and Finkelstein, 2011). The eligibility and generosity of subsidy policies usually depend on households' income. However, we still do not fully understand how the joint earnings and medical spending dynamics affect adverse selection. In contrast to many textbook models of insurance demand, real-world insurance demand does not only depend on medical risk. Individuals also face considerable uncertainty in earnings 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. For example, subsidies may be less efficient in models with earnings dynamics. In the textbook adverse selection model, subsidies reduce adverse selection by motivating healthier individuals to buy health insurance because demand only depends on medical risk (Akerlof, 1970; Einav and Finkelstein, 2011). However, in models incorporating earnings dynamics, individuals' willingness to pay also depends on earning uncertainty and its correlation with medical risk. Therefore, subsidies can pull people with high medical costs because medical risk no longer has straight forward impact on willingness to pay like in the textbook model.

This paper aims to investigate the impact of earnings dynamics on adverse selection in the health insurance markets. I begin by estimating the individual-level willingness to pay when individuals consider earning uncertainty and its correlation with medical spending when choosing to be fully insured or uninsured. Using a novel dataset that links Utah All-payer Claims Data to the earnings records derived from the UI database, I empirically estimate a model of how individuals predict joint dynamics of earnings and medical spending. In the model, individuals face uncertainties about health, job mobility status, and employers. Then, I study adverse selection by aggregating the individual-level willingness to pay to a market-level analysis. I find that incorporating earnings dynamics 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.

I begin by presenting a binary insurance choice model. Risk-averse individuals choose between being uninsured or fully insured to maximize the expected utility. Individuals are not only uncertain about the medical risk when choosing insurance. They are also uncertain about earnings and the correlation between earnings and medical spending. The willingness to pay is thus the maximum price the individuals are willing to pay for a fully covered health insurance plan.

Conceptually, individuals who face different earning uncertainty and the correlation between earning and medical spending can have different willingness to pay for health insurance even if they face the same medical risk. The direction is theoretically ambiguous. The expected utility of being uninsured is lower for individuals who face more volatile earnings. Thus, they have a higher incentive to purchase health insurance. At the same time, individuals with more volatile earnings are also more likely to face states with low resources. A fixed nominal insurance premium reduces consumption utility by a greater amount in lower resource states, therefore causing reductions in individuals' willingness to pay for health insurance.

Furthermore, correlation also matters for the willingness to pay. This discussion is motivated by the dependence between earnings and medical spending documented in the literature (e.g., Dobkin et al., 2018; Cochrane, 1991; Charles, 2003; Chung, 2013; Meyer and Mok, 2013; Poterba, Venti, and Wise, 2017; Lockwood, 2022). Individuals who face negatively correlated earnings and medical spending tend to be more willing to pay than those whose earnings and medical spending are independent. The intuition is that the negative correlation reallocates resources from low-resource states to high-resource states, 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 high-resource states to low-resource states.

Heterogeneity in earnings dynamics can further cause wealth inequality. Individuals with different earnings dynamics have different motivations to save and also face different difficulties in accumulating assets. 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.

To empirically estimate the individual-level willingness to pay for health insurance, I first model how individuals predict the joint dynamics of earnings and medical spending. My model 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 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 residuals. 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 this dataset provides probabilistic information about the network structure of the labor market, I can model the permanent component of earnings as changes in job mobility status and employer characteristics.

To incorporate precautionary savings as a substitute for formal insurance, I estimate the consumption-saving strategies of individuals by a life-cycle model. Individuals are assumed to enter the labor market at age 26 with zero assets, face uncertainty over earnings, and derive no utility from left-over assets after death. The assets are estimated by combining simulated past paths of individuals and the consumption-saving strategies estimated from the life-cycle model.

I then aggregate the individual-level willingness to pay to study adverse selection at the market level. My results show that the average willingness to pay estimated in models incorporating earnings dynamics is lower, especially for individuals with higher medical risk. The equilibrium take-up rate is 5.2% higher, and the premium is 17.2% lower, which is a net impact of a downward shifted demand curve and a steeper average cost curve. Moreover, the socially efficient take-up rate is 17% lower in models with earnings dynamics.

Finally, I investigate how the efficiency of subsidies changes when incorporating earnings dynamics. When applying a uniform subsidy, deadweight loss reduction is lower in models with earnings dynamics. Moreover, counterfactual simulations show that if offering more subsidies to the lower-earning group, the deadweight loss is not reduced as efficiently as uniform subsidies or offering more subsidies to the median-earning group. Low earners tend to face lower expected earnings and higher earning risk. Moreover, because earnings and medical spending tend to correlate negatively, low earners are also more likely to be high-cost consumers. Therefore, subsidies that target low-earning groups are motivating these high-cost people to enroll. 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 earnings 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.

My work also relates to the growing literature on subsidy policies for health insurance — including in the ACA context (Tebaldi, 2022; Jaffe and Shepard, 2020), in the Massachusetts healthcare reform (Finkelstein et al., 2019; Aizawa and Fang, 2020), and in Medicare Part D (Decarolis, 2015; Decarolis et al., 2020). My work contributes to this literature by studying a nearly population-level sample in Utah with rich labor and health dynamics heterogeneity. This paper finds that subsidy may be less efficient in reducing deadweight loss in models incorporating earnings dynamics, stressing the importance of considering heterogeneous earnings dynamics among consumers when designing subsidy policies.

II Conceptual Framework

This section presents a model of individual insurance choices when earnings dynamics are incorporated. This model allows me to discuss why individuals who face the same medical risk can have different willingness to pay for insurance in a model with earnings dynamics.

II.1 A Model of Insurance Choice

This is a model of individual behavior, so I omit i subscripts to simplify notation. In Section VI, I discuss how to aggregate the individuals' insurance decisions into market demand to investigate the impact of earnings dynamics on adverse selection. At the beginning of period t, individual i is characterized by two objects: $f(w_t, m_t)$ and A_t. The individual is uncertain about possible pair of earnings w_t and medical spending m_t that can realize in period t. The first, $f(w_t, m_t)$, represents the probability density function (PDF) of the joint distribution of earnings and medical spending this individual expect for period t. I further denote the PDF of the marginal distribution of earnings and medical spending as $f(w_t)$ and $f(m_t)$ respectively. The second object is A_t, which represents the nonstochastic assets individual i holds at the beginning of period t.

Insurance choice. — Before earning and medical spending for the period t are realized, individuals face a binary insurance choice I_t. Individuals can purchase full health insurance at p or stay uninsured. Earning reductions are not insurable in this model because health insurance will only cover the medical spending the individual can face. After choosing insurance, the earnings and medical spending for period t are realized.

I assume that individuals are risk-averse expected utility maximizers, with the von Neumann Morgenstern (vNM) utility function as $u(.)$. The individual also faces the consumption floor $\underline{c}$. Whenever his resources fall under the consumption floor, he receives a money transfer to guarantee his resources are above $\underline{c}$. Following the above assumptions, if the individual i chooses to be uninsured ($I_t = 0$), the expected utility is:

$$EU_{I_t=0} = \int_{w_t} \int_{m_t} u(\max[A_t + w_t - m_t, \underline{c})]) f(w_t, m_t) dmdw \tag{1}$$

However, if he purchases full-coverage health insurance ($I_{it} = 1$) priced at p, his expected utility is:

$$EU_{I_t=1}(p) = \int_{w_t} u(\max[A_t + w_t - p, \underline{c}])f(w_t)dw \tag{2}$$

The individual's willingness to pay g_t for fully covered health insurance is given by

$$g_t = \arg\max_p [EU_{I_t=1}(p) \geq EU_{I_t=0}] \tag{3}$$

The individual will buy the plan if his willingness to pay is larger than or equal to the price offer he receives from the insurers.

To estimate the individuals' willingness to pay in this binary choice model, we need to estimate the joint distribution of earnings and medical spending $f(w_t, m_t)$ and assets A_t. Section IV discusses how I model and empirically estimate the joint distribution of earnings and medical spending, including how individuals predict the possible combinations of (w_t, m_t) and the probability of realizing each combination. Finally, in Section V, I introduce how to estimate the assets individuals hold when choosing insurance.

In Section VI, I aggregate the estimated individual-level willingness to pay into market-level analysis and discuss how earnings dynamics affect adverse selection. Furthermore, in Section VII, the willingness to pay estimates are applied to the counterfactual analysis of the efficiency of subsidies when incorporating earnings dynamics.

II.2 How Earnings Dynamics Influence Willingness to Pay

This section discusses why theoretically, if earnings dynamics are incorporated into the insurance choices, individuals' willingness to pay may differ even if they face the same medical risk. I first consider three parameters of the joint distribution of earnings and medical spending: (1) the mean of earnings $\mu_w = \int w_t f(w_t)dw_t$, (2) the variance of earnings $\sigma_w^2 = \int (w_t - \mu_w)^2 f(w_t)dw_t$, and (3) the correlation between earning and medical spending ρ. I will introduce the joint distribution details and how to empirically estimate it in Section IV. Second, I discuss the impact of assets and the consumption floor on individuals' willingness to pay. For the following discussion, individuals are assumed to face the same marginal distribution of medical spending.

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

First, higher earning variance leads to higher consumption volatility. [1] Risk-averse individuals derive lower expected utility from volatile consumption. Figure 1 helps to illustrate the first channel. For individuals who face higher earning variance, the uninsured option can lead to two consumption realizations with equal probability: c_1^H and c_2^H. For those whose earning variances are lower, the possible consumption realizations change to c_1^L and c_2^L. 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 variance are worse off if choosing to be uninsured, making them more willing to purchase health insurance.

Second, higher earning variance increases the expected utility cost of premiums. Individuals with higher earning variance are more likely to be in a low-resource state. A fixed nominal insurance premium reduces the consumption utility by a greater amount when individuals face lower resources. Therefore, they are expected to give up more utility for the same premium. The more "expensive" insurance in terms of utility leads to a lower willingness to pay.[2]

The mean of earnings μ_w has an ambiguous effect on willingness to pay. — How the mean of the earnings affects the willingness to pay can also be explained as the net impact of the two forces. First, individuals with a lower mean of earnings derive lower expected utility from the uninsured choice. Therefore, they have a higher incentive to purchase health insurance.[3] Second, individuals with a lower mean of earnings consider insurance more expensive in terms of utility. [4]

Correlation between earning and medical spending ρ — If earnings and medical spending are not independent, what would happen to the willingness to pay for health insur-

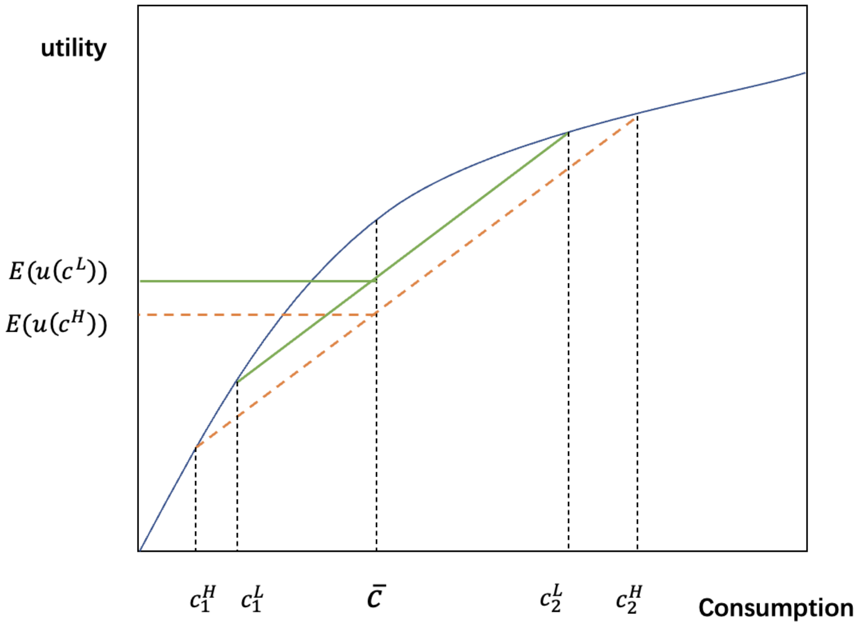
[1] To see this mathematically, the variance of consumption when choosing to be uninsured is $\sigma^2_{w-m} = \sigma^2_w + \sigma^2_m$, which increases with the variance of earning σ^2_w. This is under the assumption that both earnings and medical spending are independent and normally distributed.

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

[3] As illustrated in Figure A.1 in Appendix A, facing the same level of earning volatility, 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 $\bar{c}_H$.

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

Figure 1: Higher earning variances lead to higher consumption volatility



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

ance? 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.[5] Moreover, this correlation does not affect the expected utility cost of insurance premiums. Therefore, a negative correlation between earnings and medical spending unambiguously increases the willingness to pay.

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

Assets A_t. — Assets affect the willingness to pay because individuals buy insurance to protect assets by reducing out-of-pocket medical spending and medical debt (Finkelstein et

[5]The consumption volatility $\sigma^2_{w-m} = \sigma^2_w + \sigma^2_m - \rho\sigma_w\sigma_m$ increases if earnings and medical spending are negatively correlated ($\rho < 0$), and decreases if the correlation is positive ($\rho > 0$).

al., 2018). Moreover, individuals with different earnings dynamics can accumulate different levels of assets. First, they have different saving motivations. Second, negative earning shocks can reduce wealth levels. Moreover, individuals are harder to accumulate wealth after persistent shocks, such as unemployment.

Consumption floor $\underline{c}$. — So far, my discussion of how earnings dynamics affect willingness to pay assumes that the consumption floor is never hit. The consumption floor works by transferring wealth to individuals when they face extremely low-resource states. The ability to claim bankruptcy policy is one example. The consumption floor further influences the willingness to pay for health insurance because individuals with different earnings dynamics differ in how much protection they obtain from the consumption floor. For example, individuals with a lower mean of earnings, more volatile earnings, or a negative correlation between earnings and medical spending are more likely to face states with lower resources than the consumption floor.

III Data

As discussed in Section II, the earnings dynamics can theoretically affect the willingness to pay for health insurance. Thus, empirical analysis of how earnings dynamics affect adverse selection would require panel data on individual-level earnings and medical utilization. I use data from the 2013-2015 All-Payer Claims Database (APCD) linked to earnings records derived from the Utah unemployment insurance (UI) database. Data from the APCD provide 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. I use Johns Hopkins ACG software to calculate annual health risk scores in the APCD. Researchers and commercial insurers widely use health risk scores to describe or predict patients' healthcare costs and set insurance premiums. For each worker-quarter-year, the earnings data contain the thousand-tile in which each worker's total quarterly earnings from all jobs fell. It also reports the average earnings level of all the workers in that thousand-tile of quarter-year. Moreover, the earnings file also reports a measure of compensation at the employer level, which is calculated by dividing the firm-specific total payroll in the quarter by the number of employees in the firm in the same quarter. To protect confidentiality, the average payroll at the firm-quarter-year level is reported after a white noise term is added. The white noise component is constructed by randomly drawing from a normal distribution with a mean of zero and a standard deviation of \$50. All workers at the same firm in the same quarter have the same firm-level average payroll, which is rounded to the nearest cent. Blocks of coworkers have the same average payroll in each quarter over time. Therefore, this dataset provides probabilistic information about the network structure of the labor market.

Sample Selection. — To construct my sample, I begin with 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. Furthermore, I focus on the individuals that are always 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.[6] One reason to focus on always insured workers is that I can only observe medical utilization for insured people in the data. In this model, I use their medical utilization information to study their demand for health insurance in a hypothetical market where they purchase insurance by themselves. In the real world, most of them receive insurance from their employers or heavy subsidies from ACA markets. I further focus on the workers for who I can construct person earning types and their employers' types. I will introduce the details of these types in Section IV. Moreover, I focus on people who earn a positive amount for at least one quarter from 2013-2015 because people who have earned nothing may have exited the labor force. 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 I can construct types for the workers and (5) whether the worker is employed for at least one quarter.[7]

[6]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).

[7]How the detailed summary statistics change with different sample selection criteria is given in Table B1 in Appendix B.

Table 1: Number of observations change with sample selection criteria

	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 changes by sample selection criteria. This table reports the number of unique individuals observed, and the number of person-quarter observations. 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 insured people in all quarters in 2013-2015. In Row 4, I restrict to people who are enrolled in plans with a large enough number of enrollees. In Row 5, I restrict the sample to people who are linked to employers so that we can construct firm earning level types and uncertainty types (details introduced in Section IV). In Row 6, I consider the sample size change if we focus on those employed for at least one quarter from 2013-2015 so that we could limit the impact of including individuals who have exited the labor force.

IV Model of Earnings and Medical Spending

I assume that individuals have constant relative risk aversion (CRRA) preferences with a coefficient of 2 and face the same consumption floor when making insurance choices. Therefore, as discussed in Section II.1, two important objects are needed to estimate willingness to pay. The first object is the joint distribution of earnings and medical spending predicted by individuals for period t. The second object is the assets individuals hold before the insurance choices.

In this section, I discuss the estimation of the first object. I specify a model of how individuals predict earnings and medical spending in period t and empirically estimate the model using the data introduced in Section III. The estimation of assets also requires the estimation of the joint distribution of earnings and medical spending, which will be introduced in Section V.

I assume that individual i knows the PDF of the joint distribution of earning and medical spending $f(w_t, m_t)$ for the period t.[8] From Section IV.1 to Section IV.3, I discuss the estimation of each possible combination of earning and medical spending (w_t, m_t). In Section IV.4, I show how to estimate the probability of realizing each combination.

IV.1 Earning Prediction

I begin with a model of individual i's prediction of log earnings in each possible state of the world. I assume that individual i's log earning in world τ is given by

$$ln(w_t^\tau) = R_w(\theta_{wt}^\tau) + \epsilon_t^\tau \tag{4}$$

where $R_w(\theta_{wt}^\tau)$ is the component of the log earning that is predicted by the type $\theta_{wt}^\tau \in \Theta$ individual i faces in the world τ.[9] The types θ_{wt}^τ include demographic characteristics like age and gender, which are directly observable in the data. The types also capture individual i's health status, skills that are rewarded equally across employers, job mobility status, and employer characteristics. ϵ_t^τ is the random draw of log-earning residuals. I first introduce how I construct the health and earning types. Second, I discuss how individuals use these types to predict earnings in each possible state of the world.

[8]This is an individual prediction model, so I omit i subscripts to simplify notation.

[9]The massive number of heterogenous workers and employers can make it challenging to predict the probability of each world, which will be introduced in Section IV.4. Therefore, I follow Abowd et al. (2019) and Bonhomme et al. (2018) using a latent-type framework.

IV.1.1 Health and Earning types

Health types. — 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 equal quartiles. Moreover, because only annual risk scores are observed, I assume that individuals face the same health type in each quarter of the year.

Person earning types and Firm earning level types. — In the labor market, the agents are workers, indexed by $i \in \{1...I\}$ and employers, indexed by $j \in \{1...J\}$. I assume that on entry to the labor market, individual i samples his person earning type from six latent ability types $a_i \in \mathcal{A}$. It is interpreted as a combination of skills and other factors that are rewarded equally across employers. Likewise, employer j samples its firm earning level type from four latent types $k_j^{\mu} \in \mathcal{K}^{\mu}$. I interpret it as the pay premium that is paid by the employer j to all employees. One example of this premium is an efficiency wage premium.

To construct them, I follow Abowd et al. (1999, also known as AKM) by estimating a linear model with the additive person and firm fixed effects. I run the following regression on the sample of workers from the year 2011 to 2017.

$$ln(w_{ijt}) = \alpha_i + \phi_{j(it)} + \psi_t + \eta_{ijt} \tag{5}$$

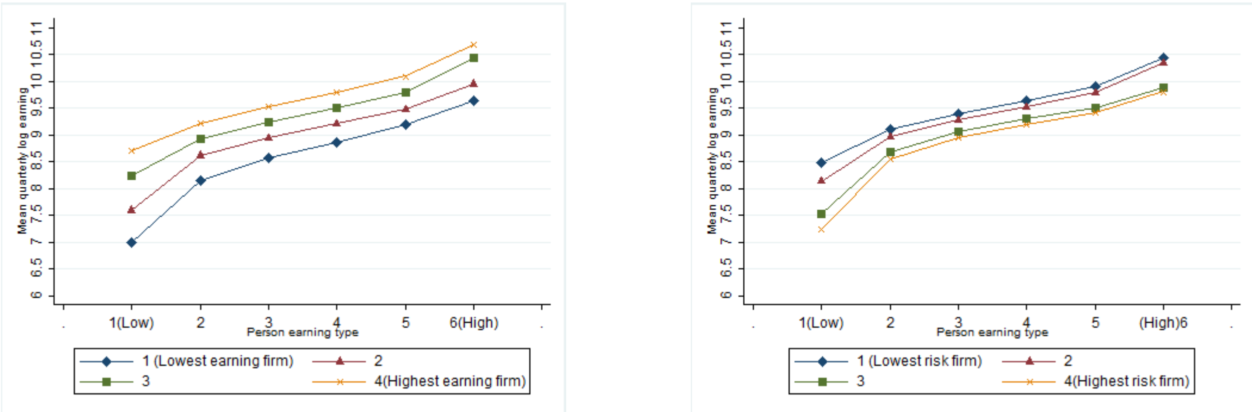
w_{ijt} stands for the observed earning of individual i who works for employer j in period t. γ_i is the person fixed effects. $\phi_{j(it)}$ is the firm fixed effects. ψ_t is the year-quarter fixed effects. η_{ijt} is an error component.

Because the two-way fixed effects model is estimated on a short-term panel from 2011 to 2017, the person fixed effects α_i also reflect the impact of age on the pay premium. To adjust the age effect, I first regress α_i on eight age groups in 5-year bins.[10] Then, I estimate the residuals $\hat{\alpha_i}$ 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 level type and type 4 standing for the highest firm earning level type.

Firm earning risk types. — Employer j also samples its firm earning risk type from

[10]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

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.

four types $k_j^\sigma \in \mathcal{K}^\sigma$. I interpret it as a proxy for the degree of earning uncertainty that employees face inside firm j. To construct it, I first calculate the log earning difference between subsequent quarters t and $t-1$ for each employee who consistently works in each firm from $t-1$ to t.

$$\Delta ln(w_{i(t-1,t)}) = ln(w_{it}) - ln(w_{i,t-1}) \tag{6}$$

Second, I calculate the standard deviation of the log earning difference for each firm j as SD_j and group the firms into four categories with an equal amount of firms based on SD_j. I only keep the firms with at least 20 log earning differences during 2013-2015 to reduce the imprecision of standard deviation. The firm earning risk types can take values from 1 to 4, with 1 standing for the lowest risk type and 4 standing for the highest risk type.

Descriptive statistics: firm types and person earning types. — In Figure 2, I plot the mean log earnings of each person type by firm earning level types and firm earning risk types. Figures 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 uncertainty about earnings.

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 a negative correlation between earning level type and risk type: low-earning type firms contain a higher share of high-risk firms than higher-earning firms.

Job mobility types. — I consider four types of job transitions between $t-1$ and t. Individual i is classified as a stayer if he stays in the same firm. If an individual i changes employer, he is considered a mover. I allow the possibility that the workers move to a firm with the same type as the original firm. If the individual was not employed in $t-1$, but employed in t, he is classified as newly employed. Finally, an individual can be not employed in t and receives an earning of zero.

Descriptive statistics: health types. — Table 2 reports descriptive statistics on the person-quarter observations with missing earnings filled as zero.[11]The summary statistics show a potential negative correlation between earnings 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.

[11]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 2, I filled the quarters with missing earnings with zero earnings.

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

	(1) All mean	(2) Health type = 1 (Healthiest) mean	(3) Health type = 2 mean	(4) Health type = 3 mean	(5) Health type = 4(Sickiest) 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. Columns 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.

IV.1.2 Earning determination

As stated in Section IV.1, individual i predicts the log earning in one state of the world by summing two components: the component of the log earning predicted by the types θ_{wt} (mean of log-earnings) and a random draw of the log earnings. The log of earnings for employed workers in period t is given by

$$ln(w_{it}) = a_i\beta_a + d_{it} \times k^{\mu}_{it}\beta_d + k^{\sigma}_{it}\beta_k + H_{it}\beta_H + X_{it}\beta_X + \epsilon_{it} \tag{7}$$

a_i is the 1×6 vector that describes the category of the six person earning types individual i samples when entering the labor market. $d_{it} \times k^{\mu}_{it}$ has a dimension of 1×12, which is an interaction term between job mobility types and the destination firm earning level type. It describes whether the individual is a stayer, mover, or newly employed from $t-1$ to t. Moreover, it further describes, conditional on the job mobility type, which category of the firm earning level type his destination employer belongs to. k^{σ}_{it} is of dimension 1×4 and describes the firm earning risk type the individual works for in period t. H_{it} has a dimension of 1×16, which documents the health type transitions from $t-4$ to t. The vector X_{it} includes demographic characteristics, such as age groups, gender, and year-quarter dummies. β_a, β_d, β_k, and β_H are parameters with dimension 6×1, 12×1, 4×1, and 16×1, respectively, that describe the effect on the level of log earnings associated with membership in the various heterogeneity types. The ϵ_{it} is heteroscedastic and normally distributed with mean 0. I assume that ϵ_{it} is uncorrelated with person earning type a_i, interaction term between job mobility types and destination firm earning level types $d_{it} \times k^{\mu}_{it}$, firm earning risk types k^{σ}_{it}, health type transitions H_{it} and time-varying covariates X_{it}.

I assume that individual i predicts the log earning following equation 7 for one particular world if he is employed in this world in period t. I further assume that individuals believe that the log earning residuals are random draws from a normal distribution $N[0, var(\hat{\epsilon}(k^{\sigma}_{it}))]$, where $var(\hat{\epsilon}(k^{\sigma}_{it}))$ is the sample variance of the estimated log-earning residuals by firm earning risk type.

IV.2 Medical Spending Prediction

In this section, I discuss how individuals predict the log medical spending in each possible state of the world. The log medical spending is predicted by two components: the component of the log medical spending predicted by types θ_{mt} and a random draw of the log medical spending.[12] The log annual medical spending is given by[13]

$$ln(m_{iy(t)}) = \gamma_m ln(m_{i,y(t)-1}) + X_{iy(t)}\gamma_X + H_{it}\gamma_H + \xi_i\gamma_\xi + r_{iy(t)}\gamma_r + \nu_{iy(t)} \tag{8}$$

$y(t)$ denotes the year that contains the quarter of interest. $m_{i(y(t)}$ and $m_{i,y(t)-1}$ are continuous variables, and represent the annual log total medical spending in year y and the past year $y-1$. $X_{iy(t)}$ includes time-varying observables, including gender, age groups, and year dummies. H_{it} has a dimension of 1×16, which documents the health type transitions from $t-4$ to t. ξ_i is a vector that documents whether the worker has diabetes or hypertension.[14] $r_{iy(t)}$ represent the average actuarial value of their health insurance of the year y.[15] γ_m, γ_X, γ_H, γ_ξ, and γ_r are parameters that describe the effect on the level of log medical spending associated with the lagged log medical spending, time-varying covariates, health type transitions, chronic conditions indicators, and the average actuarial values of insurance plans. $\nu_{iy(t)}$ is heteroscedastic and normally distributed with mean 0. I assume that $\nu_{iy(t)}$ is uncorrelated with lagged log medical spending $ln(m_{i,y(t)-1})$, time-varying observables $X_{iy(t)}$, health type transitions H_{it}, chronic conditions indicators ξ_i, and the average actuarial value of their health insurance $r_{iy(t)}$.

I assume that individual i predicts the log medical spending following equation 8 for one particular world. I further assume that individuals believe that the log medical residuals are random draws from a normal distribution $N[0, var(\hat{\nu}(h_{it}))]$, where $var(\hat{\nu}(h_{it}))$ is the sample variance of the estimated log medical spending residuals by health type in t.

IV.3 Estimates of Earning and Medical Spending

In this section, I present empirical estimates for the earning determination equation (equation 7) and the medical spending prediction equation (equation 8). 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 who are among the healthiest group in both periods $t-4$ and t. They are also stayers in firms with the lowest earning level type. Moreover, they belong to the category of the lowest person earning type and work in firms with the lowest earning risk type. 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

[12] Because only the annual health risk score is observed, I assume individuals first predict the annual medical spending for the year that contains the quarter of prediction interest. Then the quarterly medical spending prediction is obtained by multiplying the annual prediction by $\frac{1}{4}$.

[13] I add $1 to the zero medical spending observations because the Logarithm function is undefined at zero.

[14] If I ever observe this individual receiving treatment or diagnosis of diabetes or hypertension from 2013 to 2015 in the data, I consider this person always has diabetes or hypertension during the 3 years.

[15] An individual can change health insurance during the year of interest, so I use the quarterly average of the actuarial value of the insurances he enrolled in a year.

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 on medical services.

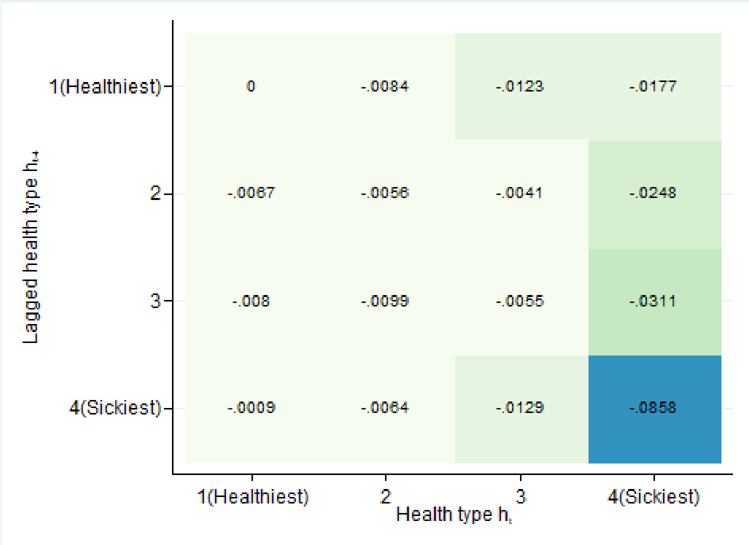
Figure 4 reveals a negative correlation between earnings and medical spending. Panel (a) reports the differences in the mean of log earning relative to the reference state: among the healthiest group in both periods $t-4$ and period t. Panel (b) shows how health type transitions influence medical spending prediction. Sicker individuals are expected to face higher log medical spending.

Table 3: Some parameter estimates for log earning and medical spending equations

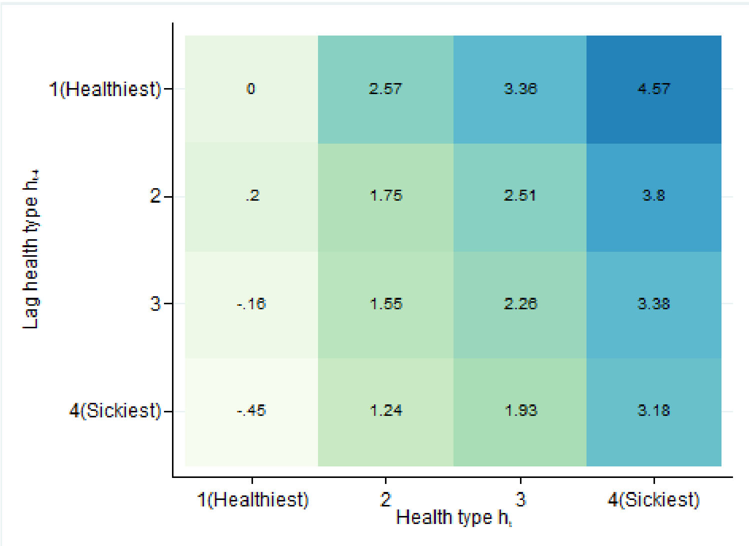
	Log Quarterly Earning	Log Annual Medical Spending
Person type 2	0.795*	
	[0.002]	
Person type 3	1.112*	
	[0.001]	
Person type 4	1.385*	
	[0.001]	
Person type 5	1.682*	
	[0.002]	
Person type 6	2.219*	
	[0.002]	
Male	0.050*	–0.431*
	[0.001]	[0.005]
Age 31-35	0.109*	0.022*
	[0.001]	[0.011]
Age 36-40	0.230*	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 earning level 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). 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 transitions on the mean of log earning and medical spending



(a) Log quarterly earning

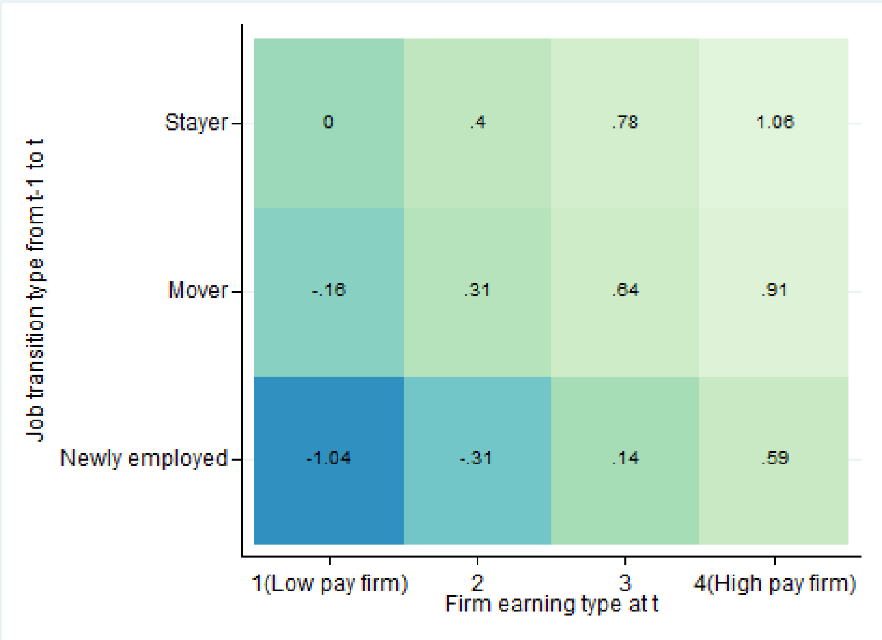


(b) Log annual medical spending

Note: This figure reports the parameters of health type transitions in the earning equation (equation 7) and medical spending equation (equation 8). Panel (a) reports the parameters of health-type transitions in the log earning equation: β_H. The reported numbers can be interpreted as the differences in the mean of log earnings relative to the reference type: among the healthiest group in both periods $t-4$ and period t. Panel (b) shows how health type transitions influence the prediction of log annual medical spending, which is the parameters γ_H in equation 8. The reported numbers can be interpreted as the differences in the mean of log medical spending relative to the reference type: among the healthiest group in both periods $t-4$ and period t.

Figure 5 reports the impact of job mobility status on the mean of log earnings. The reference type is the stayers who remain working in firms with the lowest firm earning level.

Figure 5: Impact of Job Transition Types on the mean of log earning



Note: This figure reports the parameters of the interaction term between job mobility transitions from $t-1$ to t and destination firm earning level types in t ($d_{it} \times k^{\mu}_{it}$) in equation 7. The reported numbers can be interpreted as the differences in the mean of log earnings relative to the reference type: stayers who remain in firms with the lowest firm earning level type. There are three job mobility types. Stayers are those who do not switch employers from $t-1$ to t. Movers are those who change employers. New earners are those who are not employed in $t-1$ and get payment in t. 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.

On average, conditional on the same job mobility status, the workers who end up moving firms with a higher earning level type earn more. Moreover, conditional on moving firms with the same earning level type, stayers are predicted to earn more than movers and newly-employed workers. 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. 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 residuals and log medical spending residuals. The standard deviation of the log earning residual is higher for firms with higher earning risk types. The standard deviation of the log medical spending residuals is stable across health types except for the group who are predicted to face the lowest medical risk. It shows that the uncertainty over the log medical spending is exceptionally high for the lowest medical spending group. One reason could be costly medical treatment for accidents, which are unpredictable with past medical utilization and diagnosis.

Table 4: Sample Standard deviation of the log earning and medical spending residuals

Panel A: log earning residuals	
Firm earning uncertainty type	Standard deviations
1(Lowest uncertainty)	0.35
2	0.46
3	0.58
4(Highest uncertainty)	0.75
Average	0.49
Panel B: log medical spending residuals	
Health type	Standard deviations
1(Healthiest)	2.36
2	0.91
3	0.87
4(Sickiest)	1
Average	1.95

Notes: This table reports the sample standard deviation of the log earning residuals ($\sqrt{var(\hat{\epsilon}(k^{\sigma}_{it}))}$ in equation 7) by firm earning risk type k^{σ}_{it} and log medical spending residuals ($\sqrt{var(\hat{\nu}(h_{it}))}$ in equation 8) by health type h_{it}.

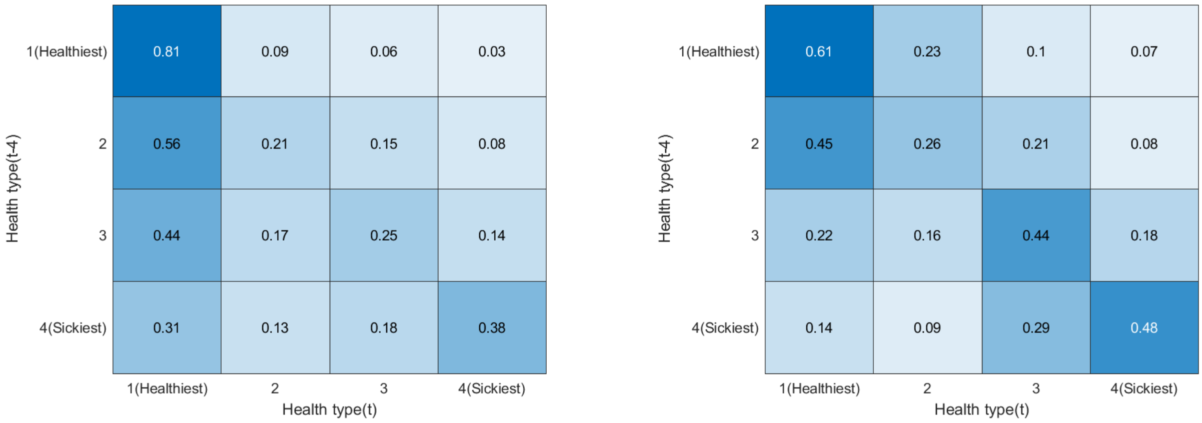
IV.4 Health and Employment Transitions

In this section, I discuss how individual i predicts the probability of realizing each possible combination of earning and medical spending. I assume that the individual predicts the probabilities in two steps. First, he predicts the probability of realizing the health and employment types. Second, conditional on the types realized, he predicts the probability of the random draws of log earning and log medical spending residuals.

As mentioned in Section IV.1 and Section IV.2, I assume that log earning residuals ϵ_{it} and log medical spending residuals ν_{it} are independently drawn from $N[0, var(\hat{\epsilon}(k^{\sigma}_{it}))]$ and $N[0, var(\hat{\nu}(h_{it}))]$, respectively. In practice, I discretize them using quadrature methods.

Prediction Process of Types. — The individual i first predicts health types for period t, based on his health type in period $t-4$, gender, and age. I denote the probability as $Pr(h_{it})$. Second, conditional on each possible realization of health type in period t, he predicts the job mobility types d_{it}. The probability is denoted as $Pr(d_{it}|h_{it})$. Third, conditional on health type h_{it} and job mobility types d_{it}, he predicts the probability of working in different types of firms in period t, which is denoted as $Pr(k_{it}|d_{it}, h_{it})$. The probability of realizing the types $Pr(h_{it}, d_{it}, k_{it}) = Pr(k_{it}|d_{it}, h_{it})Pr(d_{it}|h_{it})Pr(h_{it})$. In this section, I introduce how each step of this prediction process is modeled and estimated.

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.

Health Type Transitions. — I allow the transition probabilities for health to depend on health type four quarters ago $h_{i,t-4}$, gender, and age group (in 5-year bins). I follow Atal et al. (2021) to estimate it by fitting the transitions observed in the data from 2013-2015 into a multinomial logit model specified as:

$$\pi_{it}^{j} = \gamma_j X_{it} + \omega_j L_{i,t-4} + \lambda_j X_{it}^{age} \times L_{i,t-4} + \eta_{it}^{j} \tag{9}$$

where π_{it}^{j} represents the log odds for $h_{it} = j$. X^{it} includes the indicators for the age group individual i belongs to in period t, and his gender. $L_{i,t-4}$ is a set of indicators for the categories of health types four quarters ago. $X_{it}^{age} \times L_{i,t-4}$ is the interactions of age groups and $L_{i,t-4}$. γ_j, ω_j, λ_j are the associated parameter vectors.

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.

Job Mobility Type Transitions. — I assume that the transition probabilities of job mobility types depend on current health types h_{it}, past job mobility types $d_{i,t-1}$, person types a_i, age groups, and gender. The transitions are estimated using a multinomial logit model, with details given in Appendix C.

Firm type transitions. — Conditional on the possible health type h_{it}, and job mobility type d_{it}, individuals further predicts the types of their new employers in period t if they change employers from $t-1$ to t. There is no need to predict the firm-type transitions if the individuals are stayers because the firm types will remain unchanged. I assume that for movers, the transition probabilities of firm types depend on gender, age group, person earning types, health type, past firm earning level, and risk types. Newly-employed workers predict the probabilities of their new employers by gender, age groups, and person earning types. The transitions are estimated using a multinomial logit model, with details given in Appendix C.

V Life Cycle Model with Precautionary Savings

As discussed in Section II.1, assets that individuals hold before the insurance decisions for period t is one important object for estimating the willingness to pay for health insurance. However, one empirical difficulty is that I do not observe assets directly in the data. In this section, I introduce how I estimate the assets if individuals face the heterogenous earnings dynamics estimated in Section IV. Earnings dynamics can cause wealth-holding inequality (De Nardi and Fella, 2017). Higher uncertainty in labor market outcomes 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.

V.1 Life Cycle 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 the CRRA utility function with a risk aversion parameter of 2: $u(c) = -c^{-1}$.[16]

Because assets are not directly observed in the data, 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

[16]Individuals' utility doesn't depend on health status.

65 and begin to receive constant paychecks from social security each quarter until death.[17] Moreover, I assume individuals always follow the earning determination equation (equation 7) and the transition matrices estimated in Section IV when they predict earnings for each quarter during the life cycle.[18] 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.

The next period's assets are given by:

$$A_{t+1} = \tau_t(rA_t + w_t) + b_t - c_t \tag{10}$$

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 $\underline{c}$.

$$b_t = \max\{0, \underline{c} - \tau_t(rA_t + w_t)\} \tag{11}$$

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

$$V_t(A_t, \delta_t, w_t) = \max_{c_t, A_{t+1}} \{u(c_t) + \beta s_t E_t V_{t+1}(A_{t+1}, \delta_{t+1}, w_{t+1})\} \tag{12}$$

subject to equations 10 and 11. s_t stands for the probability that an individual is alive at period $t+1$, conditional on gender and being alive at period t. w_{t+1} is the predicted earning in $t+1$ that is associated with possible type realization δ_{t+1} and random draws of log earning residuals.

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

$$V_t(x_t, \delta_t, w_t) = \max_{c_t, x_{t+1}} \{u(c_t) + \beta s_t E_t V_{t+1}(x_{t+1}, \delta_{t+1}, w_{t+1})\} \tag{13}$$

subject to:

$$x_t = A_t + \tau(rA_t + w_t) + b_t \tag{14}$$

[17] Women receive \$3293 and men receive \$4589 per quarter. The numbers are calculated using Table 5.J3 from Annual Statistical Supplement, 2014:
https://www.ssa.gov/policy/docs/statcomps/supplement/2014/5j.html#table5.j3

[18] 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.

$$A_{t+1} = x_t - c_t \tag{15}$$

$$x_{t+1} = x_t - c_t + \tau(r(x_t - c_t) + w_t) + b_{t+1} \tag{16}$$

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

$$x_t \geq \underline{c} \tag{17}$$

The nonnegative assets require that:

$$c_t \leq x_t \tag{18}$$

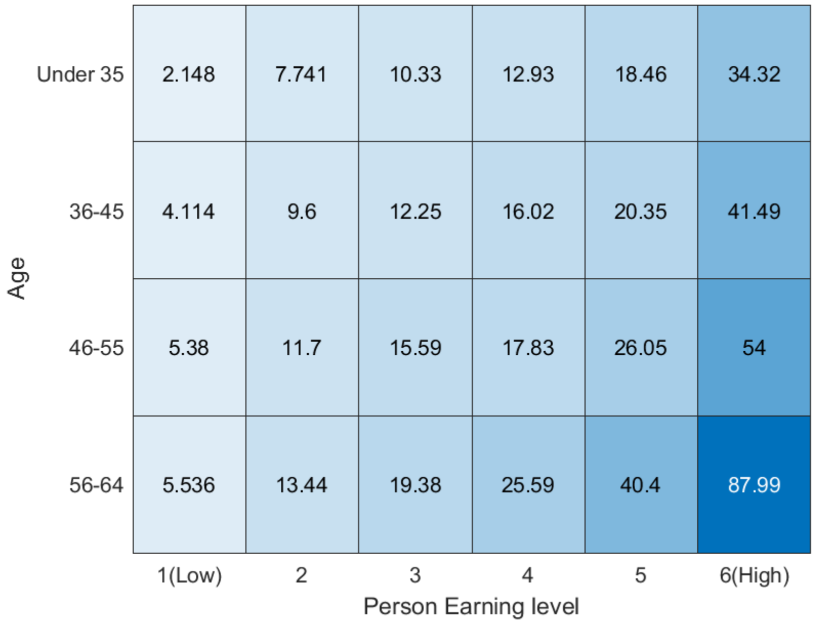
The estimation of assets for an individual in the sample follows two steps. First, I simulate one potential past path of type realizations for this individual. Second, I simulate the assets by combining the consumption-saving strategies estimated from life-cycle models and his simulated past life path.

V.2 Estimated wealth distribution

Figure 7 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 7: 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.

VI Market Aggregation and Adverse Selection

This section aggregates the individual-level willingness to pay for health insurance to market demand to study how incorporating earnings dynamics affects adverse selection. In Section IV, I model and estimate how individuals predict the joint dynamics of earnings and medical spending for period t. In Section V, I estimate the assets that individuals hold at the beginning of period t using a life-cycle saving model. As mentioned in Section II.1, individuals' willingness to pay can be calculated with these two components.

In this section, I focus on a randomly selected approximated 1% subsample and end up with $N = 3219$ individuals. I study how they calculate their willingness to pay for a health insurance plan that can fully cover their medical cost in the next quarter t under four models.[19] I start with the baseline model that the only heterogeneity among the consumers is the medical spending risk. I then sequentially add different sources of heterogeneity among consumers. The details of the four models will be introduced in Section VI.1. I then introduce market equilibrium and social efficiency in Section VI.2, which are applied to compare the welfare and adverse selection of these four models. Finally, in Section VI.3 and Section VI.4, I present the comparisons between the four models and discuss the impact of earnings

[19]Empirically, I focus on the insurance choice problem for the second quarter of the year 2014.

dynamics on adverse selection.

VI.1 Models of different degrees of heterogeneity

This section introduces the four models with different levels of heterogeneity in earnings dynamics among consumers. I assume that for individual i, he predicts the same medical spending distribution for period t across the four models of interest, but his asset level and his prediction of the joint dynamics of earnings and medical spending differ across models. I further assume that all individuals have CRRA utility with a risk aversion parameter of 2 and face a consumption floor at $2000.

I begin by introducing the model that considers all sources of heterogeneity in earnings dynamics among individuals, which I also call as "Full-heterogeneity" model (or Model 4) in the following discussion. I introduce this model first because it is easier to define the other models based on it. When making decisions for health insurance, an individual i holds A_i and predicts the joint distribution of earnings and medical spending for period t as $f(w_{it}, m_{it})$. The estimation of assets is introduced in Section V, and how he predicts the joint distribution of earnings and medical spending is presented in Section IV.

The baseline model, which I also call as "No-heterogeneity" model (or Model 1) in the following discussion, considers a sample of individuals who only differ in medical risk. In this "No-heterogeneity" model, individual i holds the average asset of the sample $\bar{A}$. Moreover, he predicts that for all possible states of the world, he gets the sample average of the mean earning $\bar{\mu}_{wt}$, which is calculated in two steps. First, individuals calculate the mean of the earning distribution they face.

$$\mu_{iwt} = \int w_{it} f(w_{it}) dw_{it} \tag{19}$$

where w_{it} is the variable that documents the earning realization in different states of the world for individual i. $f(w_{it})$ is the PDF of his predicted earning distribution. Second, the sample average is given as $\bar{\mu}_{wt} = \frac{1}{N}\sum_i \mu_{iwt}$.

Based on the baseline model, I add differences in assets. In this model with differences in assets (also called Model 2 in the following discussion), individuals now hold A_i at the beginning of period t. I further add differences in the mean of earning distribution. In this model (Model 3), individual i predicts to face μ_{iwt} in every state of the world.

VI.2 Market Equilibrium and Social Efficiency

In this section, I introduce how to aggregate individual-level willingness to pay for health insurance to market-level analysis, including market equilibrium and social efficiency outcomes. I also introduce some statistics of interest to compare adverse selection and welfare across the four models discussed in the previous section (Section VI.1). The statistics of interest include take-up rates for health insurance, insurance premiums, consumer surplus, and deadweight loss.

VI.2.1 Aggregation to the Market

In the health insurance market, N individuals, indexed by $i \in \{1...I\}$, face the choices between a full coverage health insurance plan and being uninsured. Individual i calculates willingness to pay for the health insurance plan as g_i. I further assume perfect competition among insurers.

VI.2.2 Market Equilibrium

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

$$q^* = \frac{1}{N}\sum_i \mathbf{1}(g_i \geq p^*) \tag{20}$$

Where $\mathbf{1}(g_i \geq p^*)$ equals 1 if $g_i \geq p^*$. 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

$$CS^* = \frac{1}{N}\sum_i [(g_i - p^*)\mathbf{1}(g_i \geq p^*)] \tag{21}$$

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

VI.2.3 Social Efficiency

The textbook adverse selection model calculates the socially efficient take-up rate and premiums by finding the intersection between demand and marginal cost curves. However, when earnings dynamics are considered, the marginal cost curves may not be monotonic. Willingness to pay for health insurance is no longer solely determined by medical risk but is also affected by earning uncertainty and its correlation with medical risk. Therefore, an individual with a higher willingness to pay does not necessarily face higher medical risk. This non-monotonicity creates difficulty in accurately finding the intersection. I introduce two measures of socially efficient outcomes.

Social Planner Measure. — The first measure I consider is to measure social efficiency from the perspective of a social planner with full information about the distribution of willingness to pay and medical costs. I consider it socially efficient to cover individuals whose willingness to pay is above the expected medical cost. This measure of social efficiency cannot be obtained in general under a single pricing assumption. The socially efficient take-up rate is given as

$$q^o = \frac{1}{N}\sum_i [\mathbf{1}(g_i \geq z_i)] \tag{22}$$

The socially efficient level of consumer surplus is given as

$$CS^o = \frac{1}{N}\sum_i [(g_i - z_i)\mathbf{1}(g_i \geq z_i)] \tag{23}$$

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.

$$DWL^o = \frac{1}{N}\sum_i [(g_i - z_i)\mathbf{1}(g_i \geq z_i)] - \frac{1}{N}\sum_i [(g_i - z_i)\mathbf{1}(g_i \geq p^*)] \tag{24}$$

Smoothed Marginal Cost Measure. — In the second measure, I assume that policymakers 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 for welfare evaluation. I denote the socially efficient premium as p^{mo}.

The take-up rate under this measure is given by

$$q^{mo} = \frac{1}{N}\sum_i [\mathbf{1}(g_i \geq p^{mo}) \tag{25}$$

The consumer surplus under this measure is thus

$$CS^{mo} = \frac{1}{N}\sum_i [(g_i - z_i)\mathbf{1}(g_i \geq p^{mo})] \tag{26}$$

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

$$DWL^{mo} = \frac{1}{N}\sum_i [(g_i - z_i)\mathbf{1}(g_i \geq p^{mo})] - \frac{1}{N}\sum_i [(g_i - z_i)\mathbf{1}(g_i \geq p^*)] \tag{27}$$

VI.3 Results and Discussion

In this section, I present and discuss the differences in the four models introduced in Section VI.1. I begin with the changes in willingness to pay distribution. Then I discuss the changes in market equilibrium and social efficiency, which are introduced in Section VI.2.

VI.3.1 Willingness to pay distribution

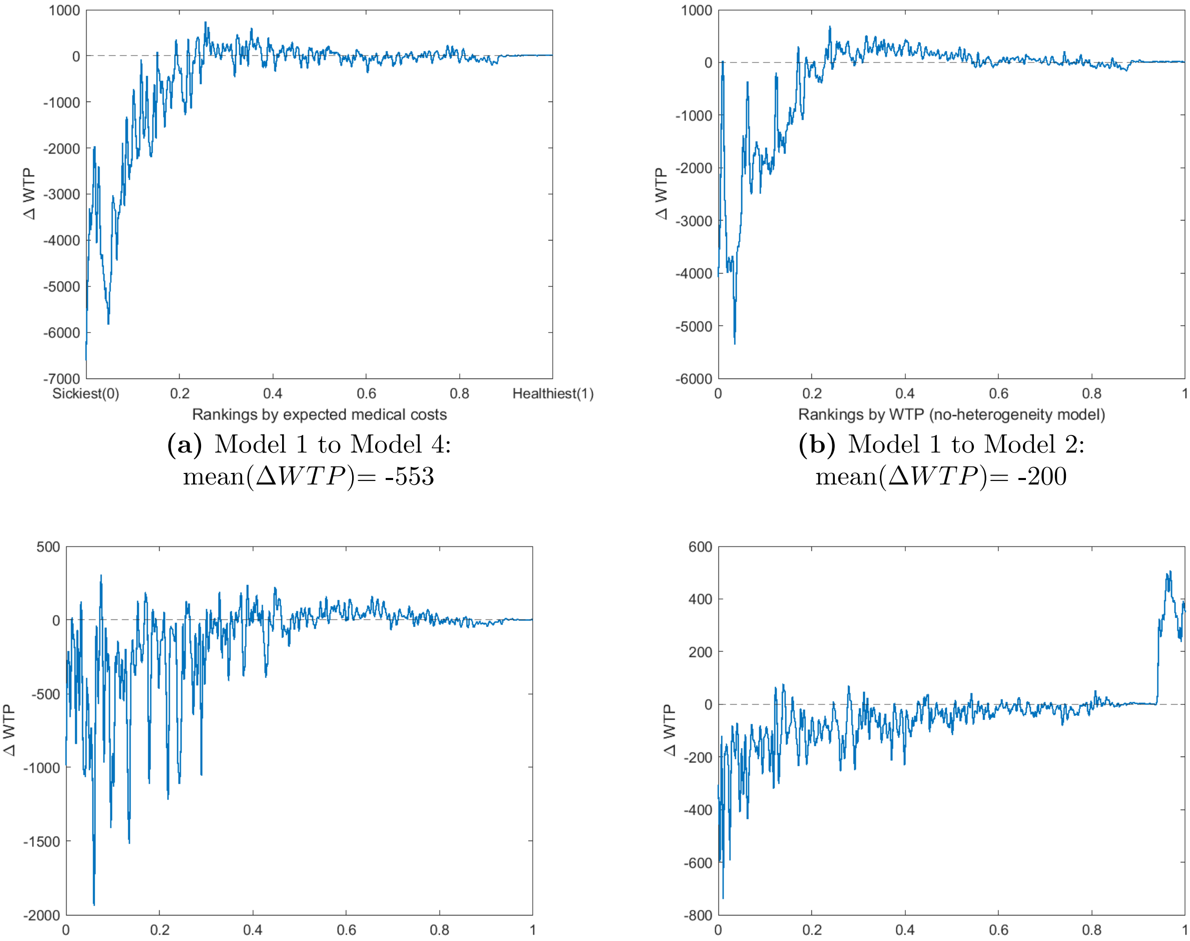
Heterogeneous changes in willingness to pay. — The changes in willingness to pay distribution can lead to shifts in the demand curve because, at each possible market price, the share of individuals who are willing to buy will change with the willingness to pay distribution. Moreover, when the correlation between willingness to pay and expected medical cost changes, individuals with higher expected medical costs may not still be the ones with a higher willingness to pay. Therefore, the marginal cost curve may also change. In Figure 8, I plot the smoothed changes in the willingness to pay when earnings dynamics are incorporated.[20]I find that, on average, ignoring earnings dynamics overestimates willingness to pay. Figure 8 also reveals heterogeneous changes in willingness to pay. Panel (a) reports that for the people who are ranked at around the first 20% of the expected medical cost distribution, their willingness to pay tends to drop after allowing different earnings dynamics. However, the willingness to pay tends to increase for people ranked from around 20% to 40%. Finally, the changes in the willingness to pay are small for people with low expected medical costs (ranked after around 60%). Therefore, Figure 8 (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 impact of adding earning uncertainty. — Model 4, the "Full-heterogeneity" model, adds earning uncertainty across different possible states of the world for the period t to Model 3, in which individuals are for sure facing the mean of the earning distribution. In Figure 8 (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 the individuals who have a high willingness to pay in Model 3.

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

Figure 8: Willingness to Pay Changes with Earnings Dynamics



(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. Four models are considered. In Model 1, the individuals only differ in medical risk. In Model 2, differences in assets are added. In Model 3, individuals are assumed to face the mean of individual-level predicted earning distribution in all states of the world. In Model 4, individuals are assumed to face the predicted earning distribution. Panel (a) plots the differences in willingness to pay estimated in Model 1 and Model 4. People are ranked based on the expected medical costs in Panel (a). In Panel (b), (c), and (d), people are ranked based on willingness to pay, which is estimated in Model 1, Model 2, and Model 3, respectively. People are ranked from the higher willingness to pay to the lower willingness to pay.

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 people have an extremely low mean of 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 resources above the consumption floor. Therefore, they consider health insurance valuable in these states.

VI.3.2 Market 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.

The changes in the outcomes are the net impact of both changes in the demand curves and average cost curves. Figure 9 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.

Table 5: Impact of Earnings Dynamics on Market Equilibrium and Social Efficiency

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: Social Efficiency: Social Planner Measure

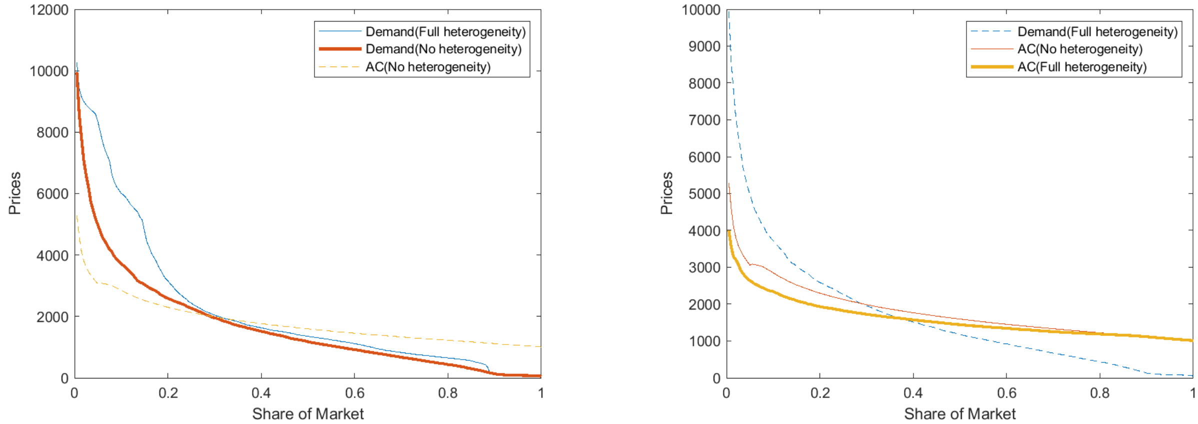
Model	Description	Take-up	Price	Consumer surplus	Deadweight loss
1	**Only differ in medical risk**	**1.000**		**1190.9**	**246.0**
	No-heterogeneity	**(0.00)**		**(27.88)**	**(12.29)**
2	Add different assets	+0.000		-200.0	-94.1
		(0.00)		(21.49)	(11.97)
3	Add different expected earning	-0.136		-370.9	-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: Social Efficiency: Smoothed Marginal Cost Measures

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 Model 1 — no-heterogeneity model. Details of the models are introduced in Section VI.1. 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 sample average mean earning $\bar{\mu}_{wt}$. Model 2 add heterogeneity in asset, and individual i holds assets at A_i. Model 3 adds the heterogeneity in the mean of earnings based on Model 3. Individual i gets the earning at μ_{iwt} in all possible states. Model 4 is the full-heterogeneity model, in which people are uncertain about earning, and the correlation between earning and medical spending is allowed. The medical risk distribution is kept unchanged in all models. All individuals are assumed to have the same constant relative risk aversion utility function with risk aversion at 2. The consumption floor is set at $2000. Panel A reports the 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 the consumption floor. Panel B reports the socially efficient take-up rate, consumer surplus, and deadweight loss under the Social Planner Measure—people with a higher willingness to pay than expected medical cost are considered as those who should be socially optimal to cover. Panel C smooths non-monotonic marginal cost curves and considers the interaction point between the smoothed marginal cost curve and demand curves as the socially efficient price. The marginal cost curves are smoothed with robust linear regression over each window of 20 points. More details can be found in Section VI.2.

Figure 9: 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 differences in predicted earning distribution and assets. 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.

Steeper average cost curves. — Adverse selection implied by the textbook 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, 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 model. 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.

VI.3.3 Social Efficiency

Significant changes happen to the estimated socially optimal outcomes. Table 5 Panel B reports the changes in socially efficient outcomes under the Social Planner Measure. This measure assumes that insurance is assigned by a social planner with full information and defines individuals willing to pay above their expected medical cost as those who 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), in which consumers only differ in medical risk. It reveals that incorporating earnings dynamics in insurance choices leads to a lower estimation of socially optimal consumer surplus and deadweight loss.

The approximation of socially efficient outcomes. —In the textbook 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, if insurance is assigned according to the interaction point between smoothed marginal cost curve and demand curves, the outcome differs from the outcome under the Social Planner Measure. Table 5 Panel C reports the socially efficient outcomes under the Smoothed Marginal Cost Measure. The socially efficient price p^{mo} is the intersection between smoothed marginal cost curves and demand curves. Individuals who are willing to pay more than p^{mo} are considered as those who are efficient to cover. This approximation causes an inaccurate estimation of deadweight loss in models with earnings dynamics. Therefore, it reveals that individualizing prices may be important for policy designs facing uncertainty in marginal cost.

VII Subsidies in Models with Earnings Dynamics

Enormous money was spent on subsidizing low-income individuals in health insurance markets. One important reason for offering subsidies is to reduce adverse selection. This section discusses how subsidy performance changes when earnings dynamics are incorporated. Intuitively, in models with earnings dynamics, individuals with a lower willingness to pay may not always be healthier. They may also be unwilling to buy insurance because of their financial situation. Therefore, subsidies that are designed based on earnings may not be as efficient in reducing adverse selection as predicted by the textbook model.

In this section, I investigate the changes in subsidy efficiency when earnings dynamics are considered. I begin by introducing how subsidies work in reducing adverse selection. Then, I introduce how I measure the efficiency of the subsidy performance. Finally, I discuss the counterfactual analysis of subsidies.

How subsidies work. — I begin by introducing how subsidy works step by step to reduce adverse selection. When the equilibrium price in the market is p^*, if an individual receives a subsidy of k_i, his price is adjusted to

$$\hat{p}_i^* = \max(p^* - k_i, 0) \tag{28}$$

Therefore, individuals face a price that is lower or equal to the equilibrium price p^* at the status quo (before subsidy is implemented).

A subsidy works in several steps to affect adverse selection. First, the lower individualized price can then motivate some uninsured individuals to buy insurance. Second, the average insurance cost will change because of the switchers. According to the textbook model, the average cost goes down because the switchers are unambiguously cheaper to cover than those insured at the status quo. However, for models with earnings dynamics, the direction and the size of the changes in average cost are ambiguous. Third, the price will adjust according to the changes in average cost, and further attracts more consumers if the equilibrium drops. The process will finally stop at a new equilibrium when insurers earn zero expected profits.

I compare the changes in equilibrium take-up rates, prices, consumer surplus, and deadweight loss before and after the subsidy. I assume that the willingness to pay is the welfare-relevant metric for evaluating the welfare of the subsidy recipients. I define the new equilibrium price after the policy as p^*_{after}. The change in equilibrium price because of subsidy is thus given by $\Delta p^* = p^*_{after} - p^*$. Notice, individuals now face the individualized price adjusted by subsidy based on this new equilibrium premium, which is given by:

$$\hat{p}^*_{i,after} = \max(p^*_{after} - k_i, 0) \tag{29}$$

The changes in equilibrium take-up rate are given by

$$\Delta q = \underbrace{\frac{1}{N}\sum_i \mathbf{1}(g_i \geq \hat{p}^*_{i,after})}_{\text{Equilibrium take-up after subsidy}(q_{after})} - \underbrace{\frac{1}{N}\sum_i \mathbf{1}(g_i \geq p^*)}_{\text{Equilibrium take-up before subsidy}(q_{before})} \tag{30}$$

The changes in consumer surplus are given by

$$\Delta CS = \underbrace{\frac{1}{N}\sum_i (g_i - \hat{p}^*_{i,after})\mathbf{1}(g_i \geq \hat{p}^*_{i,after})}_{\text{Consumer surplus after subsidy}(CS_{after})} - \underbrace{\frac{1}{N}\sum_i (g_i - p^*)\mathbf{1}(g_i \geq p^*)}_{\text{Consumer surplus before subsidy}(CS_{before})} \tag{31}$$

The deadweight loss at the status quo (before the subsidy is implemented) is given by:

$$DWL_{before} = \frac{1}{N}\sum_i (g_i - z_i)\mathbf{1}(g_i \geq z_i) - \frac{1}{N}\sum_i (g_i - z_i)\mathbf{1}(g_i \geq p^*) \tag{32}$$

The deadweight loss after the implementation of subsidies:

$$DWL_{after} = \frac{1}{N}\sum_i (g_i - z_i)\mathbf{1}(g_i \geq z_i) - \frac{1}{N}\sum_i (g_i - z_i)\mathbf{1}(g_i \geq \hat{p}^*_{i,after}) \tag{33}$$

The changes in deadweight loss are given by:

$$\Delta DWL = DWL_{after} - DWL_{before} \tag{34}$$

I further define the share of changes in deadweight loss as:

$$\Delta DWL\% = \frac{DWL_{after} - DWL_{before}}{DWL_{before}} \tag{35}$$

I also consider the social cost of raising taxes for the subsidy payments. Only individuals who are both eligible for subsidies and purchase insurance will receive subsidy payments from the policymakers. The social cost of such a subsidy is given by

$$\lambda \frac{1}{N} \sum_{i} (p^{*}_{after} - \hat{p}^{*}_{i,after}) \mathbf{1}(g_i \geq \hat{p}^{*}_{i,after}) \tag{36}$$

where λ is the marginal cost of public funds. I use $\lambda = 0.3$ as the (standard estimate of) the marginal cost of public funds (e.g., Einav et al., 2010).

Subsidies are less efficient in reducing deadweight loss in models with earnings dynamics. — Table 6 reports the different impacts of uniform subsidies[21] on adverse selection across the models that vary in heterogeneity in earnings dynamics, which are introduced in Section VII.1. The changes in equilibrium take-up rate, premiums, and consumer surplus are lower in models that incorporate earnings dynamics. Moreover, the share of deadweight loss reduced is also lower. One potential reason for the less efficient performance of subsidies is that subsidies may attract consumers with high medical risk in models with earnings dynamics. Table 7 shows that approximately 8% of the switchers have higher expected medical costs than the average cost at the status quo. This feature suggests the importance of considering the non-monotonic marginal cost curves when designing subsidies.

[21] The reason to focus on uniform subsidies instead of ACA subsidies is that I study a hypothetical market without allowing intensive margin choices between plans with different coverages. ACA subsidies are based on the prices of the second-lowest-cost silver plan. More details about ACA subsides are introduced in Section E.

Table 6: Impact of Subsidies in Models with Earnings Dynamics

Subsidy	Model	Description	ΔTake -up	ΔPremium	ΔConsumer Surplus	Social cost of Subsidy	ΔWelfare	Δ% 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 mean of earnings	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 mean of earnings	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. Four models are considered. In Model 1, the individuals only differ in medical risk. In Model 2, differences in assets are added. In Model 3, individuals are assumed to face the mean of individual-level predicted earning distribution in all states of the world. In Model 4, individuals are assumed to face the predicted earning distribution. Details of these models are introduced in Section VI.1. 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 is calculated as $\frac{1}{N}\sum_i(g_i - \hat{p}^*_{i,after})\mathbf{1}(g_i \geq \hat{p}^*_{i,after})$, where g_i is the willingness to pay, and $\hat{p}^*_{i,after}$ is the individualized premium at the new equilibrium price p^*_{after}. The social cost of subsidies is calculated using $\lambda = 0.3$ as the estimate of the marginal cost of public funds, which is given by $\lambda\frac{1}{N}\sum_i(p^*_{after} - \hat{p}^*_{i,after})\mathbf{1}(g_i \geq \hat{p}^*_{i,after})$. Welfare per person is the difference between consumer surplus and the social cost of the subsidy. Deadweight loss for the status quo (before subsidy) is calculated as $DWL_{before} = \frac{1}{N}\sum_i(g_i - z_i)\mathbf{1}(g_i \geq z_i) - \frac{1}{N}\sum_i(g_i - z_i)\mathbf{1}(g_i \geq p^*)$, where z_i is the expected medical costs. The deadweight loss after the subsidy is calculated as $DWL_{after} = \frac{1}{N}\sum_i(g_i - z_i)\mathbf{1}(g_i \geq z_i) - \frac{1}{N}\sum_i(g_i - z_i)\mathbf{1}(g_i \geq \hat{p}^*_{i,after})$. 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 No-heterogeneity	0	0	0	0
2	Add different assets	0	0	0	0
3	Add different mean of earnings	0.046 (0.012)	0.031 (0.006)	0.031 (0.006)	0.032 (0.006)
4	Add earning uncertainty Full-heterogeneity	0.076 (0.014)	0.078 (0.010)	0.078 (0.010)	0.079 (0.009)

Notes: This table reports the share of switchers after uniform subsidy that have higher expected costs 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 willing to pay 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.

More subsidies for low-earning individuals may not be the most efficient design. — In Table 8, I compare the welfare impact of three subsidy designs on the "Full-heterogeneity" Model, in which individuals differ in joint dynamics of earnings and medical spending. The three subsidies offer the same average subsidy to the sample but target different groups by their earning levels. Individuals are divided into three equal groups by their expected earnings: high-earning, median-earning, and low-earning. In the uniform subsidy design, all individuals are offered a subsidy of $400 if they choose to purchase the plan. The second subsidy design offers zero subsidies to the highest-earning group and increases the subsidy to the low-earning group to $800. The final subsidy offers $800 to the median-earning group, while the individuals belonging to the low-earning group receive only $400.

Before the equilibrium price adjustment, we see similar changes in the subsidies' take-up rates that target low-earning and median-earning groups. The take-up changes in the uniform subsidy design are around 1% lower than the subsidies that target groups by earnings. However, the average cost of the insured is significantly lower if the subsidy targets the median-earning group. As mentioned earlier, lowering the average cost by attracting healthier new enrollees is one important step to lead to a lower equilibrium price. Panel B reports the outcomes after adjusting the price to the new equilibrium. Results show the importance of considering whom to target in subsidy designs. I find that offering more subsidies to the median-earning group is more efficient than subsidies targeting the lower-earning group. It leads to a higher equilibrium take-up rate, consumer surplus, and a more significant price reduction. The welfare per person, calculated by subtracting the social cost of subsidies from the consumer surplus, is also higher. Surprisingly, subsidies targeting the lower-earning

Table 8: Subsidy Design Targeted by Earnings

Panel A: Equilibrium Price not Adjusted			
	Uniform	Low-earning	Median-earning
Take-up	0.485	0.494	0.497
Average cost	1460	1508	1435
Panel B: Equilibrium Price adjusted			
	Uniform	Low-earning	Median-earning
Take-up	0.572	0.557	0.591
Premium	1368	1445	1337
Consumer surplus	898	848	931
Social cost of subsidy	68	71	81
Welfare per person	829	777	849
Δ Deadweight loss	-68	-10	-58

Notes: This table compares three counterfactual subsidy designs on the "Full-heterogeneity" Model, which considers differences in medical risk, assets, mean of earning, and earning uncertainties. 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 \$400. Column 2 reports the results for a subsidy that targets the low-earning group with a subsidy at \$800 and offers a subsidy to the median-earning group at \$400. Column 3 reports the results for a subsidy that targets the median-earning group with a subsidy at \$800 and offers a subsidy to the low-earning group at \$400. 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 $\frac{1}{N}\sum_i(g_i - \hat{p}^*_{i,after})\mathbf{1}(g_i \geq \hat{p}^*_{i,after})$, where g_i is the willingness to pay, and $\hat{p}^*_{i,after}$ is the individualized premium at the new equilibrium price p^*_{after}. The social cost of subsidies is calculated using $\lambda = 0.3$ as the estimate of the marginal cost of public funds, which is given by $\lambda\frac{1}{N}\sum_i(p^*_{after} - \hat{p}^*_{i,after})\mathbf{1}(g_i \geq \hat{p}^*_{i,after})$. Welfare per person is the difference between consumer surplus and the social cost of the subsidy. Deadweight loss for the status quo (before subsidy) is calculated as $DWL_{before} = \frac{1}{N}\sum_i(g_i - z_i)\mathbf{1}(g_i \geq z_i) - \frac{1}{N}\sum_i(g_i - z_i)\mathbf{1}(g_i \geq p^*)$, where z_i is the expected medical costs. The deadweight loss after the subsidy is calculated as $DWL_{after} = \frac{1}{N}\sum_i(g_i - z_i)\mathbf{1}(g_i \geq z_i) - \frac{1}{N}\sum_i(g_i - z_i)\mathbf{1}(g_i \geq \hat{p}^*_{i,after})$. 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.

group reduce deadweight loss less than the other two subsidy designs. Because bad health can lead to earning reductions, individuals in the low-earning group are more likely to be unhealthy. The subsidy targeting the low-earning group can attract many individuals who value the insurance lower than expected costs.

VIII Conclusion

In this paper, I incorporate the joint dynamics of earnings and medical spending into modeling individuals' insurance choices. I study how individuals who face uncertainty over earnings and medical spending decide between being uninsured and fully insured. I empirically estimate the individual-level willingness to pay using a dataset that links Utah All Payer Claims Data to earnings records derived from the UI database. I first estimate how individuals predict the joint distribution of earnings and medical spending for a nearly population-level sample. Second, I estimate the assets via a life-cycle model in which individuals face earnings dynamics calculated in the first step.

I aggregate the individual willingness to pay for health insurance to market level and study how earnings dynamics affect adverse selection. I document significant heterogeneous changes in the willingness to pay distribution. Moreover, the willingness to pay is no longer a straightforward predictor for medical costs as in textbook models. By reducing the correlation between willingness to pay and expected medical cost, I find that models incorporating earnings dynamics predict higher equilibrium take-up rates, lower equilibrium premiums, and lower deadweight loss.

Moreover, a uniform subsidy reduces a lower share of deadweight loss in models with earnings dynamics. Counterfactual simulations also show that more subsidies to the lower-earning group cannot reduce deadweight loss as effectively as either uniform subsidies or subsidies targeted to the median-earning group. These results reveal the importance of targeting when designing income-based policies like 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 (the choice between being uninsured and insured). Allowing choices among plans with different levels of coverage could affect selection into different health insurance plans and corresponding optimal subsidy designs. Finally, studies can be done on the optimal adjustment of health insurance policies when individuals face financial crises, industry-specific shocks, or changes in other labor market policies.

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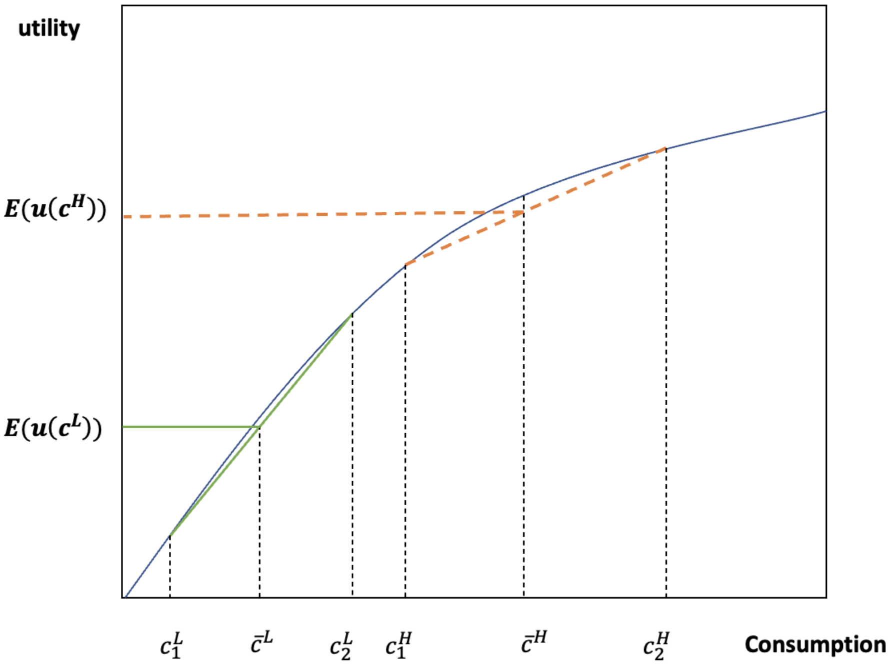
Appendix

A. More Theoretical Discussion

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



Note: This figure illustrates that individuals with a lower mean of earnings tend to have a lower expected utility of being uninsured. Facing the same level of earning uncertainty, if 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 criteria

	(1) Starting Sample mean	(2) 1. Age(25-64) mean	(3) 2. Insured mean	(4) 3. With plan characteristics mean	(5) 4. no missing types mean	(6) 5. potential stayers in labor force mean	(7) 6. potential full-time workers 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. Transition Matrices Estimations

In this section, I describe the details of how to estimate job mobility and the firm-type transition matrices.[22]

Job mobility Type transitions. — I first estimate the job mobility transitions if the individual i is not employed in period $t-1$. The transition probabilities for job mobility types d_{it} from $t-1$ to t are assumed to depend on health type h_{it}, gender, age groups (in 5-year bins), and person earning type a_i. I fit the transitions into a multinomial logit model given by

$$\pi_{it}^{j} = \gamma_j X_{it} + \omega_j L_{it} + \lambda_j a_i + \eta_{it}^{j} \tag{37}$$

where π_{it}^{j} represents the log odds for $d_{it} = j$. X^{it} includes the indicators for the age group individual i belongs to in period t, and his gender. L_{it} is a set of indicators for the categories of health types in period t. a_i is 1×6 vector that describes the category of the six person earning types individual i belongs to. γ_j, ω_j, λ_j are the associated parameter vectors.

Second, I estimate the job mobility transitions if the individual i is employed in period $t-1$. The transition probabilities for job mobility types d_{it} from $t-1$ to t are assumed to depend on health type h_{it}, gender, age groups (in 5-year bins), and person earning type a_i. I fit the transitions into a multinomial logit model given by

$$\pi_{it}^{j} = \gamma_j X_{it} + \omega_j L_{it} + \lambda_j a_i + \alpha_j D_{i,t-1} + \eta_{it}^{j} \tag{38}$$

where π_{it}^{j} represents the log odds for $d_{it} = j$. X^{it} includes the indicators for the age group individual i belongs to in period t, and his gender. L_{it} is a set of indicators for the categories of health types in period t. a_i is 1×6 vector that describes the category of the six person earning types individual i belongs to. $D_{i,t-1}$ is a set of indicators for the category of the job mobility type from period $t-2$ to $t-1$. γ_j, ω_j, λ_j, and α_j are the associated parameter vectors.

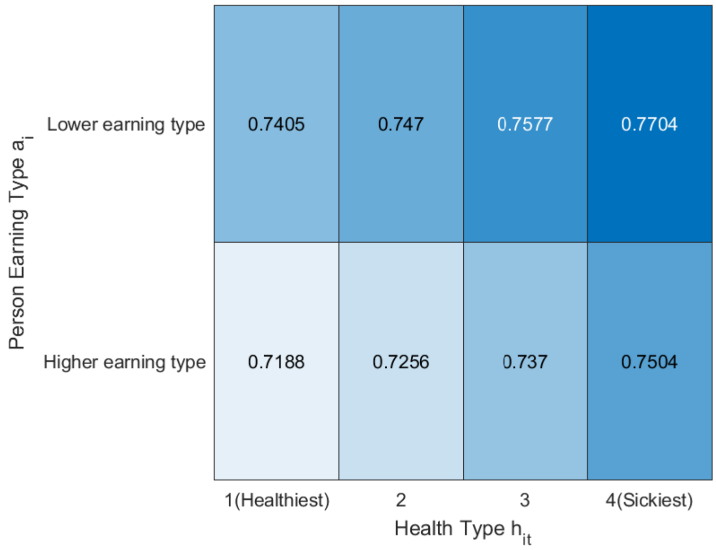
Figure C1 shows the probability of remaining unemployed in period t if currently not employed in period $t-1$. We can see that individuals with lower earning types are more likely to remain unemployed, and bad health can increase the probability of remaining unemployed.

Figure C2 shows the job mobility transitions if currently employed. We can also observe that individuals with lower earning types are less likely to stay in their current firm. Moreover, bad health increases the probability of moving or losing jobs slightly.

Firm Type Transitions. — If the individuals are stayers from $t-1$ to t, there is no need to estimate the probability of the types of the firms they work in period t because the type

[22] Only part of the transition matrices are shown, to meet disclosure requirements.

Figure C1. Probability to remain not employed



Note: This figure presents the probability to remain not employed in t if currently not employed in $t-1$. The health types are constructed using health 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 a_i are constructed from a two-way fixed effects model as explained in Section 4.1.1. The lower earning types reports are the average probabilities over people with person earning types 1, 2, and 3. The higher earning types estimates are the average probabilities over people with person earning types 4, 5, and 6.

of their employers does not change. I first estimate the probability of firm types when the individuals are not employed in period $t-1$. I assume that the type of firms they work for in period t, conditional on being newly employed, depends on their gender, age group, and person earning types. I estimate the transitions for firm earning level type and uncertainty type separately. I fit the transitions into a multinomial logit model given by

$$\pi_{it}^{j} = \gamma_j X_{it} + \lambda_j a_i + \eta_{it}^{j} \tag{39}$$

where π_{it}^{j} represents the log odds for firm earning level type $k_{it}^{\mu} = j$ (or for firm earning uncertainty type $k_{it}^{\sigma} = j$). X^{it} includes the indicators for the age group individual i belongs to in period t, and his gender. a_i is 1×6 vector that describes the category of the six person earning types individual i belongs to. γ_j and λ_j are the associated parameter vectors.

Second, I estimate the probability of their destination firm types in period t when individuals are employed in period $t-1$. These people are classified as movers. I assume that the type of firms they work for in period t, conditional on being movers, depends on their gender, age group, health types, past firm types, and person earning types. For the transitions for firm types, the multinomial logit model is given by

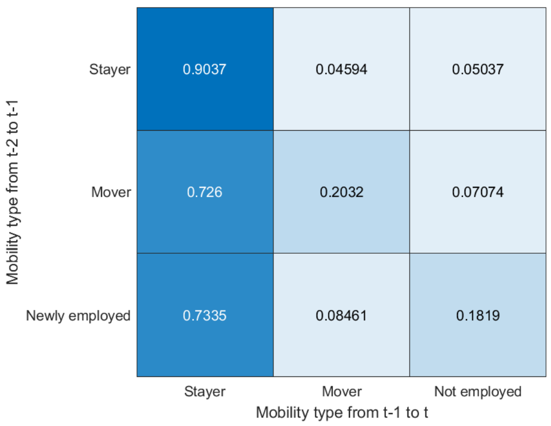
$$\pi_{it}^{j} = \gamma_j X_{it} + \omega_j L_{it} + \lambda_j a_i + \beta_j k_{i,t-1} + \eta_{it}^{j} \tag{40}$$

where π_{it}^{j} represents the log odds for $k_{it}^{\mu} = j$(or for firm earning uncertainty type $k_{it}^{\sigma} = j$). X^{it} includes the indicators for the age group individual i belongs to in period t, and his gender. L_{it} is a set of indicators for the categories of health types in period t. a_i is 1×6 vector that describes the category of the six person earning types individual i belongs to. $k_{i,t-1}$ is a set of indicators for the category of the type of firms they work for (including both firm earning level types and uncertainty types) in $t-1$. γ_j, ω_j, λ_j, and β_j are the associated parameter vectors.

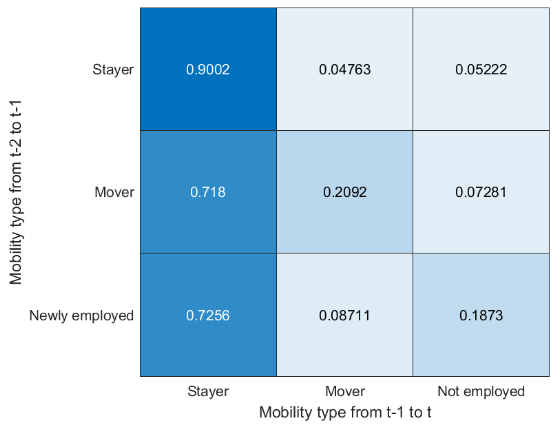
Figure C3 shows the firm-type transitions if the individuals are newly employed in period t. People with lower earning types are more likely to move to firms with lower earning level types and higher risk types.

Figure C4 and C5 show the firm-type transitions if the individuals are movers. The figures reveal that people with lower earning types are more likely to move to firms with lower earning level types and higher risk types. Moreover, bad health slightly reduces the probability of transitioning into higher-earning, lower-risk firms.

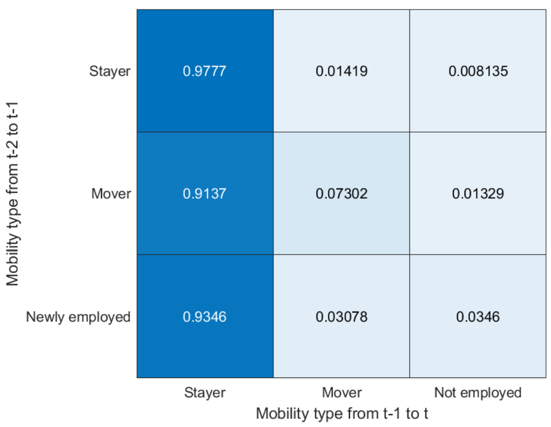
Figure C2. Job mobility type transitions for the currently employed



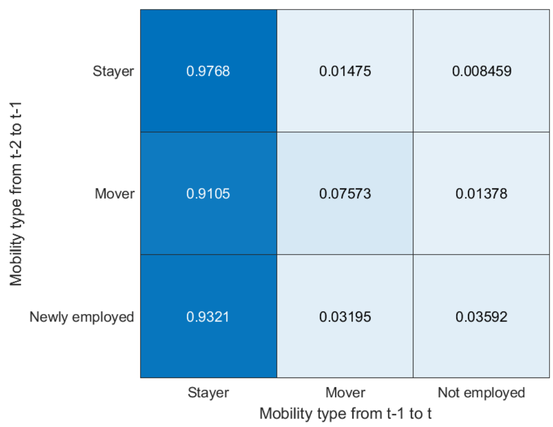
(a) $h_t = 1$, $\alpha = 1$



(b) $h_t = 4$, $\alpha = 1$



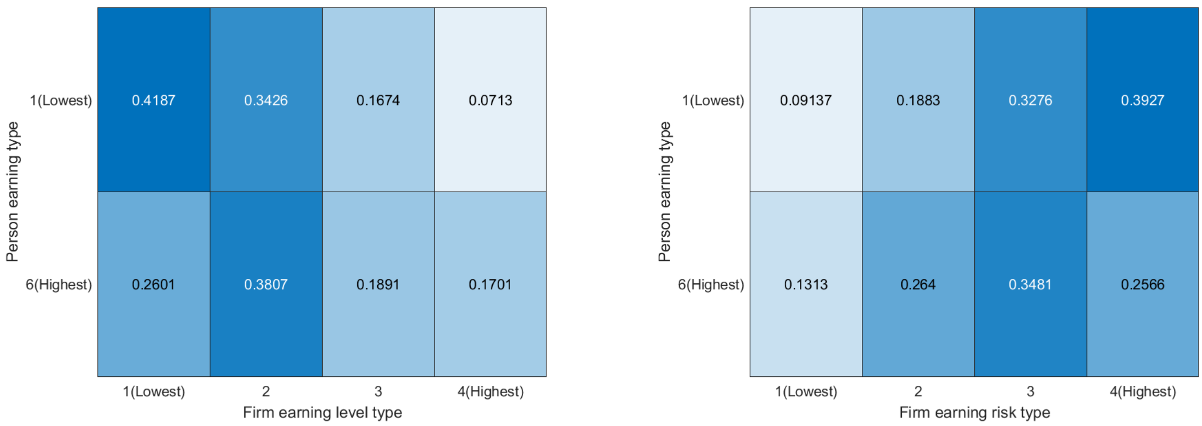
(c) $h_t = 1$, $\alpha = 6$



(d) $h_t = 4$, $\alpha = 6$

Note: This figure presents the job mobility type transitions from $t-1$ to t by health type if currently employed in $t-1$. 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.

Figure C3. Firm type transitions if newly employed

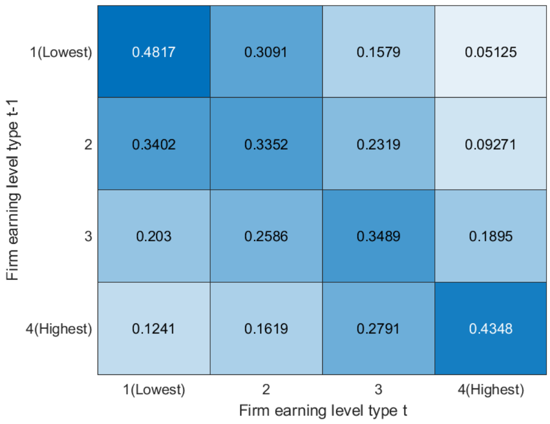


(a) Firm earning level type

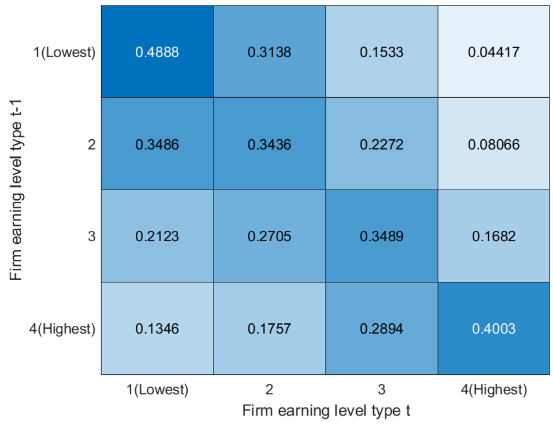
(b) Firm earning risk type

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 if newly employed from $t-1$ to t. 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.

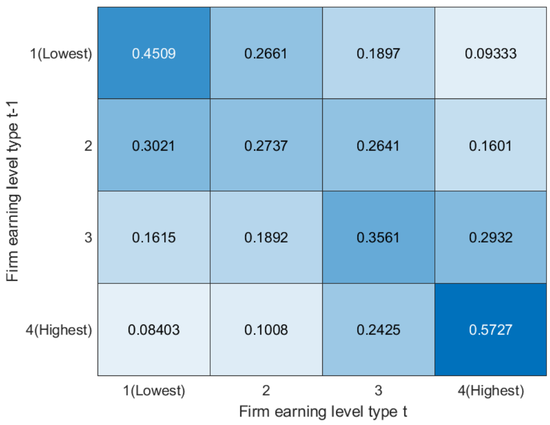
Figure C4. Firm earning level type transitions for movers



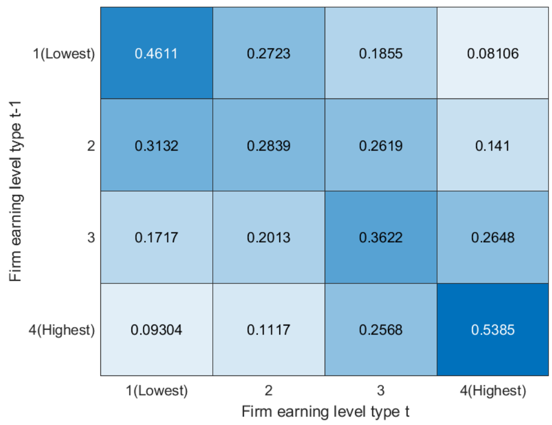
(a) $h_t = 1,\ a_i = 1$



(b) $h_t = 4,\ a_i = 1$



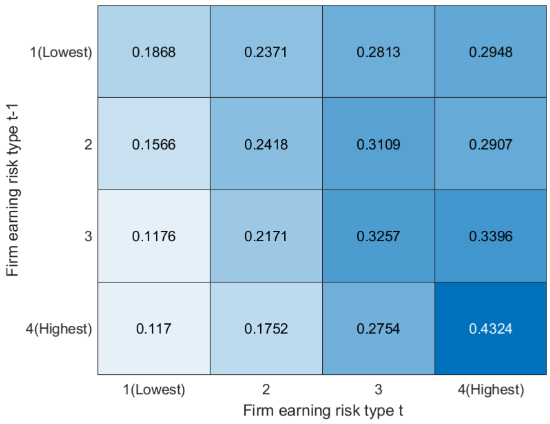
(c) $h_t = 1,\ a_i = 6$



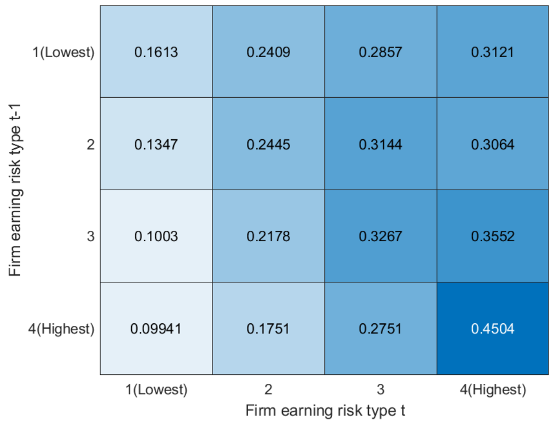
(d) $h_t = 4,\ a_i = 6$

Note: This figure presents the probability of transiting into different firm-level type k_j^{μ} in time t if change employer from $t-1$ to t. The health types h_t 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 a_i 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.

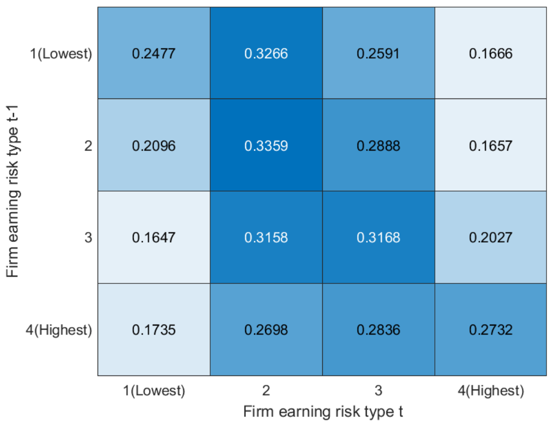
Figure C5. Firm earning risk type transitions for movers



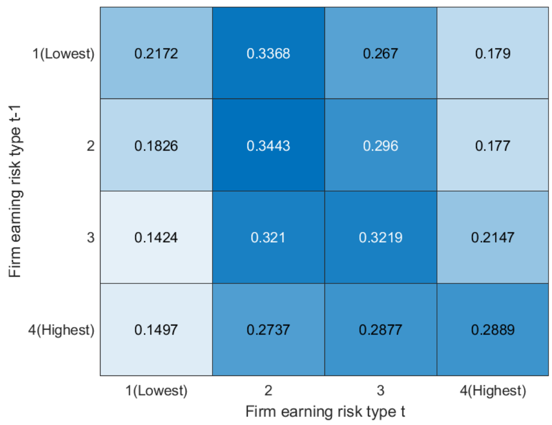
(a) $h_t = 1$, $\alpha = 1$



(b) $h_t = 4$, $\alpha = 1$



(c) $h_t = 1$, $\alpha = 6$



(d) $h_t = 4$, $\alpha = 6$

Note: This figure presents the probability of transiting into different firm risk type k_j^{σ} in time t if change employer from $t-1$ to t. The health types h_t 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 a_i 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.

D. Decompose Demand curve and Cost curves changes

In this section, I discuss the outcome differences across the four models with the textbook model, which are introduced in detail in Section VI.1. In Model 1, the individuals only differ in medical risk. In Model 2, differences in assets are added. In Model 3, individuals are assumed to face the mean of individual-level predicted earning distribution in all states of the world. In Model 4, individuals are assumed to face the predicted earning distribution.

I first discuss the impact of demand curve changes across models while keeping the cost curves in the textbook model. In this way, the changes in the equilibrium and social efficient outcomes reflect only the changes in demand curves. Second, I compare the impact of cost curves with the textbook model cost curves while keeping the demand curve estimated in the "Full-heterogeneity" model (Model 4). Keeping the demand curve unchanged across the models can separate out the impact of cost curve changes.

Demand Curve Changes. — To separate the impact of demand curve shifts, I keep the cost curves of the textbook curves and report the equilibrium and social efficient outcomes relative to the "Full-heterogeneity" model. The reason to compare with "Full-heterogeneity" model is that when studying the impact of changes in cost curves, I keep the demand curve in the "Full-heterogeneity" model. Table D1 Panel A reports the equilibrium take-up rates, price, and consumer surplus relative to Model 4. The intersection between the demand curves and the textbook average cost curves is the equilibrium price. It shows that the take-up rate and consumer surplus are lower, price is higher when considering earnings dynamics. Panel B and Panel C report the socially efficient outcomes. We observe significant differences between Model 3 and Model 4 in the socially efficient take-up rates.

Table D1. 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
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: Social Efficiency: Social Planner Measure

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)

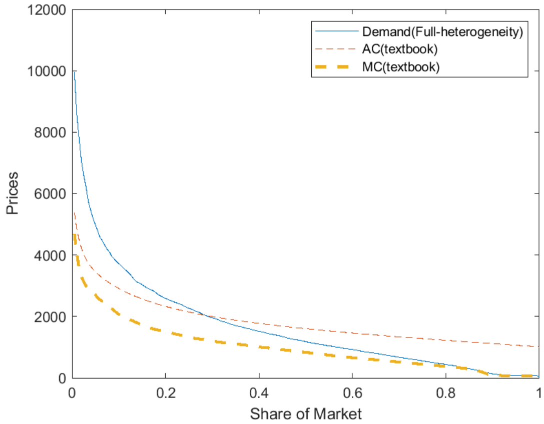
Panel C: Social Efficiency: Smoothed Marginal Cost Measures

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)

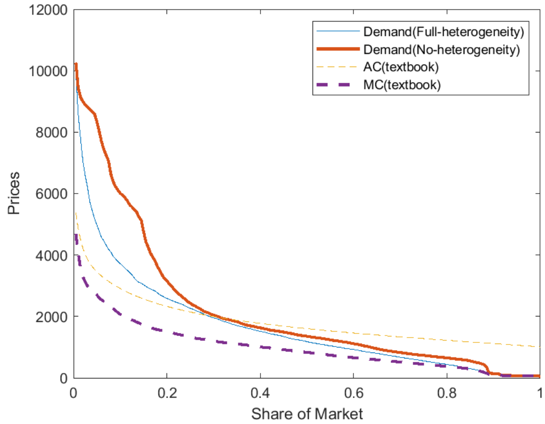
Notes: This table compares Model 1 to 3 with Model 4 — "Full-heterogeneity" model. Details of the models are introduced in Section VI.1. Model 1 is the model that allows only heterogeneity in medical risk. Individuals are holding the average asset level of the sample $\bar{A}$ and expect to earn the sample average mean earning $\bar{\mu}_{wt}$. Model 2 add heterogeneity in asset, and individual i holds assets at A_i. Model 3 adds the heterogeneity in the mean of earnings based on Model 3. Individual i gets the earning at μ_{iwt} in all possible states. Model 4 is the full-heterogeneity model, in which people are uncertain about earning, and the correlation between earning and medical spending is allowed. The medical risk distribution is kept unchanged in all models. All individuals are assumed to have the same constant relative risk aversion utility function with risk aversion at 2. The consumption floor is set at $2000. Panel A reports the 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 the consumption floor. Panel B reports the socially efficient take-up rate, consumer surplus, and deadweight loss under the Social Planner Measure—people with a higher willingness to pay than expected medical cost are considered as those who should be socially optimal to cover. Panel C smooths non-monotonic marginal cost curves and considers the interaction point between the smoothed marginal cost curve and demand curves as the socially efficient price. The marginal cost curves are smoothed with robust linear regression over each window of 20 points. More details can be found in Section VI.2.

Figure D1 plots the Demand curves relative to the demand in the Full-heterogeneity model, while keeping the cost curves in the textbook model. We can see that the changes in demand curves are not parallel shifts.

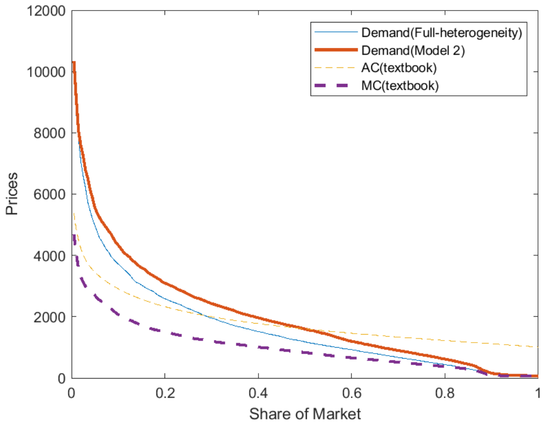
Figure D1. Compare Demand curves with the Full-heterogeneity model



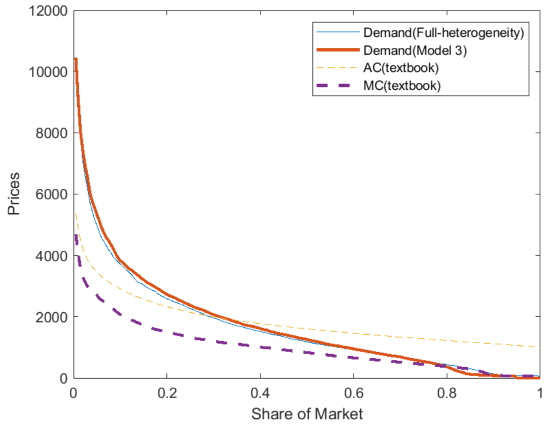
(a) Full-heterogeneity Model
s^*: 0.259[0.018]
s^o: 0.995[0.006]



(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 mean of earnings
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.

Cost Curve Changes. — In Table D2, I report the relative differences of outcomes with the textbook cost curves while keeping the demand curve estimated in Model 4, the "Full-heterogeneity" model. This table thus separates the impact of cost curves from demand curves. The numbers reported are the differences between cost curves in Models 1 to 4 and the textbook cost curves. We observe significant increases in the equilibrium take-up rate, consumer surplus, and price reductions when earnings dynamics are incorporated. We also see large decreases in the socially efficient take-up rate and deadweight loss.

Table D2. The impact of deviation from textbook marginal cost curve
Conditional on "Full-heterogeneity" Model Demand curve

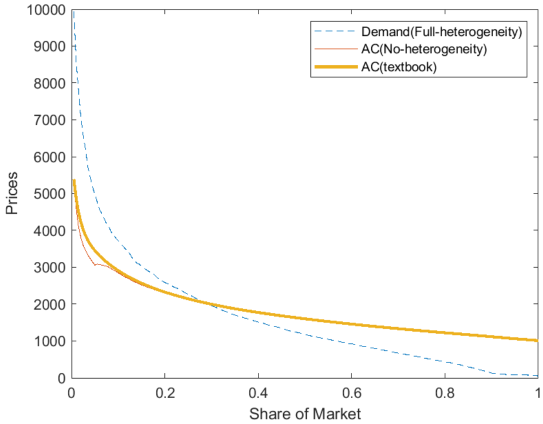
Model	Description	Take-up	Price	Consumer surplus	
Panel A: Equilibrium					
1	Only differ in medical risk	+0.006	-33.8	+8.7	
		(0.00)	(12.41)	(2.85)	
2	Add different assets	+0.030	-158.0	+42.9	
		(0.01)	(30.75)	(6.65)	
3	Add different expected earning	+0.105	-483.2	+148.4	
		(0.01)	(62.49)	(14.58)	
4	Full-heterogeneity	+0.112	-514.7	+160.0	
		(0.02)	(63.69)	(15.03)	

Model	Description	Take-up	Price	Consumer surplus	Deadweight loss
Panel B: Social Efficiency: Social Planner Measure					
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)

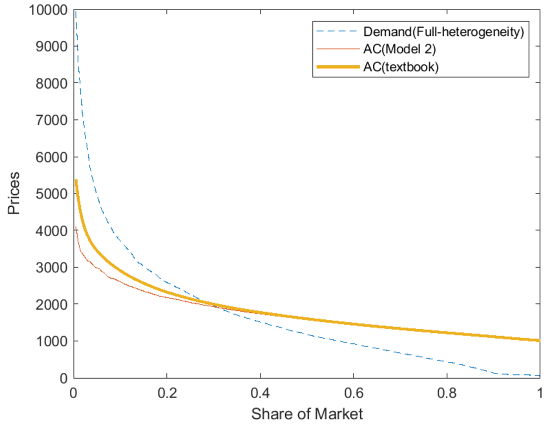
Model	Description	Take-up	Price	Consumer surplus	Deadweight loss
Panel C: Social Efficiency: Smoothed Marginal Cost Measures					
1	Only differ in medical risk	+0.005	-28.5	+0.1	-8.7
		(0.07)	(106.94)	(1.21)	(3.25)
2	Add different assets	-0.053	+77.2	-0.7	-43.6
		(0.08)	(135.73)	(1.35)	(7.05)
3	Add different 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 orders consumers by their expected medical costs. The textbook version's average cost curve is calculated based on the textbook version's marginal cost curves. Details of the models are introduced in Section VI.1. 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 sample average mean earning $\bar{\mu}_{wt}$. Model 2 add heterogeneity in asset, and individual i holds assets at A_i. Model 3 adds the heterogeneity in the mean of earnings based on Model 3. Individual i gets the earning at μ_{iwt} in all possible states. Model 4 is the full-heterogeneity model, in which people are uncertain about earning, and the correlation between earning and medical spending is allowed. The medical risk distribution is kept unchanged in all models. All individuals are assumed to have the same constant relative risk aversion utility function with risk aversion at 2. The consumption floor is set at $2000. Panel A reports the 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 the consumption floor. Panel B reports the socially efficient take-up rate, consumer surplus, and deadweight loss under the Social Planner Measure—people with a higher willingness to pay than expected medical cost are considered as those who should be socially optimal to cover. Panel C smooths non-monotonic marginal cost curves and considers the interaction point between the smoothed marginal cost curve and demand curves as the socially efficient price. The marginal cost curves are smoothed with robust linear regression over each window of 20 points. More details can be found in Section VI.2.

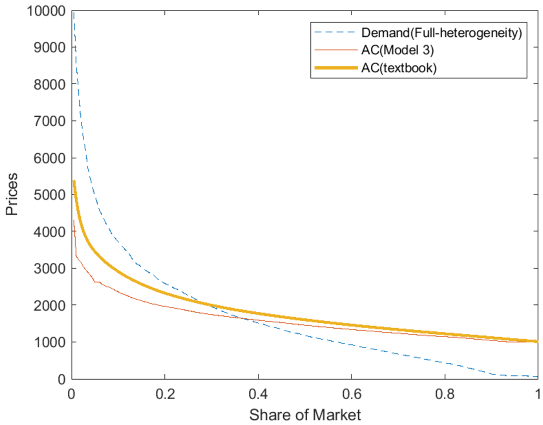
Figure D2. Compare the deviation of average cost curves from the textbook model



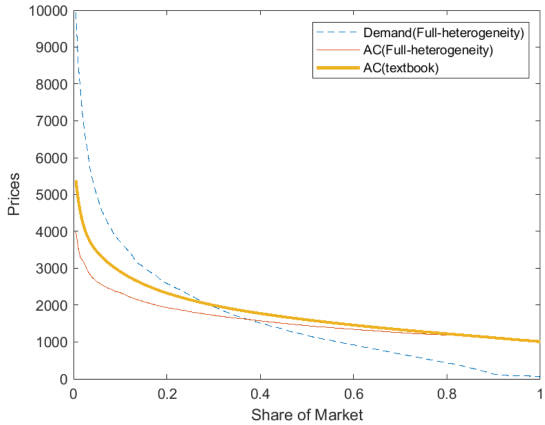
(a) Model 1: Only differ in Medical cost
Δs^*: +0.006[0.003]



(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.

E. 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 are given in Table E1. 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.

Table E1. 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

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.