Labor Market Search, Illness, and the Value of Employer-Sponsored Health Insurance

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Abstract

I generalize a search, matching, and bargaining model to allow for acute illness that prevents workers from engaging in labor market activities to investigate the productivity-enhancing effects of employer-sponsored health insurance (ESHI). I quantify monetary and non-monetary acute illness costs: deteriorated productivity, increased medical expenses, and reduced utility. I capture the less-explored channels through which ESHI enhances productivity in an employment match by reducing the length of illness episodes through frequent medical care utilization. I estimate the model using the Medical Expenditure Panel Survey. Counterfactual policies that promote ESHI reduce acute illness costs.

JEL classification: J64, J24, I12, I13

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1 Introduction

Even healthy individuals will likely contract acute illnesses, such as the common cold, influenza, or back pain, that appear unexpectedly and last for a relatively short period at some point in their careers. Workers suffering from acute illness may be absent from work, incurring unexpected and sizable costs. For instance, over 700,000 US males missed work due to illness in 2020, amounting to 1.3% of their working hours lost. Illness-related absenteeism also costs the average employer $1,685 per employee every year (Stewart et al., 2003). Employer-sponsored health insurance (hereafter, ESHI), which has been at the heart of the United States health care system, is recognized as strongly linked with the health and well-being of working people, and it can therefore be a device to lower such acute illness costs.[1] Around 70% of illnesses are classified as acute, and they are more likely to affect the daily work experience of individuals than catastrophic chronic illnesses. Nevertheless, the existing literature rarely quantifies the relative costs of acute illness that both employees and employers face because of the absence of matched employer-employee data and the short nature of acute illnesses. Furthermore, even though employees and employers demand ESHI to protect themselves from acute illness costs, most of the empirical literature only focuses on the financial protection of ESHI.[2]

I aim to quantify the non-monetary costs of acute illnesses, including the loss of productivity borne by employers and reduced utility borne by employees. Then, I aim to document less-explored economic principles that ESHI coverages might increase productivity in the sense of shortening absence days and improving equilibrium labor market outcomes and social welfare through the frequent use of medical care. To accomplish this, I develop and estimate a search model of the labor market where ESHI provision, labor market outcomes, and medical care utilization are endogenized in the presence of acute illnesses causing absenteeism.[3] Search frictions make job turnover costly and support jobs with and

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[1] ESHI covers approximately 160 million Americans, and its annual social value is about 1.5 trillion dollars (Mulligan, 2021). See Currie and Madrian (1999) and Gruber and Madrian (2002) for an excellent review.

[2] Most of the literature focuses on the following values of ESHI: risk pooling among a large group of relatively healthy individuals or tax exemptions of ESHI premiums. Firms often demand ESHI to provide large risk pools and enjoy the relative tax advantage of ESHI premiums. I argue that these are necessary but not sufficient rationales for both employees and employers to demand ESHI. For instance, more than half of firms with less than ten workers offer ESHI even though they hardly have risk pools. Also, even before the legislation that gave a relative tax advantage to health insurance benefits was passed, many firms provided employees with company doctors or group insurance contracts.

[3] The search, matching, and bargaining framework is motivated by the theoretical works of Jovanovic (1979), which are a tractable version of partial-equilibrium job search models. Examples are Flinn and Heckman (1982), Eckstein and Wolpin (1990), Postel-Vinay and Robin (2002), Dey and Flinn (2005), Cahuc et al. (2006), and Flinn and Mullins (2015).

without ESHI in equilibrium. Even if all individuals are healthy, they are at risk of contracting an acute illness that temporarily prevents workers from engaging in labor market activities, while illnesses directly involve a non-pecuniary disutility. I provide a rationale for both employees and employers to value ESHI against negative health shocks in three ways: first, ESHI makes employees less likely to experience large negative health shocks that lead to exogenous job destruction; second, it reduces the financial burdens of insured ill workers; third, it may reduce the period of acute illness by encouraging ill individuals to seek medical care. The equilibrium health insurance provision and wage determination depend mainly on search frictions, match-specific productivity, and endogenous illness conditions, thanks to the bargaining process.

To quantify the productivity-enhancing effect of ESHI on acute illness costs, I estimate the model using a Method of Simulated Moments (MSM) procedure with individual-level data from the nationally representative Medical Expenditure Panel Survey (MEPS). The estimates reveal that acute illnesses incur observed and unobserved costs in the form of reductions in utility, the value of production, wages, and workers' welfare. The average disutility of being ill for workers is estimated to be around one-third of those unemployed. Employees lose 3% of their working days due to acute illness, resulting in approximately 1,200 dollars loss of the value of production over six months. Acute illness decreases wages by around 2% and workers' welfare by around 4%. I also find that illness episodes can be shortened by more than half if individuals with acute illnesses seek medical care. Employment matches with ESHI last approximately three times longer than jobs without ESHI, increasing the overall value of the match. This result indicates that even short absences from work due to acute illness can result in significant losses, and reducing this can be another value of health insurance.

I use the estimated model to assess the welfare implications of counterfactual policies that encourage the provision of ESHI. First, I study the mandatory health insurance that forces all firms to provide health insurance in the economy. This policy lowers absenteeism, productivity loss, and medical care expenditures, thanks to the productive effect of medical care utilization, but decreases firms' profits significantly. Next, I study a policy that imposes penalties on firms that do not provide ESHI. The total penalties that firms without ESHI pay get distributed to firms providing ESHI through subsidies, leading to increases in the ESHI coverage rate. The distortions of firms' decisions decrease firms' profits at different rates; however, the reduction amount is less than in the case of mandatory health insurance.

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These policy experiments suggest that ESHI can increase workers' welfare since it reduces individuals' medical care expenditures, encourages more frequent medical care utilization, and shortens episodes of acute illness.

Related literature.   My paper makes several contributions to distinct areas of economic literature. The most closely related papers are a branch of the empirical structural literature that examines interactions between health, health insurance coverage, and labor market outcomes. In regards to the interaction between health insurance and health, a few structural papers use an analysis of an individual's medical care optimization decisions, motivated by the health capital framework developed by Grossman (1972) and empirically tested by Gilleskie (1998), Blau and Gilleskie (2008), Gilleskie (2010), Cronin (2019), and Cronin et al. (2020).[4] A few recent structural papers study interactions between health and labor market outcomes by incorporating health shocks related to self-reported disability status (Bound et al., 2010), body mass index (Harris, 2019), physical ailments (Papageorge, 2016), and mental health (Jolivet and Postel-Vinay, 2020).[5] My model tries to bridge the structural medical care choice models and the equilibrium job search models. Relative to these papers, I try to understand the relative contributions of employee- and employer-side mechanisms to quantify the productivity gains of ESHI.

This paper contributes to a growing structural search literature that measures the value of non-wage benefits in a labor market characterized by search frictions. Hwang et al. (1998) demonstrates how search frictions can interfere with the compensating differential mechanism and bias the conventional hedonic wage model estimates. This literature has been extended to treat non-wage job characteristics such as flexible hours (Blau, 1991; Bloemen, 2008; Flabbi and Moro, 2012) and non-wage amenities of a job offer (Sullivan and To, 2014; Hall and Mueller, 2018). Specifically, Dey and Flinn (2005) examine whether the ESHI system generates inefficiencies in mobility decisions using a search-matching-bargaining model. Using the framework of Burdett and Mortensen (1998), Aizawa and Fang (2020)

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[4]The theoretical background behind the relationship between demand for medical care and illness conditions is based on Grossman (1972), where medical care is used as an input to health production. Health conditions are treated like a durable stock that produces an output of healthy conditions, depreciates gradually, and may be increased by health investment. I do not incorporate health production explicitly because of a lack of life cycle effects in the model. Instead, I use different health transition shocks depending on medical care decisions to capture the positive relationship between medical treatment and health outcomes.

[5]Rust and Phelan (1997), Crawford and Shum (2005), Davis and Foster (2005), De Nardi et al. (2016), and Darden (2017) construct dynamic models studying the interaction between health outcomes and other important individual behaviors, such as saving or retirement decisions, the learning processes, or household choices.

additionally consider firm size, health status, and medical care expenditure to incorporate the main features of the US health insurance market. This framework is extended by Aizawa (2019) to analyze the optimal social insurance program and by Fang and Shephard (2019) to incorporate household decisions. I explicitly study acute illness conditions causing absenteeism and the consequent observed and non-observed costs that are relevant but overlooked or treated as latent variables. I allow individuals to respond to unexpected illness shocks by making medical care decisions to shed light on the non-wage benefits of ESHI that were often abstracted in this literature.[6]

This paper also complements the relatively small but important literature quantifying the unobserved costs of illness-related absenteeism to firms (Harrison and Martocchio, 1998). Absenteeism has been considered an important measure of productivity (Flabbi and Ichino, 2001). Unfortunately, the lack of consistent measures makes it difficult to quantify the size and welfare effects of productivity loss driven by absenteeism. Existing studies use the wage rate to estimate the size of absenteeism-related costs, based on the assumption that the loss of a healthy day is the same as the loss of production opportunity in the competitive labor market. Some studies measure absenteeism costs due to reduced work performance (Stewart et al., 2003) or the degree of lost efficiency (Hilton et al., 2008), using surveys designed for specific purposes. However, as pointed out by Pauly et al. (2002) and Nicholson et al. (2006), the firm's productivity loss can be higher than the wage rates since firms cannot completely pass on the absenteeism costs to the workers. I suggest a new framework to structurally recover unobserved illness-related productivity loss that has rarely been studied.

Outline. The rest of the paper proceeds as follows. Section 2 constructs a search-matching-bargaining model and studies its empirical implications. Section 3 describes the data, sample selection, and descriptive statistics. Section 4 describes the strategy to identify the model's parameters. Section 5 proposes the estimation method and its results, and section 6 discusses the counter-factual policy experiments. Section 7 concludes.

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[6]Other papers capture the productive-enhancing feature of ESHI in an employment match in a reduced-form way: ESHI directly decreases exogenous job destruction rates (Dey and Flinn, 2005) or improves employees' self-reported health status (Fang and Shephard, 2019; Aizawa and Fang, 2020). They implicitly assume that health insurance improves the general health conditions of workers through curative or preventive medical care. One exception is Dizioli and Pinheiro (2016) who provides a theoretical model that takes illnesses directly into account. Still, they do not provide a complete identification and estimation strategy.

2 The model

2.1 Environment

The stationary model is constructed for infinitely lived workers and firms in continuous time.[7] Workers belong to one of the health states $i \in \{H, A, S\}$: H if individuals are healthy, A if they have a moderate acute illness, and S if they have a severe acute illness.[8] The proportion of severe acute illnesses is indicated with p assigned by nature, and the proportion of moderate acute illnesses is $1 - p$. I only consider acute illnesses that are severe enough to cause an individual to be absent from the labor market. Health conditions are perfectly observable and verifiable by all the agents in the economy. I assume that individuals contract only one acute illness at a time. One acute illness type does not develop into another or a chronic illness during the episode and reduces the individual's underlying health capital. A firm and a worker cooperatively make health insurance decisions $d \in \{0, 1\}$, taking the value of 1 for firms providing ESHI and 0 for firms that do not. All agents discount the future at the common rate ρ, and there is no flow cost of the search.

With regard to labor market dynamics, search frictions characterize the labor market: a searcher can end up being unemployed or employed,[9] and a firm can fill a job vacancy or not. A healthy unemployed searcher meets an employer at the Poisson rate λ.[10] When a potential employer and a worker meet, they observe match-specific productivity x, which is ex-ante uncertain and idiosyncratic, and randomly drawn from an exogenous distribution $G(x)$.[11] Upon observing the productivity, firms and employees engage in a Nash bargaining process to determine wages and ESHI provisions by sharing the total surplus. If a searcher rejects this offer, she searches for a potential employer again. At any moment, a formed match

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[7]In the empirical analysis, one firm refers to one job or employer, so the terminologies jobs, employers, and firms are used interchangeably.

[8]Following Gilleskie (1998), Khwaja (2010), and Cronin (2019), I break down acute illnesses into moderate and severe illnesses according to severity, duration, and discomfort that the specific ICD-9-CM code cannot capture. The intuition behind the identification of the illness-specific parameters is explained in Section 4.

[9]I introduce search frictions to guarantee the presence of different types of jobs in equilibrium since these make it costly for employees and employers to change health insurance status frequently.

[10]I only allow healthy unemployed workers to search for a job because ill searchers spend at least half a day in bed because of a physical illness, injury, or a mental or emotional problem by definition and details are explained in Appendix D.2.

[11]Match-specific productivity, the quality of the match between an employee and an employer, is important in explaining wage growth (Topel, 1991; Altonji and Williams, 1992; Altonji et al., 2005) and job mobility (Mortensen, 1978; Jovanovic, 1979). I assume that the support of the distribution $G(x)$ is a non-negative real line and everywhere differentiable on its support.

can be exogenously terminated at an insurance-specific termination rate η_d. I assume that ESHI provision reduces the rate of an exogenous termination from a match (i.e., $\eta_0 > \eta_1$).[12] The magnitude of Poisson parameter η_0 for jobs without ESHI is assumed here as being greater than that of jobs with ESHI η_1, but they are allowed to be freely estimated.

A healthy individual faces a probability of getting an acute illness at the Poisson rate ν. Poisson recovery shocks capture the effects of medical treatment on potential biological health transitions in a reduced form fashion. If individuals contract a moderate illness, their recovery rate is $\zeta_{A,c}$ which depends on medical care decisions $c \in \{0, 1\}$, with 1 indicating the utilization of medical treatment. Seeking medical treatment increases the recovery rate (i.e., $\zeta_{A,1} > \zeta_{A,0}$), but incurs medical costs $m \sim M(m)$. Heterogeneity in m reflects, in part, the severity of acute illnesses. I assume severely ill workers must seek medical treatment and are subject to the lowest recovery rate. The recovery rate of illnesses depends indirectly on health insurance since covered ill employees face lower out-of-pocket costs and utilize more curative medical treatment than uncovered ones.

The risk-neutral worker's instantaneous flow utility functions are specified as follows:[13]

$$
u(w, d; x, m) = \begin{cases}
b & \text{if unemployed and not ill} \\
b - \kappa - o(d; cm) & \text{if unemployed and ill} \\
w(x, d) - k\phi d & \text{if employed and not ill} \\
\delta w(x, d) - \kappa - k\phi d - o(d; cm) & \text{if employed and ill}
\end{cases}
\tag{1}
$$

If unemployed and not ill, the instantaneous utility (or disutility) is b, summarizing all costs and benefits of being a searcher. The utility of ill unemployed individuals includes reduced utility associated with being ill κ and the possibility of paying out-of-pocket medical expenses $o(d; cm)$. The out-of-

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[12]This specification fits the empirical results, as summarized in Section 3, and captures the health-enhancing feature of ESHI in a reduced-form fashion. Following Dey and Flinn (2005), workers at jobs with ESHI are less likely to experience large negative health shocks that induce job destruction than others. My assumption is consistent with a thorough survey of empirical research examining the relationship between health insurance coverage and health outcomes (Levy and Meltzer, 2008). Also, it is supported by the 2006 Massachusetts health care reform (Zapata, 2014) and the 2008 Oregon randomized health insurance experiment (Finkelstein et al., 2012).

[13]Unfortunately, there is little prior information on the initial risks of individuals, so introducing the concave utility function makes the identification argument on the link between acute illness, productivity, and medical care utilization very weaker. Also, as seen in Einav and Finkelstein (2018), most discussions of moral hazard consider the link between changes in the risk-sharing features of health insurance and the intensive margin of medical care utilization; however, I focus on the extensive margin of medical care utilization decisions. I conduct robustness tests for a case of a concave utility for risk-averse individuals with fixed parameters in Appendix E.2.

pocket expenditure function reflects the medical treatment choice c, total medical care expenditures m, and health insurance coverage status d. When ill individuals seek medical treatment, ESHI covers some portion of the medical care expenditures. Section 4 explains how to define the out-of-pocket medical expenditure function $o(d; cm)$. and the distribution of medical care expenditures $M(m)$. I do not consider preventive treatment, so healthy workers have no medical expenses.[14] Employees receive the bargained wages $w(d; x)$ when working; during an illness, workers receive some proportion δ of their wages from paid sick leave. That is, $\delta = 0$ if paid sick leave is not provided.[15] They pay their share k of health insurance premiums ϕ if they work at a firm that offers health insurance.[16] The remaining share of the premium $1 - k$ is covered by the employer, so an insurance holder pays only $k\phi$.[17][18]

Once a firm hires an employee, the firm's instantaneous profit function from a filled job is:

$$
\pi(w, d; x) = \begin{cases} x - w(x, d) - (1 - k)\phi d & \text{if not ill} \\ -\delta w(x, d) - (1 - k)\phi d & \text{if ill} \end{cases} \tag{2}
$$

Match-specific productivity x constitutes the match's total output. An acute illness causing absenteeism reduces the value of the match to zero since ill employees cannot devote time to productive activities at the workplace. When an employee reverts to a healthy state, she becomes productive again. Firms pay labor costs $w(x, d)$ to their worker and sick leave coverage replaces a portion of the wage by δ. The providers of ESHI cannot differentiate wages based on the employees' pre-existing conditions, which are limited by regulations such as the Health Insurance Portability and Accountability Act (HIPAA) and the Equal Pay Act prohibiting discrimination or wage negotiation based on individuals' health conditions.

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[14]ESHI may improve health conditions of healthy workers through preventive care, but limited evidence supports these claims, as mentioned in Jones et al. (2019), Song and Baicker (2019), and Baicker et al. (2010).

[15]I assume that workers earn paid sick days because the average missed workdays are only around three days, and most are full-time. I consider the case when paid sick leaves are partially available in Appendix E.1 and its quantitive results are not different.

[16]Following Dey and Flinn (2005), my model ignores the tax exemption of ESHI premiums and the income tax. The relative tax advantages of ESHI might affect the wage and ESHI distributions in equilibrium. When I parsimoniously add the calibrated tax parameters to the insurance premium, it does not change the main qualitative results of the model.

[17]Although firms do not choose the share k endogenously in the model, it indirectly captures a certain fraction of firms that choose the workers' contributions to the premium when they decide to provide ESHI.

[18]The firm might raise premiums for all workers heavily if some of them incur a sufficiently high medical cost. However, I do not model this channel because information on insurance, such as self-insured or fully insured plans, is not available in the data. Details on the premiums are explained in Appendix A.2.

2.2 Medical treatment decision

Once agents contract an acute illness, they draw the medical expenses from the distribution $M(m)$. Conditional on the drawn m, moderately ill agents compare the costs and benefits of medical care utilization. They might seek medical treatment to increase the probability of recuperating even though it incurs medical expenses. Specifically, the difference between the recovery rates $\zeta_{A,0}$ and $\zeta_{A,1}$ reflects the effects of medical treatment choice c. I denote the value of being unemployed and having a moderate acute illness by $U_{A,c}(cm)$ and the value of being employed and having a moderate acute illness by $E_{A,c}(w,d;x,cm)$. Individuals with a moderate acute illness make the medical care decisions by comparing the values of seeking medical treatment or not. The endogenous medical treatment status c is determined as follows:

$$c \equiv c(w,d;x,m) = \begin{cases} 1 & \text{if } E_{A,1}(w,d;x,m) \geq E_{A,0}(w,d;x) \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

$$c \equiv c(m) = \begin{cases} 1 & \text{if } U_{A,1}(m) \geq U_{A,0} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

I simplify notation by dropping the dependence of c on state vectors $(w,d;x,m)$ for moderately ill workers.

2.3 Labor market decisions

2.3.1 Firms

The value functions for the labor demand side of the market are as follows. I assume that firms enter the market until the value of posting a vacancy becomes zero, produced through the standard free-entry condition.[19] The firm's value of the current employment contract is expressed by the sum of the flow

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[19]I do not introduce a notation for the value of an unfilled vacancy in the model. For discussions, see Mortensen and Pissarides (1994), Flinn and Mullins (2015), and Bobba et al. (2018).

profit and corresponding values:

$$F_H(w, d; x) = (\rho + \eta_d + \nu)^{-1}[x - w(x, d) - (1 - k)\phi d \tag{5}$$

$$+ \nu \left\{ \begin{array}{c} (1 - p)\{(1 - c)F_{A,0}(w, d; x) + cF_{A,1}(w, d; x)\} \\ + pF_S(w, d; x) \end{array} \right\}]$$
$$\underbrace{\phantom{+ \nu \left\{ \begin{array}{c} (1 - p)\{(1 - c)F_{A,0}(w, d; x) + cF_{A,1}(w, d; x)\} \\ + pF_S(w, d; x) \end{array} \right\}}}_{\text{contract an acute illness}}$$

$$F_{A,c}(w, d; x) = (\rho + \eta_d + \zeta_{A,c})^{-1}[-\delta w(x, d) - (1 - k)\phi d + \underbrace{\zeta_{A,c}F_H(w, d; x)}_{\text{recover from a moderate acute illness}}] \tag{6}$$

$$F_S(w, d; x) = (\rho + \eta_d + \zeta_S)^{-1}[-\delta w(x, d) - (1 - k)\phi d + \underbrace{\zeta_S F_H(w, d; x)}_{\text{recover from a severe acute illness}}] \tag{7}$$

Once a vacancy is filled, firms receive the flow profits defined in the equation (2) while being subject to the health shock ν, the recovery shocks $\{\zeta_{A,c}, \zeta_S\}$, or the termination shock η_d. Suppose the employee contracts a mild acute illness with $1-p$ or a severe acute illness with p. In both cases, they are absent from work, so their hourly productivity becomes zero throughout the illness. When a recovery shock arrives, the ill employee comes back to the workplace. There is a possibility of receiving an insurance-specific termination shock that destroys the current match.

The employer and the worker cooperatively make health insurance provision choices.[20] I define the support for match-specific productivity that makes workers and firms choose the provision of health insurance as Δ:

$$\Delta \equiv \{x : E_H(w, 1; x) \geq E_H(w, 0; x)\} = \{x : F_H(w, 1; x) \geq F_H(w, 0; x)\} \tag{8}$$

If the match-specific productivity belongs to the support, workers and firms initiate an employment contract with ESHI. I explain ESHI provision decisions in Section 2.4.

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[20]Cooperative decisions on the provision of ESHI can be treated as joint investments in individuals' health conditions. This specification is aligned with Flinn and Mullins (2015) and Bobba et al. (2018), examining the investment by the firm that drives up an individual's productivity.

2.3.2 Workers

The value of the searcher without or with an acute illness is described by:

$$U_H = (\rho + \nu + \lambda)^{-1} [b + \lambda \underbrace{\left\{ \begin{array}{c} \int_{\neg\Delta} \max\{E_H(0;x), U_H\} dG(x) \\ + \int_{\Delta} \max\{E_H(1;x), U_H\} dG(x) \end{array} \right\}}_{\text{receive a job offer}} \tag{9}$$

$$+ \nu \underbrace{\left\{ \begin{array}{c} (1-p) \int \max\{U_{A,0}, U_{A,1}(m)\} dM(m) \\ +p \int U_S(m) dM(m) \end{array} \right\}}_{\text{contract an acute illness}}]$$

$$U_{A,c}(cm) = (\rho + \zeta_{A,c})^{-1} [b - \kappa - o(0;cm) + \underbrace{\zeta_{A,c} U_H}_{\text{recover from a moderate acute illness}}] \tag{10}$$

$$U_S(m) = (\rho + \zeta_S)^{-1} [b - \kappa - o(0;m) + \underbrace{\zeta_S U_H}_{\text{recover from a severe acute illness}}] \tag{11}$$

While the searcher receives the flow utility defined in equation (1), they might receive three possible Poisson shocks: the health shock ν, the recovery shocks $\{\zeta_{A,c}, \zeta_S\}$, or the job arrival shock λ. The first term in the equation (9) refers to the option value of changing the employment states when meeting an employer at the rate of λ. The firm and the worker decide the wage and health insurance status upon a meeting. Given the negotiated wage and health insurance provision, the worker decides whether to accept the job offer by comparing the value of being employed or unemployed. The second term shows that healthy searchers contract a moderate acute illness with a probability of $1 - p$ or a severe acute illness with a probability of p when they receive the health shock ν.[21] If they are moderately ill, they decide to seek medical treatment after medical care expenditure m is drawn; if they are severely ill, they have to consume medical services for $a_m m$, where the term a_m can be thought of as additional medical costs. Recovery shocks $\{\zeta_{A,c}, \zeta_S\}$ send the ill searchers back to healthy conditions, and they enter the searching state again.

For the employee without or with an acute illness, the value of employment at a current match x and

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[21]Adverse health shocks on one match do last even after employment is terminated.

wage and health insurance provision status (w, d) is described by:

$$E_H(w, d; x) = (\rho + \eta_d + \nu)^{-1}[w(x, d) - k\phi d \tag{12}$$

$$+ \underbrace{\eta_d U_H}_{\text{exogenous seperation}} + \nu \left\{ \begin{array}{c} (1-p)\int \max\{E_{A,0}(w, d; x), E_{A,1}(w, d; x, m)\}dM(m) \\ +p \int E_S(w, d; x, m)dM(m) \end{array} \right\}]$$

$$\underbrace{}_{\text{contract an acute illness}}$$

$$E_{A,c}(w, d; x, cm) = (\rho + \eta_d + \zeta_{A,c})^{-1}[\delta w(x, d) - \kappa - k\phi d - o(d; cm) \tag{13}$$

$$+ \underbrace{\eta_d U_A(cm)}_{\text{exogenous seperation}} + \underbrace{\zeta_{A,c} E_H(w, d; x)}_{\text{recover from a moderate acute illness}}]$$

$$E_S(w, d; x, m) = (\rho + \eta_d + \zeta_S)^{-1}[\delta w(x, d) - \kappa - k\phi d - o(d; m) \tag{14}$$

$$+ \underbrace{\eta_d U_S(m)}_{\text{exogenous seperation}} + \underbrace{\zeta_S E_H(w, d; x)}_{\text{recover from a severe acute illness}}]$$

Workers may receive replacement wages $\delta w(x, d)$ when they are ill, although they do not contribute to the total output. An employee is subject to the same Poisson shocks $\{\nu, \zeta_{A,c}, \zeta_S, \eta_d\}$ as firms. Health transition shocks change workers' health conditions in the same way as the searcher. If employees receive the destruction shock η_d, they go back to the searching state. Employees cannot change insurance coverage options on the job since the model focuses on a relatively short-term period.

2.3.3 Bargaining

A firm and a worker engage in the generalized Nash bilateral bargaining to divide the total surpluses by setting optimal wage schedules and ESHI provisions. The pair of the solution is given by:

$$\{w^*, d^*\}(x) = arg \max_{w,d} S(w, d; x) \tag{15}$$

where the total surplus $S(x, d)$ is $[E_H(w, d; x) - U_H]^\alpha \times [F_H(w, d; x)]^{1-\alpha}$ and the bargaining power α is a rent-splitting parameter that states the proportion of the worker's surplus. To compute the equilibrium contract value, I first solve for the optimal wages conditional on the provision of ESHI d:

$$\widetilde{w}(x, d) = arg \max_{w|d} S(w, d; x) \tag{16}$$

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The equilibrium wage schedules of the jobs with or without ESHI $\widetilde{w}(x, d)$ are uniquely determined from the optimum equations (16). Analytical solutions to the maximization can be complex, so they are reported with a variety feature of wage equations in Appendix B.4. Wages are a convex combination of the match-specific productivity x and the worker's outside option. The higher a worker's bargaining coefficient α, the more weight that is given to the match productivity x. The more productive worker and the matched firm suffer a greater loss when the worker contracts an acute illness. Such productive ill workers are more willing to be covered by ESHI to reduce the illness period. As a result, insured employees can be more productive and receive higher wages. I preclude the possibility that firms can use observable illness conditions to negotiate with or fire workers.

2.4 Optimal decision rules and a steady-state equilibrium

2.4.1 Optimal decision rules

The optimal decision rules have the reservation utility property because the locus of wage and insurance status (w, d) can be mapped to one unique utility value. It defines a set of critical values over heterogeneous match-specific values and medical care expenditures. These critical values spread out all agents into different states.

Medical care decisions. Medical care choices affect the extent of illness costs. A moderately ill individual compares the costs and benefits of seeking medical treatment. Medical care utilization might decrease the length of illness episodes but incurs financial costs. The flow values of seeking medical treatment $E_{A,1}(w, d; x, m)$ and $U_{A,1}(m)$ are decreasing in m regardless of the employment state, but the values of not seeking medical treatment $E_{A,0}(w, d; x)$ and $U_{A,0}$ are irrelevant to m. Therefore, there exist unique critical values m^{**} and $m^*(x, d)$ that make the agent indifferent between $c = 1$ and $c = 0$:

$$m^{**} : \{m : U_{A,0} = U_{A,1}(m)\} \tag{17}$$

$$m^*(x, d) : \{m : E_{A,0}(\widetilde{w}(x, d), d; x) = E_{A,1}(\widetilde{w}(x, 1), d; x, m)\} \tag{18}$$

Medical treatment c is optimally sought by an individual with a moderate acute illness. That is, $c = 1$ if medical care expenditures are low enough (i.e., $m < m^{**}$ or $m < m^*(x, d)$); otherwise medical treatment is not sought (i.e., $c = 0$). If an individual chooses to seek medical care, ESHI directly reduces the total medical care expenditures through the out-of-pocket function $o(d; m)$. Health insurance increases the worker's utilization rate of medical services, improving her health conditions.[22] In the same direction, employers also want to provide ESHI to mitigate the reduced labor productivity driven by acute illnesses.

Health insurance provision decisions. After drawing the productivity, workers and employers compare the optimal value of the filled job with and without health insurance and simultaneously make the health insurance decision. The following match-specific productivity value $\widehat{x}$ characterizes such decisions:

$$\widehat{x} : S(\widetilde{w}(\widehat{x}, 1), 1; \widehat{x}) = S(\widetilde{w}(\widehat{x}, 0), 0; \widehat{x}) \tag{19}$$

where $\widehat{x}$ is the cutoff value that makes the firm and the employee indifferent between having ESHI or not. Nash bargaining guarantees that this threshold $\widehat{x}$ is the same for both worker and firm, so the following argument also holds:

$$\widehat{x} : \{x : E_H(\widetilde{w}(\widehat{x}, 1), 1; \widehat{x}) = E_H(\widetilde{w}(\widehat{x}, 0), 0; \widehat{x})\} \iff \{x : F_H(\widetilde{w}(\widehat{x}, 1), 1; \widehat{x}) = F_H(\widetilde{w}(\widehat{x}, 0), 0; \widehat{x})\} \tag{20}$$

For simplicity, I study ESHI decisions from the firms' side. If the match value is greater than the cut-off value $\widehat{x}$, a firm provides health insurance ($d = 1$); otherwise, a firm does not ($d = 0$).[23] Existence and uniqueness of $\widehat{x}$ is guaranteed from the elasticity of the value functions for different job types with respect to productivity x: $F_H(\widetilde{w}(x, 1), 1; x)$ is increasing in x faster than $F_H(\widetilde{w}(x, 0), 0; x)$ since there are complementarities between ESHI and the productivity of the match.[24]

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[22]This theoretical result is also consistent with the empirical results of other literature (e.g., Manning et al. (1987); Dafny and Gruber (2005); Dey and Flinn (2005); Finkelstein and McKnight (2008); Cronin (2019)).

[23]Gilleskie and Lutz (2006) and Cronin (2019) consider that an individual chooses a health insurance plan from a set of insurance options, including the option of declining ESHI. I do not directly allow the worker to decline to be covered by ESHI while accepting a job with ESHI. Nash bargaining guarantees that individuals take up health insurance when a firm offers it because disagreement over the contract type does not arise. Employees who do not take ESHI at the firm offering ESHI are classified as one at a workplace without ESHI in the model.

[24]The intuition for the different elasticities stems from two main channels. First, health insurance directly improves the value of the productivity match since jobs with ESHI can last longer than those without it. This makes the discounted value of filled jobs with ESHI larger than those without it. Second, medical care utilization and productivity complement the total surplus. Insured workers are more likely to consume medical care when hit by an adverse health shock because insurance reduces out-of-pocket medical care expenditures. Therefore, moderately ill workers with ESHI, who are likely to recuperate

Employment decisions. A searcher's crucial decision is to accept or reject a job offer. It is equivalent to the firm's decision to hold a vacancy or hire a worker, thanks to the no disagreement result implied by Nash bargaining. The value functions for the employment states are increasing in the match-specific productivity x, while the value fuctions of the unemployed states are constant in x. This feature guarantees that there exists a unique, relevant reservation value $x^*(d)$ satisfying the following equality:

$$x^*(d) : \{x : E_H(\widetilde{w}(x^*(d), d), d; x^*(d)) = U_H\} \iff \{x : F_H(\widetilde{w}(x^*(d), d), d; x^*(d), d) = 0\} \quad (21)$$

A match is realized for any $x \geq x^*(d)$. Health insurance has two opposite effects on $x^*(d)$: it increases the reservation value because employees and employers need to share insurance premiums ϕ, but it also decreases the reservation value since insured employees pay less out-of-pocket costs (i.e., $o(1; m) < o(0; m)$). Therefore, the equilibrium impacts of ESHI on labor supply decisions are ambiguous. There are three different combinations of wage and health insurance packages: (1) All firms offer ESHI, (2) No firm offers ESHI, and (3) A fraction of firms offer ESHI. Depending on which match-specific productivity values are drawn, I show that all three outcomes are possible based on the following proposition 1.

Proposition 1. *Given a set of vectors* $\{\rho, b, \kappa, \alpha, \lambda, \eta_d, \delta, \phi, k, \nu, \zeta_S, \zeta_{A,c}, p, a_m\}$ *and probability distribution functions* $\{G(x), M(m)\}$, *there exists a unique set of reservation productivity values* $\{\widehat{x}, x^*(0), x^*(1)\}$ *that determines the following optimal decision rules:*

$$
\begin{array}{lllll}
\text{(Case 1)} & x^*(0) < & x^*(1) & < \widehat{x} & \\
& & x & < x^*(0) & \iff \qquad\qquad \text{reject the match} \\
& x^*(0) < & x & < \widehat{x} & \iff \text{accept the match without ESHI } d = 0 \\
& \widehat{x} \leq & x & & \iff \quad \text{accept the match with ESHI } d = 1
\end{array}
$$

$$
\begin{array}{lllll}
\text{(Case 2)} & \widehat{x} < & x^*(1) & < x^*(0) & \\
& & x & < x^*(1) & \iff \qquad\qquad \text{reject the match} \\
& x^*(1) \leq & x & & \iff \quad \text{accept the match with ESHI } d = 1
\end{array}
$$

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quickly, contribute more to the total surplus as productivity x increases (see Appendix B.3 for more discussions).

The proof and the predicted critical values are provided in Appendix B.5. In Case (1), the firm's outside option is so low that all three outcomes can be realized. When the values of the match-specific productivity are below $x^*(0)$ (i.e., $x \in [0, x^*(0)]$), workers continue searching and firms keep the vacancy open. The firm fills the vacancy and does not offer ESHI if the match value is between $x^*(0)$ and $\widehat{x}$, or offers ESHI if x is higher than $\widehat{x}$. Case (2) illustrates a scenario where the value of the firms' outside option is sufficiently high. Firms offer ESHI as long as the match-specific value is higher than $x^*(1)$; otherwise, a match is not realized in equilibrium. In this case, firms always offer insurance once the match is formed. Figure 1 draws the cutoff values defined in proposition 1 as a function of the match-specific productivity x. I define and exploit a steady-state equilibrium for identification purposes and explain how the theoretical model captures important empirical features characterizing the US labor market in Appendix B.6.

2.5   Discussion of the model

Although the theoretical model endogenizes a richer set of employers' and employees' decisions and describes important features of the US labor market, my model has some limitations.

The first limitation is the lack of firm-size effects. Therefore, I do not consider the role of ESHI as a device to diversify the risks of employees at each job and how absenteeism may help to reduce contagion across coworkers during COVID-19. This limitation is common to search-matching-bargaining models and ex-post heterogeneous match-specific productivity parsimoniously captures size-dependent wage densities because firm size and productivity are positively correlated (Bobba et al., 2018, 2020). An extension in this direction is the equilibrium search model based on Burdett and Mortensen (1998), that have a coherent notion of firm size (e.g., Aizawa (2019); Aizawa and Fu (2020); Aizawa and Fang (2020)). As seen in van den Berg and Ridder (1998), Bontemps et al. (1999), and Bontemps et al. (2000), one caveat of this model is that predicting reasonable accepted wage distribution requires posted wages to be a function of heterogeneous time-invariant firm productivity. As a result, wages and ESHI contracts do not depend upon the short-term productivity loss driven by the arrival of an acute illness. Also, in the Burdett and Mortensen model, the estimated distribution of firm productivity has an exceedingly long right tail, making identifying productivity distribution harder.[25] Finally, as Hall and Krueger (2008)

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[25]Matched employer-employee data can progress in recovering productivity densities, but it is unavailable in the US

mentions, wage posting is much more prevalent in low-skilled workers, which is inappropriate in my sample.

Second, I do not incorporate channels that the uninsured can use to reduce medical care expenditures, such as saving technology, privately purchased health insurance coverage, uncompensated care, Medicaid, or spousal health insurance coverage. Because of these limitations, the preference of uninsured individuals for ESHI might be overestimated. I do not model savings technology and private health insurance because the amount of saved wealth held by the uninsured and the number of those insured through private health insurance is small.[26] I also do not model uncompensated care or Medicaid because I have excluded relatively poor individuals from the sample.[27] Finally, ESHI can be treated as a public good at the household level since employees with ESHI might have the option to cover spouses. However, household members are less likely to jointly change their labor supply, medical treatment, and health insurance provisions responding to acute illnesses.[28]

Third, due to not constructing life-cycle models, I do not model absenteeism decisions of patients and focus on relatively short-lived acute illnesses, not chronic and long-lasting diseases. Endogenous determinations of illness-related absences might be affected by a variety of working and firm characteristics: medical treatment, education, health status, a type of illnesses, and working conditions (for instance, see Gilleskie (1998, 2010); Hirsch et al. (2017); Bubonya et al. (2017); and Pichler and Ziebarth (2017)). However, it would increase the size of the problem exponentially in an equilibrium search model and require data on the entire history of the accumulated illness-related absences, which is not available from MEPS data but from the 1987 National Medical Expenditure Survey (NMES). Also, it is known that stationary models are weak when capturing life-cycle events (Flinn and Mullins, 2015).[29]

Fourth, I exclude the possibility of receiving job offers while working as an employee for the sake of the estimation. Ruling out on-the-job search may eliminate an important source of observed wage

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(Postel-Vinay and Robin, 2002).

[26]According to Aizawa and Fang (2020), the median value of the liquid assets held by uninsured individuals aged between 25 and 59 was around 11% of those held by the insured. From the author's calculation, only around 1% of individuals in the sample are insured through privately purchased health insurance.

[27]I can add this feature by introducing a consumption floor guaranteed by government transfer; however, this specification does not change the main implications of the model.

[28]The interesting extensions made by Dey and Flinn (2008) and Fang and Shephard (2019) incorporate labor supply decisions at the household level. Instead, my model focuses on a short-term acute illness, not catastrophic health shocks, over one year only.

[29]Recent empirical studies on health dynamics have documented the quantitative importance of incorporating both temporary and persistent health shocks (for instance, see Hosseini et al. (2022) and White (2023)). However, their partial equilibrium model does not study illness costs from the employer's side.

growth (see, among others, Topel and Ward (2006); Cahuc et al. (2006); Yamaguchi (2010); and Liu (2019)). My main data source, MEPS, does not collect information on continuous labor market histories that a unique job ID defines every worker's job through a relatively long period. This feature makes it difficult to identify job-to-job transitions and job-specific wage growth on the job, as well as illness dynamics and medical treatment decisions together.[30]

Finally, I decide not to consider the intensive margins of medical treatment, illness conditions, and health insurance. I ignore alternative forms of medical care (e.g., preventive and diagnostic care), characteristics of medical care provider types (e.g., doctors and nurses, pharmacies, hospitals, labs, and clinics), types of illness (e.g., infectious diseases, deficiency diseases, hereditary diseases, and physiological diseases), cost-sharing features of health insurance (e.g., co-payments and maximum deductible amounts), and health insurance plan types (e.g., self-insured and fully insured plans). Modeling more states would lead to an increasing and unmanageable number of states to estimate the model. I only consider the extensive margins of medical treatment, acute illness, and health insurance. Also, the intensive margin of such variables is not clear enough to be discerned (e.g., a specific recovery shock of one more visit to a doctor for a cough), considering the lack of firm-side and health insurance data.

3   Data

3.1   Description of the MEPS

Data from the Medical Expenditure Panel Survey (MEPS) is used to estimate the model. MEPS is a nationally representative longitudinal sample of US civilian non-institutionalized individuals and their families. Since 1996, a new panel of sample households has been selected each year, drawn randomly from the previous year's National Health Interview Survey (NHIS). MEPS interviews the same individuals five times over two full calendar years. I use the full-year consolidated data files from the Household Component (HC) section, collecting information on each individual's demographic characteristics, health status, medical care consumption, health insurance coverage, and labor market outcome variables. I also use the Medical Conditions (MC) section, containing detailed illness conditions at the event level.

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[30]Identifying on-the-job search parameters also requires a complicated renegotiation mechanism with information from matched employer-employee data, which is not possible in my model (Cahuc et al., 2006; Bagger et al., 2014).

Each illness condition can be linked to medical care consumption variables, including dates of medical care use and sources of medical care expenditures for each survey round.

MEPS is well-suited for the analysis. First, MEPS has detailed illness conditions accompanied by medical treatment use. Having accurate illness information is required to capture the effects of acute illness on the primitive labor market parameters and quantify the costs of illness shocks over a limited time period. Illness conditions are initially self-reported when health problems have bothered an individual over the survey period. After verifying some of the information obtained, participants' medical conditions are coded to 3-digit ICD-9-CM by professional coders. Illness condition is collected even if the individual sought no medical treatment, making it possible to minimize the censoring problem.[31] Second, MEPS records detailed and unique health-related information at each round in a relatively short period. Frequent observation of ill individuals of different labor market states is required to identify the impact of short-term health shocks on employee and employer decisions in the model. Also, MEPS includes information on medical care expenditures and the number of days missed work driven by physical or mental health problems.

3.2   Determination of the sample

I focus on 2012 since it is a period of relative stability in terms of the US medical care system before the implementation of the Affordable Care Act (ACA). To fully utilize the panel structure of the MEPS, I stack together two cohorts of individuals surveyed in 2011 and 2012 into one data set.[32] To satisfy the steady-state assumption, I only use one year of data, which still contains enough variation for identification. I impose several restrictions on the final sample in order to have relatively homogenous individuals in terms of their health conditions and labor market experience over observables assumed by the model. I restrict the sample to white males between the ages 30 and 55 with at least a high school education who participated in all interviews. I exclude any individuals who report being self-employed, in military

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[31]Gilleskie (1998, 2010) account for this censoring problem by constructing the likelihood function allowing for the estimation of the illness probability parameters when illness conditions are not observed when patients do not consume medical treatment.

[32]The estimation is based on data collected over 12 months from rounds 3,4 and 5 of the 16th panel and rounds 1, 2, and 3 of the 17th panel. The first round of the 17th panel begins in January 2012, and the final round of the 16th panel ends in December 2012. One caveat is that the interview rounds are not necessarily evenly spaced, so some rounds' reference periods can be longer than others. On average, they are about 5.4 months long, and approximately 89.1% are between 2 and 8 months long. See more details on the structure of the data in Appendix D.3.

service, with public or non-employer-sponsored health insurance during the reference period. I also rule out the samples covered by the spouse's ESHI coverage.[33] To obtain a population of healthy individuals, I drop those who report unhealthy conditions and have had a chronic illness before.[34] I limit the maximum missed workdays linked to specific ICD-9-CM codes to 31 days. The respondent's hourly wage is directly reported or calculated by dividing the salary by the number of hours worked. Wage distributions are trimmed at the bottom 1% because hourly wages greater than or equal to 75.76 dollars are top-coded for confidentiality.

In the model, individuals are described by their labor market status, employment transitions, ESHI coverage, illness conditions, and medical treatment, so I define survey respondents in MEPS accordingly.[35] First, I define a worker to be currently employed if she has a job or unemployed if she does not have a job at the interview date. I drop non-employed individuals who are retired, are unable to work because of disability or illnesses, need to take care of their family members, go to school, and take time off. If the worker holds ESHI at the current main job, the employment match is identified as the job providing ESHI. Second, I define ill individuals as those absent from work due to an acute illness at least once during the reference period.[36][37] I use the accumulated number of missed workdays associated with specific ICD-9-CM codes to measure the length of the acute illness episode in the model. It might understate the actual illness episode, but it is well suited to identify how acute illness incurs observed productivity loss information through absenteeism. Third, I define ill individuals consuming medical care as those who seek medical treatments at least once during the reference period. I utilize data on five different types of medical spending events: prescription medication purchases, emergency room visits, outpatient visits, office-based medical provider visits, and hospital inpatient stays.[38] The medical care

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[33]The sample size of each industry is small, and absenteeism rates are relatively similar across industries. Therefore, I do not consider industry-specific characteristics in the sample.

[34]Health status is defined as five integer values of self-reported health, corresponding to the excellent/very good/good/fair/poor health categories. Individuals who report fair or poor health conditions more than two times are treated as unhealthy. I do not consider healthy behaviors (e.g., exercise and non-smoking) because general health status and lagged illness conditions are closely related to healthy behaviors.

[35]MEPS collects other employment states, such as they had a job to return to or did not work at the interview date but worked during the reference period. I only consider employed workers as those who had a job at the interview date.

[36]ICD-9-CM codes characterize the types of illness conditions in the data. Acute illness conditions, such as common cold, parasitic disease, or a broken bone, are associated with a short duration and non-permanent effect on an individual's health conditions and job search behaviors. Chronic illnesses, such as heart disease and diabetes, last 12 months or longer and are never assumed fully to subside, so it permanently affects individuals' characteristics. This feature of chronic illness conditions makes it difficult to understand the transitions into and out of illness over a relatively short time in the data.

[37]MEPS asks, "What are the health problems that caused you to miss work on those days?" I explain how to use ICD-9-CM codes and the number of absence days as discerning acute ailments in Appendix D.2.

[38]I do not include dental visits, home health care, or optical care, which are usually not covered by ESHI plans. The details

utilization variables in each category can be directly linked to relevant illness conditions to precisely identify whether individuals seek medical treatment or not because of the contraction of particular acute illnesses. Medical care expenditures are defined as the sum of payments for each medical care utilization.

I construct the following sets of sample moments from the final sample: cross-sectional, dynamic, and illness-related moments. A cross-sectional sample is extracted from the intermediate round of Panel 16 and 17, covering the middle of 2012. It covers the statistics on the relative proportions of labor market states as well as wage and medical care expenditure distributions. A dynamic sample is constructed from a balanced panel of individuals over three consecutive rounds over the year. It fully captures the yearly transitions of labor market states. The illness-related moments capture statistics on individuals with at least one acute illness causing absenteeism during six months in the intermediate round of Panel 16 and Panel 17. The final estimation sample consists of 1,269 males, representing 3,807 individual-round observations. Appendix D provides further details about the construction of the panel data sets and the sample selection criteria.

3.3 Descriptive statistics

Descriptive statistics of the estimation sample are reported in Table 1, 2, and 3. The reported patterns are broadly in line with the main empirical features in the literature.

Table 1 describes the cross-sectional features of the labor market states by comparing the unemployed, insured, and uninsured workers. First, there is a significant mass in each state, and most of the workers are covered by ESHI: ESHI covers 70% of males, 24% are employed by the uninsured, and 6% are unemployed.[39] Second, insured individuals tend to report having higher wages ($27 an hour), while the average hourly wages of workers without ESHI are $15 an hour. This suggests that an employment match with ESHI is derived from the upper support of the productivity distribution. Figure 2 depicts the distribution of observed wages for workers. The wage distribution of uninsured workers is low, as their low reservation wages make it easier to accept job offers. Also, it shows that the insured employees' wage density first-order stochastically dominates the uninsured wage density.

Table 2 reports the transition probabilities of individuals' employment states at the beginning of the

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on the medical event files are explained in Appendix D.2.

[39]The aggregate average unemployment rate in 2012 from the US Bureau of Labor Statistics is around 8%, slightly higher than those in my sample because my sample has a group of relatively healthy people.

period and their states one year later. There are a number of transitions between labor market states and ESHI provisions, showing that an individual can access both types of job offers. It contrasts with a segmented view of the labor market in which there are impediments between jobs with and without ESHI. As described in the first row of Table 2, I observe that around half of the unemployed become employed after a year. Over one year, 12% of the unemployed move to jobs with ESHI, and around 39% are sorted into jobs not offering ESHI. Uninsured workers are more likely to change their labor market states than the insured. After a year, about 20% of uninsured employees become either unemployed or insured. Still, the opposite is not that much: only around 2% of insured employees change their labor market states. These observations show that job tenure is longer for workplaces providing health insurance than for others.

Table 3 describes the illness-related moments for individuals having at least one acute illness causing absenteeism at some point over six months from the intermediate round of Panel 16 and Panel 17 of the MEPS. The percentage of individuals in this ill sample is 15%. The insured are more likely to seek medical treatment when they contract acute illnesses over this period. For example, about 64% of insured workers seek medical treatment, but only 39% of uninsured workers do. The insured consumes more medical care than the uninsured since medical treatment expenditures appear to be partially covered by health insurance.[40] Patients who utilize medical care miss five workdays on average, but those who do not use it miss only two workdays over six months, which is counter-intuitive at first glance. Intuitively, if using medical care makes the disease worse, patients will not use medical care. Taking the structure of the model as given, it is possible that some serious acute illnesses, such as broken legs, require medical care, as seen in Appendix D.4, but more detailed severities within acute illnesses cannot be observed by the econometrician. Observed different patterns of missed workdays between treated patients are informative about identifying unobserved severity over acute illness conditions, and its discussion is explained in Section 4. The average cost of medical treatment is 37 dollars per hour for an illness episode. The standard deviation of medical expense payments is approximately 68, which is quite large. It shows that the distribution of medical expenses might be a mixed distribution according to various disease types within acute diseases.

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[40]The different patterns of consuming medical care utilization, depending on ESHI, might be evidence of moral hazard. For example, it provides some private demand for health insurance by ill workers who want to consume more medical treatments. I explain this limitation in detail in section 5.

4 Identification

I need to identify the following set of parameters that characterize the model:

$$
\Theta = \left\{
\begin{array}{c}
\rho, b, \alpha, \lambda, \eta_d, \mu_x, \sigma_x, \delta \\
\kappa, \nu, \zeta_{A,c}, \mu_m, \sigma_m, \phi, k, \\
p, a_m, \zeta_S
\end{array}
\right\}
\tag{22}
$$

The identification strategy has three stages. I discuss the set of the "classic" search, matching, and bargaining parameters in the first row, the health-related parameters in the second row, and the parameters describing unobserved heterogeneity in the third row.

4.1 Search, matching and bargaining parameters

The strategy to identify the labor market parameters $\{\rho, b, \alpha, \lambda, \eta_d\}$ and the match-specific distribution parameters $\{\mu_x, \sigma_x\}$ is based on Flinn and Heckman (1982). The discount rate ρ can only be jointly identified with the flow value of unemployment disutility b through the equilibrium conditions. Once the discount rate ρ is set to 5% a year, b can be identified. It is challenging to identify the bargaining power parameter α because of the lack of demand-side information, as discussed in Flinn (2006). In this case, it is common in the literature to impose a sharing rule that splits productivity equally between a worker and an employer; that is the symmetric bargaining parameter $\alpha = 0.5$ (Flinn, 2006; Flabbi, 2010b; Flabbi and Moro, 2012). I use the transition probabilities between labor market states and the steady-state proportion of workers in each state to identify the mobility parameters $\{\lambda, \eta_d\}$.[41]

I use the truncated distribution of observed wages to recover the unobserved productivity distribution parameters $\{\mu_x, \sigma_x\}$. As seen in Flinn and Heckman (1982), I assume a log-normal function with the location and scale parameters $\{\mu_x, \sigma_x\}$ since it satisfies the recoverability condition for identification and shows a good fit of the accepted wage distributions (Eckstein and van den Berg, 2007; Flabbi, 2010a):

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[41] Flinn and Heckman (1982) use unemployment duration to identify the labor market dynamics. Using transitions across labor market states over one year expresses the same identification strategy in a different way.

$$G(x; \mu, \sigma) = \frac{1}{x\sigma_x} f[\frac{\ln(x) - \mu_x}{\sigma_x}], x > 0 \tag{23}$$

where function f denotes a standard normal density function.

I calibrate the percentage of the wages that ill workers receive while absent from work because of a lack of information on accumulated absence days. According to the Bureau of Labor Statistics National Compensation Survey, full-time private industry employees who have worked for more than five years are granted paid sick leaves on an accrual basis for up to around nine days per year. Following the Kaiser Family Foundation (KFF), paid sick leave coverage often replaces 100% of workers' regular wages. I set the replacement rate δ at 100%, considering that the average absence days of ill workers in my model are estimated to be less than nine days.[42] I conduct the sensitivity analysis to show how different replacement rates influence labor market outcomes in Appendix E.1.

4.2   Health-related parameters

The second set of parameters is a set of health-related parameters $\{\kappa, \nu, \zeta_{A,c}, \mu_m, \sigma_m, \phi, k\}$. I identify the disutility from being ill κ by using the same argument I used to identify b.

I impose parametric assumptions to identify the primitive distribution of medical care expenditure the same way I identified the productivity distribution parameters. Each ill individual is assigned potential medical care expenditures m drawn from $M(m)$, and it is realized when they consume medical treatment. I assume log-normality and denote location and scale parameters $\{\mu_m, \sigma_m\}$ for the distribution function of medical care expenditures:

$$M(m) = \frac{1}{m\sigma} f\left(\frac{ln(m) - \mu_m}{\sigma_m}\right), m > 0 \tag{24}$$

Health insurance covers a partial fraction of medical care expenditures. I parametrically assume the out-of-pocket medical consumption function $o(d; m)$. I assume that the coinsurance rate for ESHI is 19%, according to statistics from the MEPS-IC. If hourly medical care expenditure is positive $o(1; m) = m \times 0.19$; otherwise $o(0; m) = m$. Additional details are explained in Appendix A.2.

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[42]Gilleskie (2010) shows that the percent of the wage replaced by sick leave coverage is estimated to be 98% for the first absence of an illness episode.

Following Flinn and Heckman (1982), I apply an identification strategy that identifies job mobility parameters by using the unemployment duration to identify both the health shocks ν and the recovery shocks $\{\zeta_{A,0}, \zeta_{A,1}, \zeta_S\}$. I use the information on how many days each worker missed workdays due to acute illness and how much their absence days differ when seeking medical treatment or not. Then, I compute the hazard rate out of the "healthy state" or "illness state." Following Flabbi (2010a), through the reparametrization of the model, I can separately recover health-related shocks $\{\nu, \zeta_{A,0}, \zeta_{A,1}, \zeta_S\}$ from the hazard rates with the information of $G(x)$ and $M(m)$ in the steady-state flow equations defined in Appendix B.6 with the help of unobserved heterogeneity over illnesses. In the model, the effects of adverse health shocks on labor productivity are reflected in the number of missed workdays due to acute illness. The amount of productivity loss due to absenteeism can be recovered using the mapping between the productivity and the bargained wage schedules.[43]

I exploit the Insurance Component of the 2012 MEPS (MEPS-IC) to calibrate the health insurance premium and the contributions of employees for single coverage. The fixed value of the premium of ESHI ϕ is 2.59 dollars per hour, which captures the total costs of providing ESHI from the firms and individuals' direct payment to have ESHI. I set the employees' contribution to the premium to 20.8%. Additional details on the calculation are in Appendix A.2.[44]

4.3   Unobserved heterogeneity

I could only subdivide all diseases into acute and chronic illnesses in the data because the econometrician cannot capture more than the clinical classification codes (e.g., influenza or respiratory infections) or the specific three-digit ICD-9-CM codes. Two main empirical considerations lead me to introduce unobserved illness heterogeneity. First, treated patients are absent from work 2.68 days more than those who are not in Table 3. Considering that individuals optimally choose to seek medical treatment or not, this empirical finding shows that there might be differences between acute illnesses that are unobserved.[45]

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[43]The production function is assumed to capture the impact of short-term changes in labor supply on the worker's productivity. Recall that when a worker is absent from the workplace because of an illness, productivity becomes zero in that period, while healthy individuals can be productive all the time as usual.

[44]If a risk pool attracts a certain portion of unhealthy individuals, premiums at the workplace need to be adjusted. However, calibrated ESHI premiums do not reflect such channels. Because of the lack of firm-size information, I cannot incorporate the risk pool of insured employees. Instead, I minimize this problem by having relatively homogenous healthy agents in the sample.

[45]The model predicts that ill individuals optimally choose to consume medical care to recuperate quickly and stay productive at the workplace; otherwise, they are unwilling to seek medical treatment because of medical expenses. However,

Ignoring unobserved heterogeneity during estimation will lead to biased parameter estimates. For example, the model will tend to explain the long duration of this illness episode for treated patients as a situation where the more patients use medical care, the worse their health condition becomes.[46] Second, medical care price distributions are likely correlated with the unobserved severity of illness. Intuitively, the sicker a worker gets, the more expensive she has to pay for medical expenses. By introducing the unobserved heterogeneity over illness conditions, my utility-maximizing search model can better explain medical care's productive effects and the distribution of medical care expenses in the data.

Following the literature, I introduce severe and moderate acute illnesses that approximate unobserved heterogeneity.[47] Unobserved heterogeneous illness types are specific to illness episodes and medical treatment, not individuals. I denote severe acute illness with $i = S$, and its proportion in the population with p. Severe illnesses are characterized by exogenous medical treatment, a recovery rate ζ_S, and a positive scalar for medical care expenditures a_m, which increases the overall distribution of medical care expenditures $M(m)$ (similar to TFP parameters). For instance, 62% of people with a cold seek treatment, but 100% of people with a broken leg seek treatment. I denote moderate acute illness with $i = A$ and its proportion in the population with $1 - p$. Moderate illnesses have a recovery rate $\zeta_{A,0}$ if patients do not seek medical treatment and a recovery rate $\zeta_{A,1}$ if they do. Different recovery rates exhibit $\zeta_{A,1} > \zeta_{A,0} > \zeta_S$ to capture the severity of illness and productive effects of medical treatment. I specify that $m|S = a_m m$ with $a_m > 1$ and $m|A = m$, which means that individuals with severe illnesses are assumed to have a higher direct cost of medical treatment on average.

For identification, I utilize information on longer absences from work for patients who seek medical treatment than those who do not. Introducing unobserved illness types can generate different missed workdays depending on the severity of illness among treated patients. I treat the duration of acute illness for treated patients in the data as an integration of illness durations with mild acute illness and severe acute illness. I also have large standard errors in the distribution of medical expenditures in the data.

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individuals who receive exceptionally unobserved severe illness shocks are more likely to consume medical care, as discussed in Appendix D.4. If this were the case, ill individuals who consume medical treatment would have more missed workdays than those who do not consume in the sample.

[46]On top of unobserved heterogeneity, omitted variables for lagged health status might exacerbate the reverse causality. I address this issue by deleting samples of having chronic illness and lagged wellness over the life cycle.

[47]Keane and Wolpin (1997, 2010) show how to introduce unobserved heterogeneity in the literature. There are similar examples in the search-theoretic models of the labor market (Eckstein and Wolpin, 1995; Sullivan, 2010; Bobba et al., 2020) and in the health economics literature (Gilleskie, 1998; Khwaja, 2010; Cronin, 2019) to improve the fit of the model and lend more credibility to the estimated parameters by introducing unobserved heterogeneity in the model. Gilleskie (1998, 2010) show that introducing additional unobserved heterogeneity of illness types does not improve the model's fit.

I treat the observed medical expenditure as a mixture of the medical care expenditures of the different unobserved illness types to identify a scale parameter a_m.

5 Estimation

5.1 Estimation method

I estimate the model using the method of simulated moments (MSM).[48] MSM minimizes a weighted average distance between sample moments and simulated moments from the model. I estimate a set of the parameters $\widehat{\Theta}_{MSM}$ in the space Ω by minimizing the following quadratic distance function:

$$\widehat{\Theta}_{MSM} = \arg \min_{\Theta \in \Omega} [M_{N,R}(\Theta) - m_N]^T W_N^{-1} [M_{N,R}(\Theta) - m_N] \tag{25}$$

where $M_{N,R}(\Theta)$ is the vector of the simulated moments evaluated at Θ based on R simulations for N sample observations. m_N is the vector of the corresponding sample moments derived from the data set of size N. The symmetric, positive-definite weighting matrix W_N is a diagonal matrix with elements equal to the inverse of the bootstrapped standard errors of the corresponding vectors of m_N.[49]

The advantage of this strategy is to employ a large amount of information characterizing the wage distributions, job mobility, and health-related moments. I choose the following moments in the estimation procedure to exploit the identification strategy in Section 4: the first moments are cross-sectional, related to employment state and insurance coverage status. I use the proportions of individuals in each labor market state. Also, I use the mean and standard deviation of the accepted wage distributions for a job with or without ESHI. The second set of moments utilizes the yearly transition probabilities across employment states and health insurance coverage status. The final set of moments captures the health-related information: medical care expenditures distributions and the proportion and number of absent days of ill individuals who seek medical treatments by ESHI.

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[48]The method is commonly used to estimate nonlinear models numerically in other search literature (see, among others, Dey and Flinn (2008); Flabbi and Moro (2012); Flinn and Mullins (2015); Bobba et al. (2020)).

[49]Under the assumption, I use the population value of the sample moments (i.e., $\plim_{N \to \infty} m_N = m$). Del Boca et al., 2014 shows that the consistency of MSM estimators for positive definite matrix W_N is obtained under standard conditions (i.e., $\plim_{N \to \infty} \widehat{\Theta}_{MSM} = \Theta$) . I compute the bootstrapped standard errors using a re-sampling method, following Del Boca et al. (2014). In practice, I re-sample the original N sample observations a total of 100 times.

5.2 Parameter estimates

Table 4 presents the parameter estimates of the model, together with the bootstrapped standard errors. The first set of parameters describes the search, matching, and bargaining process. Durations are measured in a month, so the point estimate of the job offer arrival rate λ, 0.11, implies that a healthy unemployed worker meets a firm every nine months on average. In contrast, ill agents do not receive job offers, constituting the additional cost of acute illnesses. There is a significant difference in the estimates of the job destruction rates between job types. The estimated parameters of the job destruction rates η_d imply that, on average, a job without health insurance will exogenously terminate after two years, while a job with insurance will dissolve after twenty years.[50] This effect stems from the positive impact of ESHI on the productivity of the match. The flow value of unemployment b is estimated to be negative, which commonly generates enough wage variation in the search literature (Hornstein et al., 2011).

The second set of parameters characterizes the health-related parameters. The estimated arrival rate of an acute illness ν implies that individuals contract an illness every two and a half years. It generates around 15% of the population having at least one acute illness over six months. Recovery rates of individuals having severe illnesses ζ_S show that they take around ten days off to recover from an illness. The differences in the estimated values for the recovery shocks of individuals with moderate illnesses $\zeta_{A,c}$ generate the returns to seeking medical treatment. Moderately ill workers who consume medical care tend to have shorter illness episodes than those who do not: individuals who seek medical treatment take less than one day to recover from illnesses but about two days if they do not seek it. Medical care utilization can reduce the costs of moderate sickness by shortening their episodes, although it incurs medical care expenditures. It becomes another motivation for workers to value ESHI since insurance decreases the marginal cost of medical treatment. Figure 3 plots the estimated Weibull survivor functions for ill workers based on the estimated duration of each illness type. It clearly shows the effect of medical treatment on reducing the number of sick days in the case of moderate illness. Contracting an illness costs 3 dollars per hour (in psychic terms), which means that individuals are willing to pay 3 dollars to recover from acute illnesses. Or the average disutility of being ill is estimated to be around one-third

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[50]Although I do not directly observe employment durations in the sample, those estimates are similar to other estimates in the structural search literature showing that the estimated rate of job separations for the uninsured is greater than the rate for the insured (e.g., Dey and Flinn (2005)).

of the average disutility of being unemployed, which is commonly estimated in the search literature. In terms of the unobserved heterogeneity in illness conditions, individuals have a 27% chance of getting severe illnesses when receiving an illness, and it leads to 21% higher medical care expenditures. The estimated medical care expenditure distribution parameters $\{\mu_m, \sigma_m\}$ imply that the average medical care expenditure is about 37 dollars per hour during illness episodes.

5.3 Predicted values

Table 5 reports the predicted labor market and health-related values recovered from the structural parameters. The values are computed by simulating the labor market histories of each individual based on the corresponding estimated parameters in Table 4. In Table 5, the average realized match-specific productivity is around 40 dollars per hour, higher than that found in similar studies. While other papers (e.g., Dey and Flinn (2005); Bobba et al. (2018); Flinn and Mullins (2015)) assume that the primitive match-specific productivity explains the total value of the employment match between employees and employers completely, I allow workers' absences during an episode of acute illnesses at the workplace to affect productivity. As a result, a large value of match-specific productivity generates relatively small variations in different wage densities.[51] Insured workers' average offered wages are 40% higher than those of uninsured workers.[52] These wage differentials are slightly smaller than those observed wages in the data. It demonstrates that accepted wages are affected by workers' endogenous decisions to accept or reject job offers. The estimated job arrival rate in Table 4 predicts that unemployed searchers accept a job offer on average every nine months.

Table 5 reports predicted health-related outcomes. I see large differences in the duration of illness episodes across heterogeneous illness types and medical care decisions. Across individuals with a moderate acute illness, those who consume medical care stay less than one day in the illness state, thanks to the productive effects of medical care on illness. Consequently, those who consume medical care are exposed to fewer illness-related costs (both monetary and non-monetary). To calculate absenteeism rates

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[51]Although match-specific productivity is drawn from the same primitive distribution $G(x)$, it makes a stark difference in the realized productivity between the two jobs. It supports the first case of Proposition 1 that searchers are pickier in accepting jobs providing ESHI, considering that $x^*(1)$ is higher than $x^*(0)$.

[52]Offered wages are calculated over the relevant support of x, but accepted wages are the endogenous equilibrium outcomes of workers' and firms' optimal decisions. In this sense, as pointed out by Eckstein and Wolpin (1995), offered wages are closer to a primitive of the model than the accepted wages.

and subsequent absenteeism costs, I use the number of absent days and the number of available workdays over six months. According to the International Organization for Standardization (ISO), the absenteeism rate is measured as follows:

$$\text{Absenteeism rate} = \frac{\text{total number of absent days}}{\text{number of available work days in a given period}}$$

I set the number of available workdays over six months at 122 days. Following the formula, I calculate an absenteeism rate of 3% as the rate of unplanned absences due to acute illnesses. This is close to the average values found in the US Bureau of Labor Statistics (BLS) in 2012. The absenteeism rates are linked to the potential forgone productivity that is not realized due to illness, and I can approximate the unobserved productivity losses with the help of hourly wages and estimated productivity in Table 5. A simple back-of-the-envelope cost analysis suggests that productivity losses due to acute illness causing absenteeism in one year are between 790 dollars (based on hourly wages) and 1,200 dollars (based on productivity) per employee.[53]

5.4   The fit of the model

To evaluate the ability of the model to capture individuals' search behavior in the presence of illnesses, I compare the observed and simulated moments. Overall, the model fits well the important moments of the observed data, but some mismatches occur because of a relatively parsimonious set of parameters.

Table 6 replicates well the statistics of observed wages by insurance status and the proportions describing labor market states. The mean wage distributions for different insurance statuses fit well, though it is less distributed. The estimated proportion of the unemployed is higher than those in the sample because I try to match the high persistence of the unemployment state in the transition probabilities as reported in Table 7.[54] Table 7 shows that the model replicates important features of the dynamic moments. The model successfully generates significant transitions between labor market states, but sometimes it

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[53]In a perfectly competitive labor market, the wage rate is equal to the marginal productivity of labor. I introduce search frictions, so 790 dollars are the lower bound of productivity loss due to absenteeism in a frictional labor market.

[54]I decide to fit the mean of hourly wages for two types of jobs since the relationship between ESHI, and its wage levels is important in capturing the productivity-enhancing effect of holding insurance. When I try to match the standard deviation of wage densities better, it changes the critical values defined in Section 2, leading to a poor fit on the proportion of both jobs and the shape of wage densities of the insured.

overestimates or underestimates the persistency in some states.[55]

Table 8 shows that the model successfully replicates illness-related moments. The predicted proportion of ill workers who decide to utilize medical treatment conditional on access to health insurance matches well with the data. The model also generates the productive effect of medical treatment and trends that the insured are more likely to seek treatment, as predicted in the model. It also delivers a reasonably good replication of the portion of individuals who have had an acute illness for six months and the duration of the patient's acute illnesses. The introduction of the unobserved heterogeneity over acute illness smooths differences between the model's predictions and the sample moments.

6 Counterfactual experiments

Given model estimates, I provide the economic costs of acute illnesses by comparing the benchmark model to a counterfactual with no acute illness. Next, I conduct two policy experiments to assess the value of ESHI when acute illnesses are present: (1) mandatory health insurance policy where all employers must provide ESHI, and (2) policy that assesses flow penalty to employers that do not provide ESHI (and flow subsidy if they do provide ESHI).

6.1 Costs of acute illness

This section aims to highlight the impacts of acute illness on labor market outcomes and welfare. I compute the new equilibrium for each value of different acute illness shocks ν with the estimated parameters reported in Table 4. I document costs of acute illness as the relative difference between wages, total values of production, and workers' welfare that agents realize in the benchmark model and those they would realize if there is no acute illness counterfactually. To isolate the net impacts of ESHI on labor market outcomes, I only consider jobs without ESHI.[56]

Figure 4 displays relevant costs of acute illness computed at the various acute illness shocks over the range. I denote the benchmark value of ν with a vertical dotted line in all panels. Panel (a) shows that as

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[55]This mismatch comes from the trade-off between the transition probabilities and the steady-state portion of labor market states. When I improve the fit of this movement, it comes at the cost of having a higher ESHI rate and higher mean wages for the insured.

[56]I decrease the destruction rates of jobs with ESHI until ESHI covers no individuals. I also quantify acute illness costs in the model where two types of jobs exist in equilibrium, and the main qualitative results do not change.

the acute illness shock ν increases, the share of individuals who experience at least one acute illness over six months increases proportionally. It is a straightforward result of the increased probability of receiving a health shock. The size of lost production increases as more individuals contract an acute illness over six months, as shown in Panel (b).[57] Panel (c) and (d) show that an acute illness shock decreases average wages and workers' welfare. Increases in acute illness costs are indirectly taken into account in the form of a lower total surplus. When I use the Present Discounted Values (PDV) of the lifetime utility as a workers' welfare, these illness costs directly enter into workers' welfare. Through a Nash-bargaining process, firms can partially share illness costs with the worker. As a result, acute illness costs lower workers' wages as well. Additionally, I only allow acute illness shocks ν to become zero and keep other parameters at the old equilibrium. In this new equilibrium, accepted wage increases by around 2%, and workers' welfare increases by around 4%. It implies that acute illness potentially lowers accepted wages and workers' welfare more than the size of illness shocks. These results also show that absenteeism costs are much higher than labor costs, giving employers incentives to provide ESHI to increase their profits. It implies that, without considering equilibrium effects, acute illness costs might be underestimated.

6.2 Policy experiments

I use the estimates presented to compute the equilibrium effects of policy interventions on illness costs, labor market outcomes, and welfare. From the simulated samples, I calculate three sets of criteria by which one might reasonably evaluate the policy experiments.[58] The first set measures the cost of illness by calculating absenteeism rates, productivity loss rates, and medical care expenditures. The second set represents features of unemployment states and two types of jobs: accepted wages, unemployment duration, and unemployment rate. The final set measures welfare by exploiting the steady-state equilibrium results of the model. For workers, their welfare is measured by the PDV of the lifetime utility of participating in the labor market.[59] For employers, I calculate the average of firms' per-worker profits. More detailed explanations of the definitions of each criteria are presented in B.7.

I study the effects of mandatory health insurance policy, in which all firms must provide health

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[57]The value of lost production refers to the extent of the forgone productivity since ill workers do not contribute to the output. It can be calculated by multiplying the total amount of time absent from work by the hourly productivity.

[58]I simulate labor market histories for each new value of the policy parameters.

[59]It refers to the population expectation of ex-ante values of participating in the labor market and contracting an illness.

insurance, and searchers now only receive job offers with ESHI. Also, I study the employer mandate penalties in the following ways.[60] I assume that a firm that does not provide ESHI receives a flow penalty of one dollar for each worker, which is 2,080 dollars annually. Then, all collected taxes are endogenously redistributed to firms providing ESHI in the form of the flow subsidy. The policy incentivizes firms to provide ESHI by lowering the marginal cost of providing health insurance.

The top panel in Table 9 shows that the policy reduces various illness costs. The mandatory health insurance policy increases the medical treatment utilization rate for ill individuals by 8% compared to the benchmark model. It implies that ESHI reduces the marginal costs of medical treatment, and more ill individuals consume medical care quickly to recuperate from illness conditions. As a result, absenteeism and productivity loss rates decrease by around 19%. The employer mandates penalties also decrease the hourly medical cost, absenteeism, and productivity loss rates from 11% to 15% because workers consume more medical care by 4%.

The middle panel in Table 9 reports the impacts of the policies on labor market outcomes. The implications of the mandatory health insurance policy for the distribution of accepted wages are ambiguous. On the one hand, following Proposition 1, matching with jobs providing ESHI requires the productivity to be large enough to compensate for the cost of ESHI. On the other hand, the flow profits of employers with lower preferences for ESHI might become reduced because the employers are forced to provide health insurance even though it might not be optimal. This is why the policy decreases accepted wages by around 2%, which is relatively small. The employer mandates penalties increases the proportion of employees with ESHI by 14%.[61] Also, average accepted wages increase by around 2% because more workers have ESHI associated with higher accepted wages. Reduction of the cost of ESHI increases employment and unemployment duration as a mandatory health insurance policy. As a result, the unemployment rate increases by 7% because more workers enter the searching state than workers leave. After both policies, unemployed workers are pickier in accepting job offers, leading to a higher average duration of unemployment.

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[60]Under the ACA, if an employer does not offer ESHI coverage, they are required to pay penalties. Employers are required to pay 2,260 dollars per employee in 2017 if they do not provide ESHI. The ACA Employer Mandate applies to all large employers with 50 or more full-time employees in the previous tax year. I do not consider the firm-size effect; therefore, I assume that the employer mandate penalty applies to all employers in the model.

[61]The employer mandates penalties increases the reservation value $x^*(1)$ but decreases the reservation value $x^*(0)$, following the second case of proposition 1. It means that workers with very low productivity lose their jobs without ESHI, but slightly less productive workers are inflowed to jobs with ESHI.

The bottom panel in Table 9 shows that firms' welfare becomes significantly lower, but workers' welfare does not when two policies are imposed. The mandatory health insurance policy shrinks the support of productivity corresponding to acceptable job matches.[62] Firms are prevented from extracting full benefits from workers when making workers healthier after paying the costs of ESHI. The impacts on workers' welfare are straightforward: workers' ex-ante welfare increases by 5%. Also, the presence of the flow subsidy shifts the value function of the filled job with ESHI to the left. At the same time, the flow penalty decreases the profits of the filled job without ESHI. As a result, average firms' profits become 16% lower in the post-policy environment than in the pre-policy regime. The workers' welfare increases thanks to the provision of ESHI: workers who value ESHI enjoy a portion of additional subsidies with the employers providing ESHI through the bargaining process. Also, uninsured workers who do not value ESHI do not accept a job offer from employers with ESHI. This setting improves workers' welfare while reducing firms' welfare, although this cost is partly transferred to workers.

In conclusion, the policy implies that ESHI can be valuable to employees who might receive acute illness shocks. However, healthcare policies only targeting higher ESHI coverage rates can be burden-some to firms because they might distort the optimal ESHI provision decisions that firms would make otherwise. Therefore, looking at the ESHI coverage rate and other equilibrium effects is essential when evaluating the policy. Also, the penalties imply a redistribution of welfare from firms to workers, but its impacts on overall welfare are relatively small. Since relatively fewer firms finance the subsidy, not all firms provide ESHI. Despite the small magnitude of policy impacts, it significantly reduces illness costs for workers, reducing employers' welfare slightly, comparable to mandatory health insurance. If more workers put a higher value on ESHI, this policy becomes more efficient than mandatory health insurance.

7 Conclusion

Even healthy individuals are on the verge of experiencing a potentially significant loss in welfare in the event of unexpected acute illness. Considering that ESHI is the primary source of insurance coverage in the US, I study whether and how employees and employers value ESHI to reduce acute illness costs

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[62]For instance, the productivity within the support of $[x^*(0), \widehat{x}]$ in Figure A2 was previously matched with jobs with-out ESHI becomes unfilled. Note that the interval $[x^*(0), \widehat{x}]$ shows an efficiency gain of having the option to offer health insurance, allowing for more matches and subsequent utility (or profits) for employers and employees.

potentially.

I develop a rich search model of the labor market that allows for match-specific and illness-specific heterogeneity in an environment where ESHI provision, wages, and medical treatment during acute illness are endogenously determined. I propose an identification strategy to estimate the model's structural parameters using the MEPS. The estimated model assesses the quantitative importance of less-explored acute illness costs, such as deteriorated productivity, increased medical expenses, and reduced utility. Health insurance coverage reduces not only healthcare spending but also the number of absence days by encouraging healthcare choices. As a result, ESHI provision is productive as firms and workers choose the optimal reaction against illness shocks.

I perform two counterfactual experiments related to the higher ESHI coverage rates: mandatory health insurance and employer mandate penalties. Higher equilibrium ESHI coverage rates from the policies reduce the various illness costs thanks to frequent medical care utilization of patients. However, there is a redistribution of welfare from firms to workers because the policy shrinks firms' decision sets or distorts their decisions. Therefore, choosing the ESHI coverage rate as the sole policy goal might be misleading. Instead of shutting down this channel, changing their marginal decision through subsidies and penalties might reduce welfare losses stemming from inefficient ESHI provisions.

There are a number of promising avenues for future research. First, although I only focus on relatively healthy individuals, it is important to quantify the costs of other health problems, such as disability or chronic illness, and their relationships with other labor market outcomes. In that case, my framework may be extended to assess the effect of other programs, such as Social Security Disability Insurance (SSDI) program on health outcomes. Second, incorporating channels of health capital accumulation, where individuals can improve their underlying health conditions through investments in time or money can be an interesting extension (Becker, 1962; Acemoglu and Pischke, 1999; Fang and Gavazza, 2011) . By treating health capital as a form of general human capital, firms cannot fully internalize the returns of providing wellness programs (e.g., on-site fitness centers, yoga classes, and smoking cessation programs), and it might lead to the under-provision of such programs from the socially optimal level.

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Tables and Figures

Table 1: CROSS-SECTIONAL MOMENTS: LABOR MARKET STATES

	Unemployed	Insured Employee	Uninsured Employee
Proportion (%)	6.03	69.79	24.19
Hourly Wages: Mean		26.65	15.14
Hourly Wages: SD		13.66	8.33

NOTE: Cross-sectional moments are based on the intermediate round of Panel 16 and Panel 17 of the Medical Expenditure Panel Survey (N=1,269). The sample includes nonagricultural healthy white males aged between 30 and 55 with at least a high school education. The insurance status of the job is defined according to whether or not workers have employer-sponsored health insurance through their employers. Earnings figures are measured in dollars per hour.

Table 2: DYNAMIC MOMENTS: YEARLY TRANSITION RATES

	Employment States at $t + 1$		
Employment States at t	Unemployed	Uninsured Employed	Insured Employed
Unemployed	47.95	39.73	12.33
Uninsured Employed	10.07	79.48	10.45
Insured Employed	0.57	1.13	98.30

NOTE: The balanced panel of individuals was followed for one year over 2012 of the MEPS. The table shows yearly transition probabilities across the labor market states for individuals. The sample includes nonagricultural healthy white males aged between 30 and 55 with at least a high school education. The insurance status of the job is defined according to whether or not workers have employer-sponsored health insurance through their employers.

Table 3: ILLNESS-RELATED MOMENTS

		No Medical Treatment	Medical Treatment
At least one acute illness (%)		14.99	
Average missed work days		2.29	4.97
Proportion: (%)	If uninsured	61.38	38.62
	If insured	35.71	64.29
Medical payments: Mean			37.58
Medical payments: SD			67.85

NOTE: Illness-related moments are extracted from individuals who contracted any acute illness over six months during the intermediate round of Panel 16 and Panel 17 of the MEPS survey data. The sample includes nonagricultural healthy white males aged between 30 and 55 with at least a high school education. The medical treatment states are defined according to whether or not individuals have consumed any curative care due to acute illness during illness episodes.

Table 5: ESTIMATION RESULTS: PREDICTED VALUES

	Predicted Values	Standard Error
Labor market:		
Average hourly realized productivity:		
Employees	41.017	3.514
Uninsured employees	20.888	1.427
Insured employees	46.734	3.724
Variance of hourly realized productivity:		
Employees	377.817	27.135
Uninsured employees	19.712	1.142
Insured employees	331.742	24.242
Average hourly offered wages:		
Uninsured employees	15.853	1.245
Insured employees	26.133	1.432
Average duration of receiving a job offer:		
Unemployed searcher	9.438	0.785
Health:		
Average duration of illness episode:		
Severe illness	9.430	0.653
Moderate illness with medical treatment	0.693	0.047
Moderate illness without medical treatment	2.068	0.103
Absenteeism rate:		
Employees	3.231	0.135

NOTE: The estimates are computed using the simulated labor market histories of 2,000 individuals, based on the estimates presented in Table 4. Health-related outcomes are measured over six months. Standard errors are calculated with 100 bootstrap replications. The productivity and earning figures are measured in dollars per hour. The average duration of searching states and illness episodes is measured in a month.

Table 4: PARAMETER ESTIMATES

Parameters		Estimates	Standard Error
Labor market:			
Unemployment utility	b	-9.1579	0.4882
Job arrival rate	λ	0.1060	0.0051
Separation rates	$\eta_{\{d=0\}}$	0.0159	0.0023
	$\eta_{\{d=1\}}$	0.0065	0.0004
Match specific productivity	μ_x	3.4273	0.1642
	σ_x	0.5088	0.0291
Health:			
medical care expenditures	μ_m	3.2169	0.1453
	σ_m	1.2125	0.0612
Recovery rates	$\zeta_{A,\{c=0\}}$	14.9997	0.5891
	$\zeta_{A,\{c=1\}}$	40.4067	1.3498
	ζ_S	3.0964	0.1507
Health shock	ν	0.0302	0.0025
Disutility of being ill	κ	2.9515	0.0984
Proportion of severe illnesses	p	0.2697	0.0466
Scale factor of severe illnesses	a_m	1.2128	0.0121

NOTE: The table reports the parameter estimates with their standard errors. The model is estimated through the Method of Simulated Moments using the Nelder-Mead simplex algorithm, and the bootstrap standard errors are computed using 100 replications. The definition of the parameters is explained in Section 5.

Table 6: THE FIT OF THE CROSS-SECTIONAL MOMENTS

	Unemployed		Insured Employee		Uninsured Employee	
	Data	Model	Data	Model	Data	Model
Proportion (%)	6.03	10.20	69.79	71.72	24.19	17.93
Hourly Wages: Mean			26.65	27.78	15.14	15.97
Hourly Wages: SD			13.66	8.71	8.33	2.11

NOTE: Cross-sectional data are obtained from the intermediate round of Panel 16 and Panel 17 of the MEPS survey data (N=1,269). The insurance status of the job is defined according to whether or not workers have ESHI through their employers.

Table 7: THE FIT OF THE DYNAMIC MOMENTS

	Data			Model		
	Employment States at $t + 1$					
Employment States at t	Unemp.	Ins.	Unins.	Unemp.	Ins.	Unins.
Unemp.	47.95	12.33	39.73	37.19	38.69	24.12
Ins.	0.57	98.30	1.13	5.10	93.92	0.98
Unins.	10.07	10.45	79.48	12.82	2.56	84.62

NOTE: The stacked panel of individuals was followed for one year over 2012 of the MEPS. The table shows yearly transition probabilities across the labor market states for individuals. The insurance status of the job is defined according to whether or not workers have employer-sponsored health insurance through their employers.

Table 8: THE FIT OF THE ILLNESS-RELATED MOMENTS OVER SIX MONTHS

		Data		Model	
		No Treat.	Treat.	No Treat.	Treat.
At least one acute illness (%)		14.99		16.10	
Proportion: (%)	If insured	64.29	35.71	64.06	35.94
	If uninsured	38.62	61.38	35.63	64.37
Average missed workdays		2.29	4.97	2.13	5.08
Medical payments: Mean			37.58		33.61
Medical payments: SD			67.85		62.00

NOTE: Illness-related moments are extracted from individuals who contracted any acute illness over six months during the intermediate round of Panel 16 and Panel 17 of the MEPS. The medical treatment states are defined according to whether or not individuals have consumed any curative care during an illness episode.

Table 9: THE EQUILIBRIUM EFFECTS OF THE COUNTER FACTUAL POLICIES

	Benchmark	Mandatory ESHI		Penalties	
		Results	Differential (%)	Results	Differential (%)
Health-related outcomes:					
Absenteeism rate (%)	3.23	2.62	-18.91	2.76	-11.44
Productivity loss rate (%)	3.40	2.75	-19.00	2.86	-13.76
Hourly medical expenses ($)	40.99	34.79	-15.14	36.97	-14.18
Medical treatment rate (%)	59.19	63.80	7.79	61.54	3.97
Labor market outcomes:					
ESHI coverage rate (%)	71.49	100.00	39.87	81.48	13.96
Mean wages ($)	23.07	22.71	-1.54	23.44	1.62
Employment duration (months)	49.87	51.88	4.04	51.23	2.73
Unemployment duration (months)	13.76	14.49	5.28	15.29	11.13
Unemployment rate (%)	8.32	7.01	-15.67	8.89	6.84
Welfare outcomes:					
Workers' PDV of the search ($)	215.82	226.75	5.07	228.64	5.94
Firms' flow profits ($)	12.83	9.83	-23.40	10.78	-15.96

NOTE: A simulated sample of 2,000 individuals is based on the estimates reported in Table 4. Differentials indicate how much the results changed due to the policy compared to the benchmark model. The PDV denotes present discounted values. Productivity loss rate refers to the portion of the realized average value of production out of the potential average value of production, which is derived from the environment without acute illness. Mandatory health insurance means firms can only offer a contract with health insurance. The employer mandates penalties mean that firms pay a penalty of one dollar if they do not provide health insurance, and the total penalties are distributed to firms that provide health insurance through subsidies. For a more detailed description of the policy, see Section 6.
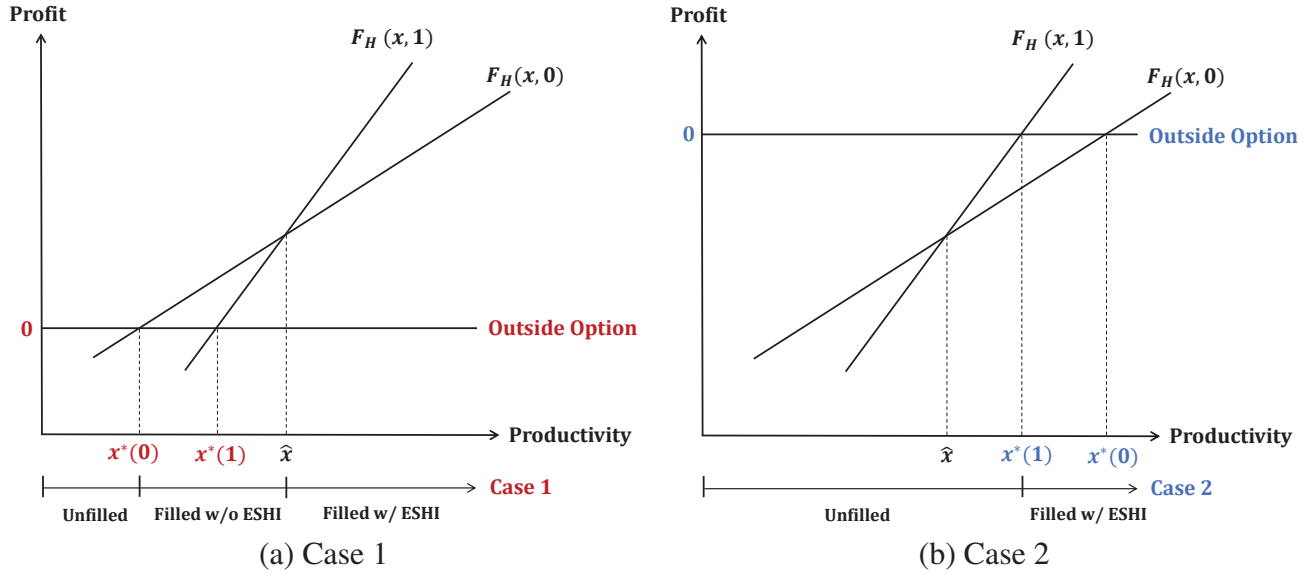
Figure 1: DIFFERENT EQUILIBRIUM OUTCOMES DEPENDING ON THE CRITICAL MATCH VALUES

NOTE: The figures report the critical values of match-specific productivity $\{x^*(0), x^*(1), \widehat{x}\}$. $x^*(d)$ is the cut-off value for a firm to hire an employee, and $\widehat{x}$ is the cut-off value for a firm to provide health insurance. I assume that employers post vacancies at no cost, so all firms have an outside option value of zero. Depending on the value of the outside option, there are two cases: case 1 is based on the inequality $x^*(0) < x^*(1) < \widehat{x}$ and case 2 is based on the inequality $\widehat{x} < x^*(1) < x^*(0)$. It generates different equilibrium outcomes that are defined in Proposition 1. For the definitions of $F(1)$ and $F(0)$, see section 2.
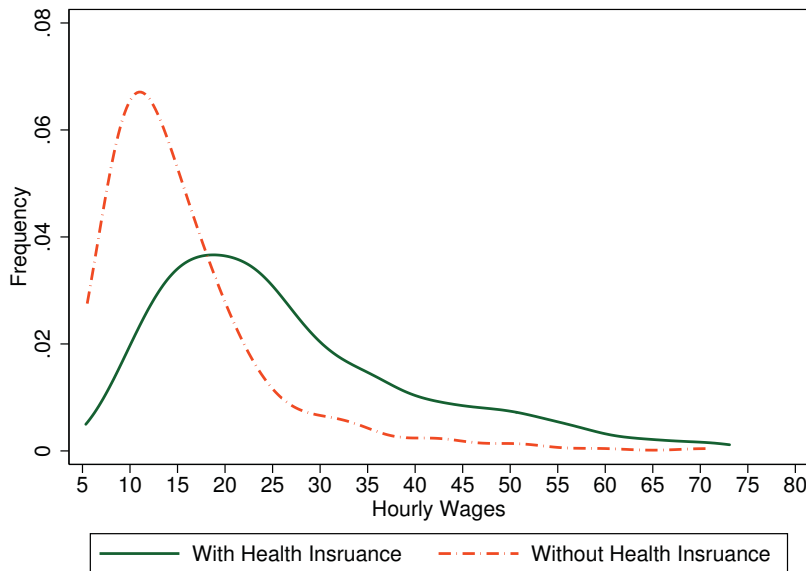

Figure 2: OBSERVED WAGE DENSITIES

NOTE: Wages are based on the intermediate round of Panel 16 and Panel 17 of the Medical Expenditure Panel Survey (N=1,269). The sample includes nonagricultural healthy white males aged between 30 and 55 with at least a high school education. The insurance status of the job is defined according to whether or not workers have employer-sponsored health insurance through their employers.
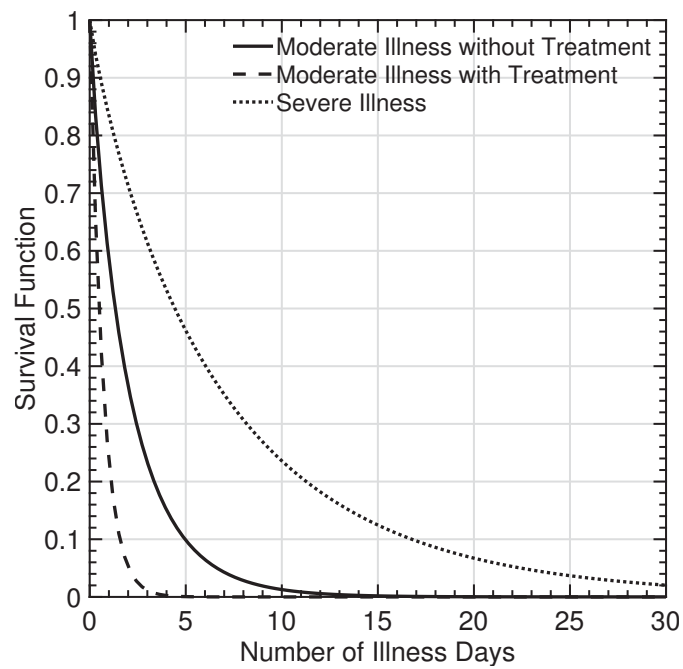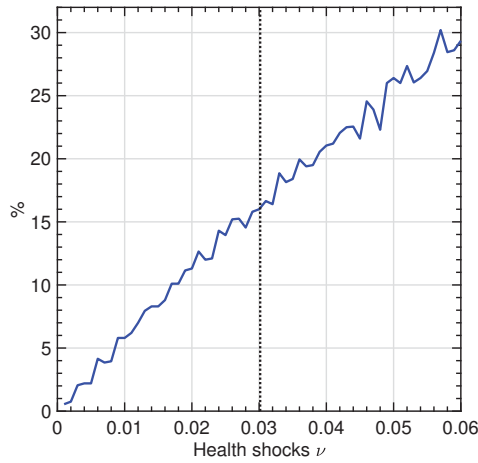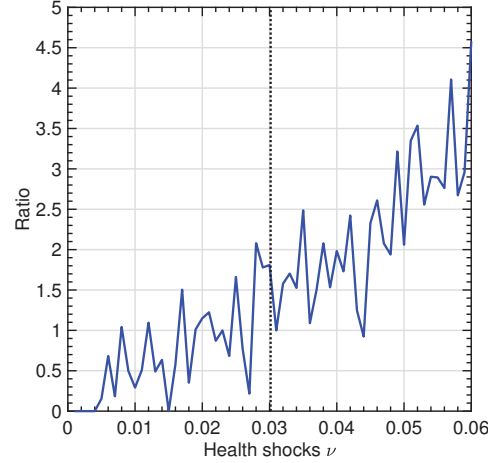
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Figure 3: PREDICTED SURVIVAL FUNCTIONS BY ILLNESS TYPES

NOTE: The estimates are computed using the simulated labor market histories of 2,000 individuals, based on the estimates presented in Table 4. I fit Weibull distributions to the survival function associated with an illness duration of ill workers.
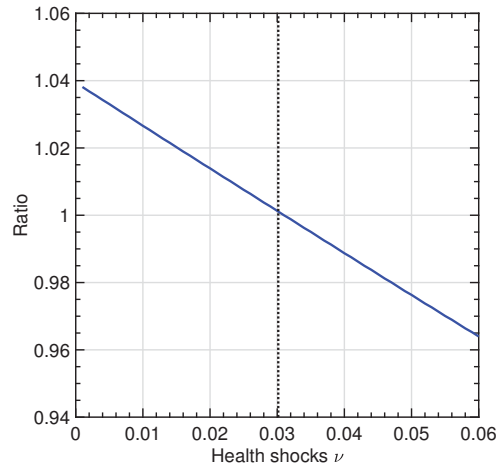
(a) Share of ill individuals

(b) Value of lost production (Benchmark = 1)
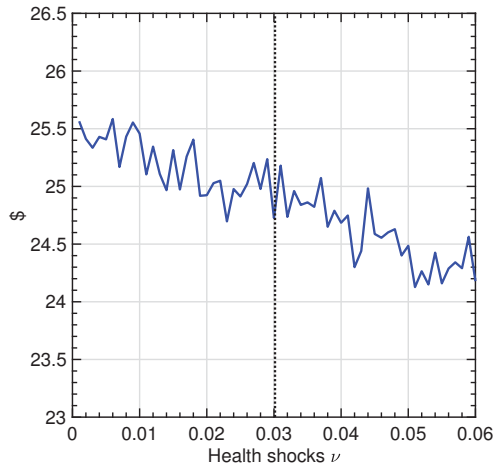
(c) Mean accepted wages

(d) Workers' PDV of the search (Benchmark = 1)

Figure 4: COSTS OF ACUTE ILLNESS

NOTE: For each value of the health shock parameters, I derive the share of ill individuals, value of lost production, and mean accepted wages from a simulated sample of 2,000 individuals, fixing the other estimates reported in Table 4. I compute workers' present discounted values (PDV) of the searching state by calculating the value of the searching state of healthy individuals for different health shock parameters. The vertical lines are set at the estimated values of the health shock in the benchmark model. Panel (a) shows the share of individuals with at least one acute illness over six months. Panels (b) and (c) show, respectively, the total value of production that is not realized due to acute illness and the average wages of workers. Panel (d) includes workers' present discounted values (PDV) of the searching state.

Appendices

A   Institutional context and parameters

A.1   Institutional context

The advantages of employer-sponsored health insurance (ESHI) are straightforward, even though there are costs to providing it. On the employers' side, health insurance coverage increases employees' productivity through improvements in their health capital. On the employee side, ESHI reduces medical care expenditures associated with sudden health shocks. As the interests of both sides coincide, ESHI has been the main source of health insurance coverage for workers and firms in the US. For example, the fraction of working-age populations with ESHI was about 58% in 2018. When considering employees and employers, the equilibrium search model in the paper is well suited to understanding how ESHI reduces the costs of acute illnesses. It also needs to be consistent with the empirical features of US labor markets to generate credible parameter estimates and conduct relevant policy experiments.

The US medical care system has been developed to make health insurance more accessible to those who change jobs. The Consolidated Omnibus Budget Reconciliation Act (COBRA), passed in 1985, provides employees who leave their jobs with the option to access their employer's health insurance coverage for up to eighteen months after leaving. Gruber and Madrian (1994) find that one more year of continuation benefits increases job mobility by 10%. I do not model COBRA since I cannot track down the labor market histories of individuals in the MEPS, which are necessary to model such options. Also, Dey and Flinn (2005) show that ESHI does not lead to significant inefficiencies in job mobility decisions.

As seen in Figure A1, the fraction of workers covered by ESHI has decreased over 20 years. To reverse this trend, the ACA was passed in March 2010 to increase the availability of health insurance plans for uncovered individuals. Specifically, the ACA dependent mandate affects the labor supply decisions of young adults on an extensive and intensive margin because it extends dependent coverage to the children of the insured up to the age of 26. Also, the ACA employer mandate requires large employers to provide a specified percentage of their full-time equivalent employees and their families with minimum essential healthcare insurance (effective in 2015). Similarly, the ACA introduces the

individual mandate, premium and cost-sharing subsidies for low-income workers, and a limited open-enrollment period to increase health insurance coverage rates. Finally, the ACA aims to protect against adverse selection by insurers through the risk-adjustment program, the single risk pool requirement, and uniform market rules. Unfortunately, analyzing the main features of the ACA requires information on firm size and interactions between family members that are not relevant in my framework. I do not study the ACA with my model, except for the employer mandate policy.

Figure A1: PERCENTAGE OF PEOPLE COVERED BY ESHI, 2001-2018
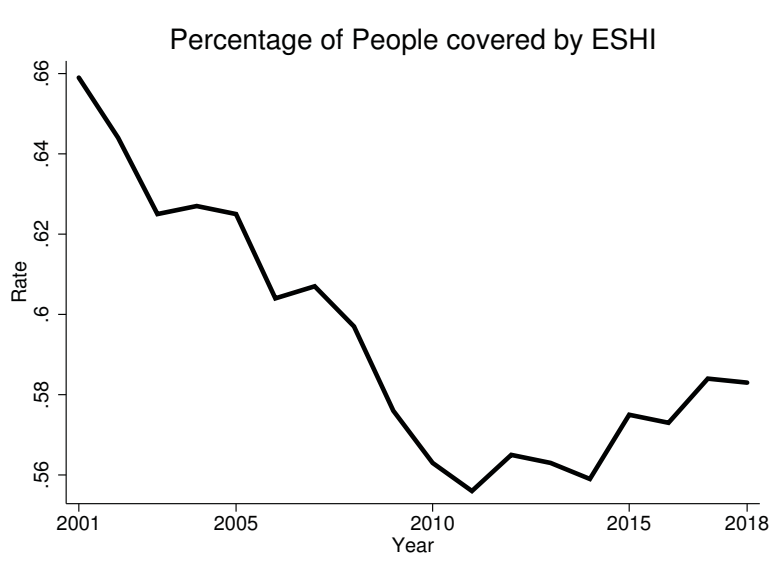
SOURCES: The Kaiser Family Foundation (KFF) Employer Health Benefits Survey, 2020; KFF analysis of the National Health Interview Survey (NHIS), 1999-2018.
NOTE: Individuals are non-elderly male individuals aged under 65.

A.2   Institutional parameters

I calibrate some health insurance parameters outside of the estimation process. First, I extract the average total single premium in dollars per enrolled employee at private-sector establishments that offer ESHI, following the 2012 MEPS statistical brief. Hourly insurance premiums are set to be 2.59 dollars.

Second, to derive the percent of total premiums contributed by employees k, I use MEPSnet/I.C. tool, which calculates national statistics and trends of ESHI premiums.[63] I use the average total contribution (in dollars) per enrolled employee for single coverage at the same establishments. From my calcula-

[63]MEPS-HC does not have information on the exact cost of health insurance for employers and employees. These are available in the MEPS Insurance Component but only accessible in one of the data centers.

tions, it is noteworthy that employee contributions for single coverage in private sectors have remained relatively constant, from 20.1% in 2008 to 20.8% in 2012. Accordingly, the percent of total premiums contributed by employees enrolled in ESHI was 20.8% in 2012, and it can be assumed to be stable over time. Therefore, k is set to 20.8% of the ESHI premium, while $1 - k$ represents the remaining 79.2% paid by employers.[64]

Third, the coinsurance rate represents the percentage of medical expenses insured workers pay after considering the deductibles and the out-of-pocket maximum. Health insurance plans are characterized by a non-linear budget constraint. However, I do not have enough information on such cost-sharing structures of ESHI and accumulated medical care expenditures within a year in the MEPS, so I only consider coinsurance rates. I set the coinsurance rate to be 19%, using the mean value of coinsurance rates for private-sector employees enrolled in a single plan.[65]

B Model

B.1 Derivation of value functions

I introduce only the derivation of the unemployment value functions of healthy searchers. The other cases can be similarly derived. The value function of the searching state for a healthy worker is given by the

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[64]Different group health insurance plans, such as fully insured or self-insured plans, have a different extent to which the employer takes the financial risk for providing health care benefits to its employees. For example, employers collect premiums from enrollees and take on the responsibility of paying their workers' claims if their plan is fully insured. According to the Employee Benefit Research Institute (EBRI), around 33% of the participants in private employment-based plans are insured through self-insured group health insurance plans. However, I do not consider such different health insurance plans because of the lack of insurance data.

[65]In an earlier version of this paper, I try to identify health insurance premiums ϕ and employee contributions k by utilizing the different locations and the extent of the overlapped area between the accepted wages distribution for jobs offering ESHI $w(x, 1)$ and for jobs not offering ESHI $w(x, 0)$. In particular, I exploit the following wage differentials between $w(\widehat{x}, 1)$ and $w(\widehat{x}, 0)$ around the reservation value $\widehat{x}$ at which firms are indifferent to providing ESHI or not:

$$\Delta \equiv w(\widehat{x}, 0) - w(\widehat{x}, 1) > 0$$

Intuitively, wages of jobs with health insurance are lower than jobs without health insurance around $\widehat{x}$; workers have to bear the costs related to insurance provision in the form of low accepted wages $w(\widehat{x}, 1)$, generating positive Δ. This discontinuity Δ represents the existence of the overlapped area in support of the accepted wage distributions. When ignoring equilibrium effects, an increase in premium ϕ increases the firm's marginal costs of offering ESHI, moving the location of the reservation value $\widehat{x}$ to the right. Given that $\widehat{x}$ governs the location of the overlap, the higher ϕ, the smaller the overlap. Such overlaps constitute the mixture distributions from a collection of wage distributions conditional on health insurance status. However, introducing the acute illness costs weakens the separate identification of such parameters because those shift wage densities down. With the help of fixed parameters, I can replicate the entire support area of the productivity and associated wage densities.

total utility (or disutility) from unemployment and three main events that may happen after a period $\triangle t$: staying in the unemployment state, meeting an employer, or receiving an acute illness. Other possible events are happening with a negligible probability $o(\triangle t)$. The following discrete-time approximation can express this process:

$$U_H = b + (1 + \rho\triangle t)^{-1} \times [\nu \underbrace{\left\{ \begin{array}{c} (1-p)\int \max\{U_{A,0}, U_{A,1}(m)\}dM(m) \\ +p\int U_S(m)dM(m) \end{array} \right\}}_{\text{contract an acute illness}}]$$

$$+ \lambda \underbrace{\left\{ \begin{array}{c} \int_{\neg\triangle} \max\{E_H(0;x), U_H\}dG(x) \\ + \int_{\triangle} \max\{E_H(1;x), U_H\}dG(x) \end{array} \right\}}_{\text{receive a job offer}} \triangle t]$$

$$+ (1 - \nu - \lambda)U_H\triangle t + o(\triangle t) \tag{26}$$

After rearranging terms and using the Poisson process assumption that $\lim_{\triangle t \to 0} \frac{o(\triangle t)}{\triangle t} = 0$ as $\triangle t \to 0$, this expression converges to the value functions as mentioned in the model.

B.2   Derivation of wage equations

Conditional on the provision of health insurance, the analytical expressions for wages of employees who are matched with different types of jobs are derived:

$$\begin{aligned} w(x,0) &= \alpha[x + \nu\left\{ \begin{array}{c} (1-p)\{\int_{\neg\Phi} F_{A,0}(w,0;x)dM(m) + \int_{\Phi} F_{A,1}(w,0;x)dM(m)\} \\ +pF_S(w,0;x) \end{array} \right\}] \\ &+ (1-\alpha)[(\rho+\nu)U_H \\ &- \nu\left\{ \begin{array}{c} (1-p)\int \max\{E_{A,0}(w,0;x), E_{A,1}(w,0;x,m)\}dM(m) \\ +p\int E_S(w,0;x,m)\}dM(m) \end{array} \right\}] \end{aligned} \tag{27}$$

$$\begin{aligned} w(x,1) &= \alpha[x - (1-k)\phi + \nu\left\{ \begin{array}{c} (1-p)\{\int_{\neg\Phi} F_{A,0}(w,1;x)dM(m) + \int_{\Phi} F_{A,1}(w,1;x)dM(m)\} \\ +pF_S(w,1;x) \end{array} \right\}] \\ &+ (1-\alpha)[(\rho+\nu)U_H + k\phi \\ &- \nu\left\{ \begin{array}{c} (1-p)\int \max\{E_{A,0}(w,1;x), E_{A,1}(w,1;x,m)\}dM(m) \\ +p\int E_S(w,1;x,m)\}dM(m) \end{array} \right\}] \end{aligned} \tag{28}$$

Considering the number of possible closed-form wage equations, I solve the model by evaluating the wage equations in a discretized grid of productivity and medical care expenditures.

B.3 Features of optimal decision rules

I only consider the case of $m^*(x,0) < m < m^*(x,1)$, meaning that the insured with a moderate acute illness always seek medical care and the uninsured do not ($c = 1$ if $d = 1$ and $c = 0$ if $d = 0$); other cases are similar but simpler. After inserting the wage equations into value functions, I can compare different value functions to derive the reservation values that define the agent's optimal decisions.

The rearranged value functions of a filled job become:

$$
\begin{aligned}
\frac{A(d)}{(1-\alpha)} F_H(w, d; x) \quad = \quad & B(d)(x + \eta_d U_H - k\phi d) \\
- \quad & A(d)U_H - C(d)(1-k)\phi d \\
+ \quad & \nu \left\{ \begin{array}{l} (1-p)(\rho + \eta_d + \zeta_S)(\eta_d U_{A,c}(m) - k\phi d - \kappa - m) \\ +p(\rho + \eta_d + \zeta_{A,c})(\eta_d U_S(m) - \kappa - m) \end{array} \right\}
\end{aligned}
$$

where :

$$
\begin{aligned}
A(d) \quad = \quad & (\rho + \eta_d + \nu)(\rho + \eta_d + \zeta_{A,c})(\rho + \eta_d + \zeta_S) \\
& -(1-p)\nu\zeta_{A,c}(\rho + \eta_d + \zeta_S) - p\nu\zeta_S(\rho + \eta_d + \zeta_{A,c}) \\
B(d) \quad = \quad & (\rho + \eta_d + \zeta_{A,c})(\rho + \eta_d + \zeta_S) \\
C(d) \quad = \quad & (\rho + \eta_d + \zeta_{A,c})(\rho + \eta_d + \zeta_S) \\
& +\nu(\rho + \eta_d + \zeta_S) + p\nu(\rho + \eta_d + \zeta_{A,c})
\end{aligned}
$$

I express terms $A(d), B(d)$, and $C(d)$ as a function of ESHI. A critical match value for being employed $x^*(d)$ is expressed as:

$$
\begin{aligned}
x^*(d) \quad = \quad & -(\eta_d U_H - k\phi d) \\
+ \quad & \frac{A(d)}{B(d)} U_H + C(d)(1-k)\phi d \\
- \quad & \frac{\nu}{B(d)} \left\{ \begin{array}{l} (1-p)(\rho + \eta_d + \zeta_S)(\eta_d U_{A,d}(m) - k\phi d - \kappa - m) \\ +p(\rho + \eta_d + \zeta_{A,c})(\eta_d U_S(m) - \kappa - m) \end{array} \right\}
\end{aligned}
$$

With the rearranged critical values, I derive decision rules in Table A1.[66] It presents the implied reservation values for transitions out of unemployment $x^*(d)$ and for the provision of ESHI $\widehat{x}$ at the productivity of the realized matches. It supports the second case of Proposition 1, generating all three labor market outcomes in this economy. Also, I report optimal decision rules for medical care utilization.

Table A1: ESTIMATES OF THE CRITICAL VALUES

Estimated critical values over x	
$x^*(0)$	11.935
$x^*(1)$	17.548
$\widehat{x}$	28.076
Estimated critical values over m	
$E_x[m^*(x,0)]$	49.619
$E_x[m^*(x,1)]$	49.968
m^{**}	26.803

NOTE: The estimates are computed using the simulated labor market histories of 2,000 individuals, based on the estimates presented in Table 4. Standard errors are calculated with 100 bootstrap replications. Let $x^*(0)$, $x^*(1)$, and $\widehat{x}$ be a critical match for the acceptance of employment without insurance, with insurance, and for the provision of insurance, respectively. Let $m^*(x,0)$, $m^*(x,1)$, and m^{**} be a critical match for the medical care utilization conditional on the health insurance provisions and employment states. Details are explained in Section 2.

Figure A2 contains graphs of two critical values of medical care expenditures for the employed and the unemployed, holding other values fixed except for medical care expenditures. It is clear that when m is low enough, the value functions of individuals seeking medical treatment are larger than the others.

Next, Figure A3 plots the simulated density function of estimated match-specific productivity. The lower line refers to $x^*(0)$, and the line to the right refers to $x^*(1)$. The last right line is $\widehat{x}$. It also supports Case 2 of Proposition 1 in the paper.

---

[66]I do not report other critical values in the paper, but they can be similarly derived.
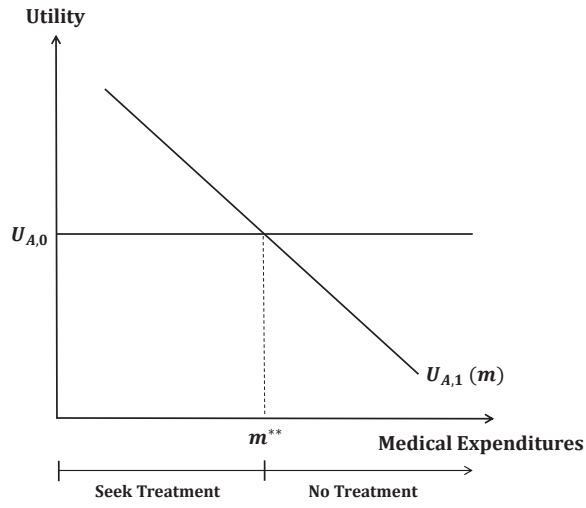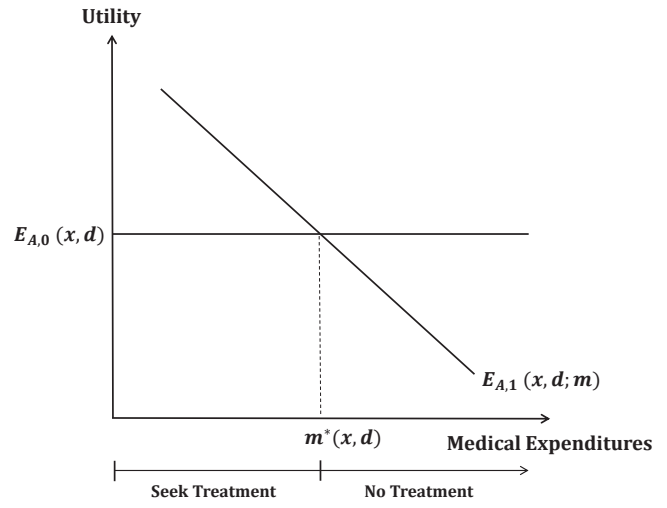
(a) Unemployed individuals with illness   (b) Employed individuals with illness

Figure A2: CRITICAL VALUES OF MEDICAL CARE EXPENDITURES

NOTE: The figures report the critical values of medical care expenditures $\{m^*, m^{**}\}$ at which an ill individual decides to consume medical care. For the definitions of $U_{A,0}, U_{A,1}, E_{A,0}$, and $E_{A,1}$, see section 2.
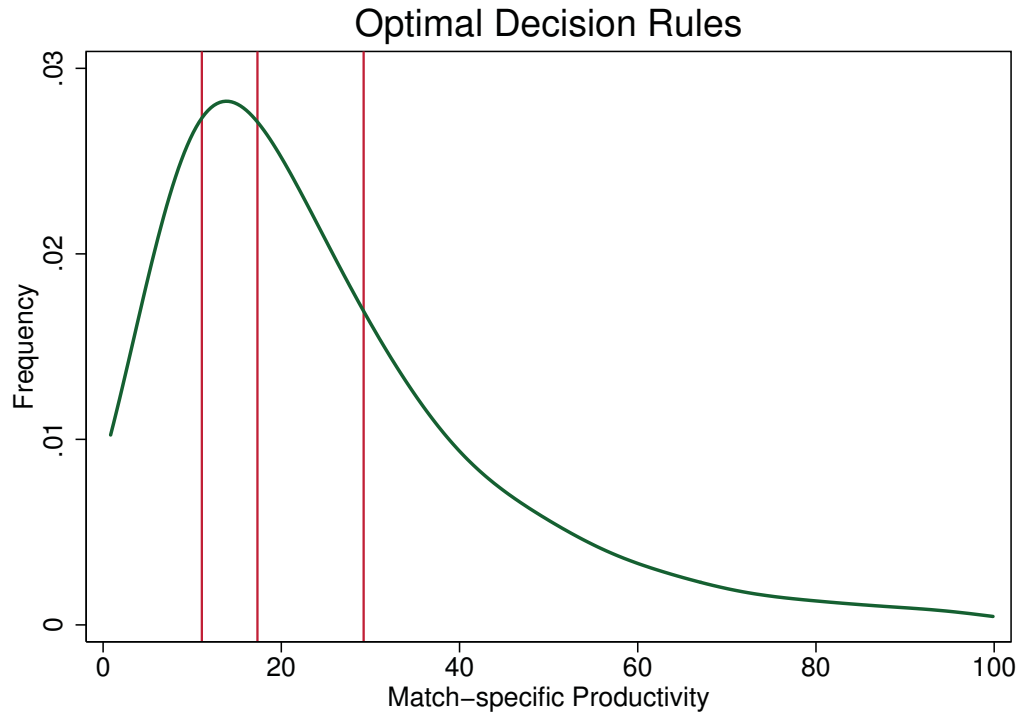

Figure A3: OPTIMAL DECISION RULES OVER MATCH-SPECIFIC PRODUCTIVITY

NOTE: The lower line refers to $x^*(0)$ and the line to the right refers to $x^*(1)$. The last right line is $\widehat{x}$. The definition of critical values is explained in Section 2.

B.4 Features of wage equations

Wages are increasing in productivity x, with the others held constant. The higher the productivity that is drawn, the higher wage densities that are generated. This property is a source of different accepted wage densities conditional on ESHI.

To prove this feature, I insert the rearranged value functions of filled jobs into the bargained wage equations defined in (27) and (28). Then, I derive the closed-form solutions for the wage equations after some algebra:

$$
\begin{aligned}
w(x,d) \quad = \quad & \frac{\alpha}{C(d)}[B(d)x - C(d)(1-k)\phi d] \\
+ \quad & \frac{(1-\alpha)}{C(d)}[A(d)U_H - B(d)(\eta U_H - k\phi d) \\
- \quad & \nu \left\{ \begin{array}{c} (1-p)(\rho + \eta_d + \zeta_S)(\eta_d U_{A,c}(m) - k\phi d - \kappa - m) \\ +p(\rho + \eta_d + \zeta_{A,c})(\eta_d U_S(m) - \kappa - m) \end{array} \right\}]
\end{aligned}
$$

where :

$$
\begin{aligned}
A(d) \quad = \quad & (\rho + \eta_d + \nu)(\rho + \eta_d + \zeta_{A,c})(\rho + \eta_d + \zeta_S) \\
& -(1-p)\nu\zeta_{A,c}(\rho + \eta_d + \zeta_S) - p\nu\zeta_S(\rho + \eta_d + \zeta_{A,c}) \\
B(d) \quad = \quad & (\rho + \eta_d + \zeta_{A,c})(\rho + \eta_d + \zeta_S) \\
C(d) \quad = \quad & (\rho + \eta_d + \zeta_{A,c})(\rho + \eta_d + \zeta_S) \\
& +\nu(\rho + \eta_d + \zeta_S) + p\nu(\rho + \eta_d + \zeta_{A,c})
\end{aligned}
$$

It is obvious that $\frac{\partial w(x,d)}{\partial x} = \frac{\alpha B(d)}{C(d)} > 0$, which is enough to prove it, given $B(d)$ and $C(d)$ are positive. Figure A4 plots Nash bargained wages over the support of productivity. It clearly shows that wages are increasing in productivity.

B.5 Proof and features of proposition 1

I only report the expressions for Case 2 of Proposition 1 since other cases are a specialization of it with similar arguments. I must prove that the value functions satisfy a single-crossing condition for each reservation value. Following the assumption of the theoretical model and empirical results, I assume that

Figure A4: NASH-BARGAINED WAGES WITH AND WITHOUT ESHI

(a) Wages with ESHI

(b) Wages without ESHI
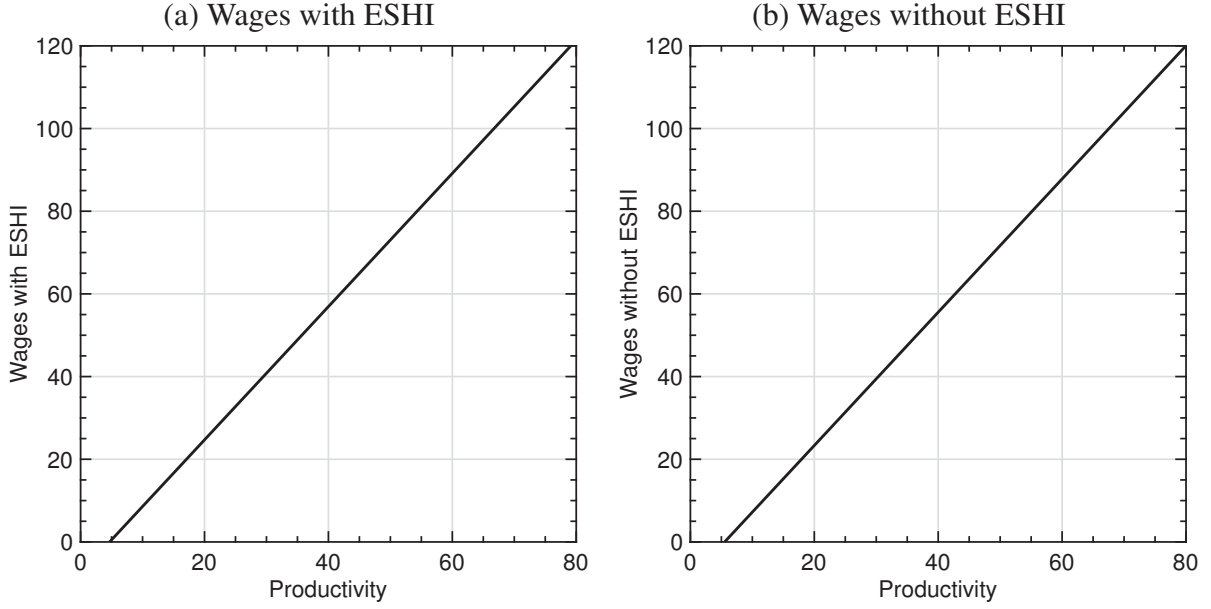
NOTE: The figures report Nash-bargained wages with or without ESHI over the support of match-specific productivity.

the following inequalities hold: $\zeta_{A,\{c=1\}} > \zeta_{A,\{c=0\}} > \zeta_S$ and $\eta_0 > \eta_1$.

First, the value functions for two types of filled jobs should satisfy a single-crossing condition to prove the existence and uniqueness of the reservation values $\{x^*(0), x^*(1)\}$. By plugging the wage equations into the value functions for a filled job, it is obvious that the value functions for two types of jobs are linearly increasing in x:

$$\frac{\partial F_H(w, d; x)}{\partial x} = \left(\frac{B(d)}{A(d)}\right) \quad (1 - \alpha) > 0$$

This guarantees that each value function crosses value functions of unfilled jobs only once over the support of productivity, considering that two value functions have different positive slopes. Intuitively, longer job tenure and a speedy recovery from illness contribute to a steeper slope of value functions for jobs providing ESHI. Those mechanisms decrease the productivity loss due to illness, so firms receive more surplus from additional drawn productivity when providing ESHI. The value of being vacant is the horizontal line that does not depend on productivity. As a result, the optimal decision rule is character-ized by the support of match-specific productivity, which is divided into three regions in relation to the reservation values $\{\widehat{x}, x^*(0), x^*(1)\}$.

Second, I need to show that the value function's slope for a filled job offering health insurance is

steeper than the slope for a job not providing health insurance, in order to guarantee the existence and uniqueness of $\widehat{x}$. Given the assumptions on the parameters, it is enough to show that $\frac{\partial F_H(w,1;x)}{\partial x} > \frac{\partial F_H(w,0;x)}{\partial x} \iff B(1)A(0) - B(0)A(1) > 0$, following the relationship:

$$
\begin{aligned}
B(1)A(0) - B(0)A(1) &= (\rho + \eta_0 + \nu)(\rho + \eta_0 + \zeta_{A,1})(\rho + \eta_1 + \zeta_{A,1})(\rho + \eta_1 + \zeta_S)(\rho + \eta_0 + \zeta_S) \\
&- (1-p)\nu\zeta_{A,0}(\rho + \eta_1 + \zeta_{A,1})(\rho + \eta_1 + \zeta_S)(\rho + \eta_0 + \zeta_S) \\
&- p\nu\zeta_S(\rho + \eta_0 + \zeta_{A,0})(\rho + \eta_1 + \zeta_{A,1})(\rho + \eta_1 + \zeta_S) \\
&- (\rho + \eta_1 + \nu)(\rho + \eta_1 + \zeta_{A,1})(\rho + \eta_0 + \zeta_{A,0})(\rho + \eta_1 + \zeta_S)(\rho + \eta_0 + \zeta_S) \\
&+ (1-p)\nu\zeta_{A,1}(\rho + \eta_0 + \zeta_{A,0})(\rho + \eta_1 + \zeta_S)(\rho + \eta_0 + \zeta_S) \\
&+ p\nu\zeta_S(\rho + \eta_1 + \zeta_{A,1})(\rho + \eta_0 + \zeta_{A,0})(\rho + \eta_0 + \zeta_S) \\
&= (\rho + \eta_1 + \zeta_S)(\rho + \eta_0 + \zeta_S)(\rho + \eta_1 + \zeta_{A,1})\big[\underbrace{(\rho + \nu)(\zeta_{A,1} - \zeta_{A,0})}_{>0} \\
&+ \underbrace{\rho(\eta_0 - \eta_1)}_{>0} + \underbrace{\eta_0(\eta_0 - \eta_1)}_{>0} + \underbrace{(\zeta_{A,1}\eta_0 - \zeta_{A,0}\eta_1)}_{>0}\big] \\
&+ (1-p)\nu(\rho + \eta_1 + \zeta_S)(\rho + \eta_0 + \zeta_S)\big[\underbrace{\rho(\zeta_{A,1} - \zeta_{A,0})}_{>0} + \underbrace{\zeta_{A,1}\eta_0 - \zeta_{A,0}\eta_1}_{>0} \\
&+ p\zeta_S(\rho + \eta_1 + \zeta_{A,1})(\rho + \eta_0 + \zeta_{A,0})\underbrace{(\eta_0 - \eta_1)}_{>0}\big] \\
&> 0
\end{aligned}
$$

Finally, depending on the rankings between the three reservation values $\{x^*(0), x^*(1), \widehat{x}\}$, one of the cases of Proposition 1 can be realized after productivity is drawn.

I explain the main predictions of my model with a focus on Case (1) of Proposition 1. First, different optimal decision rules generate a significant measure of workers in each state as a result of different draws of match-specific productivity. Therefore, the model generates a high percentage of firms providing ESHI in an economy if the critical value $\widehat{x}$ is low enough.

Second, observed wage differentials between jobs with and without ESHI reflect productivity differentials and the theory of compensating wage differentials. On average, insured employees have higher accepted wages than uninsured employees because they are more productive. The reservation productivity to accept a job offer with ESHI, $x^*(1)$, is higher than the one to accept a job offer without it $x^*(0)$.

For searchers to match with firms providing ESHI, productivity should be large enough to compensate for the costs of getting access to ESHI. Given the productivity-enhancing effects of health insurance, the match with ESHI lasts longer and becomes a more productive match. Note that individuals who are likely to be matched to productive jobs with ESHI receive relatively higher wages. The differences in reservation productivity generate wage differentials that reflect productivity differences. On the other hand, insured workers are willing to accept a lower wage in exchange for non-wage benefits of ESHI compensating for wage losses. As a result, they receive lower net wages than uninsured employees given the same productivity x, following the theory of compensating differentials.[67]

Third, acute illnesses can be costly to both employers and employees. Monetary costs of medical care expenditures and non-monetary costs of decreased utility directly reduce employees' utility. In addition, acute illnesses directly affect the total surplus, with absenteeism corresponding to zero marginal product during the period of acute illnesses. As a result, illness costs indirectly decrease the accepted wages by shrinking the present discounted values of future surplus. All such costs generate incentives to invest in ESHI for both employers and employees.

Finally, my model captures changing ESHI provision over time by allowing workers and firms to respond to updated labor market states. Ex-ante identical workers and firms may make different ESHI provision decisions in different periods since health shocks or exogenous termination shocks affect their reservation value. New ESHI provision decisions can be made whenever a match is formed by responding to the updated optimal decision rules. The model can, therefore, explain the transitions between different job types from the workers' and firms' sides over the period.

B.6 A steady-state equilibrium

I define a steady-state equilibrium only when $m^*(x,0) < m < m^*(x,1)$ (i.e., only insured agents seek medical treatment), following the first case of Proposition 1 since other cases are straightforward specializations of these expressions.

By using the wage schedules and critical values, the equilibrium value functions of the filled jobs and

---

[67]Han and Yamaguchi (2015) builds the theoretical labor market model where job characteristics and worker productivity are heterogeneous to derive similar results, but they assume that the labor market is frictionless.

the employed can be expressed in the following way with $x^*(d)$:

$$A(d)E_H(w, d; x) = C(d)w_0$$

$$+ B(d)(\eta U_H - k\phi d)$$

$$+ \nu \left\{ \begin{array}{c} (1-p)(\rho + \eta_d + \zeta_S)(\eta_d U_{A,d}(m) - k\phi d - \kappa - m) \\ +p(\rho + \eta_d + \zeta_{A,1})(\eta_d U_S(m) - \kappa - m) \end{array} \right\}$$

$$= \alpha B(d)[x - x^*(d)] + A(d)U_H$$

And,

$$F_H(w, d; x) = \frac{(1-\alpha)B(d)[x - x^*(d)]}{A(d)}$$

where :

$$A(d) = (\rho + \eta_d + \nu)(\rho + \eta_d + \zeta_{A,c})(\rho + \eta_d + \zeta_S)$$

$$- (1-p)\nu\zeta_{A,c}(\rho + \eta_d + \zeta_S) - p\nu\zeta_S(\rho + \eta_d + \zeta_{A,c})$$

$$B(d) = (\rho + \eta_d + \zeta_{A,c})(\rho + \eta_d + \zeta_S)$$

Therefore, the following equilibrium value functions of the employment states can be rearranged:

$$E_H(w, d; x) = \alpha \frac{B(d)}{A(d)}[x - x^*(d)] + U_H$$

With the rearranged equilibrium value functions and the optimal decision rules described in Proposition 1, I can derive the following equilibrium conditions.

Definition 2. Given a set of parameters $\{\rho, b, \kappa, \alpha, \lambda, \eta_d, \delta, \phi, k, \nu, \zeta_S, \zeta_{A,c}, p, a_m\}$ and probability distribution functions $\{G(x), M(m)\}$, **a steady-state equilibrium** in an economy is the vector of value functions of unemployment $\{U_H, U_{A,0}, U_{A,1}(m), U_S(m)\}$ that solves the equilibrium equations (29), (30),

(31) and (32).

$$U_H = (\rho + \nu)^{-1}[b + \frac{\lambda \alpha B}{A}\left\{ \begin{array}{c} \int_{x^*(0)}^{\widehat{x}}[x - x^*(0)]dG(x) \\ + \int_{\widehat{x}}^{\infty}[x - x^*(1)]dG(x) \end{array} \right\} \tag{29}$$

$$+ \nu\left\{ \begin{array}{c} (1-p)\{\int_0^{m^{**}} U_{A,1}(m)dM(m) + \int_{m^{**}}^{\infty} U_{A,0}dM(m)\} \\ +p\int U_S(m)dM(m) \end{array} \right\}]$$

$$U_{A,0} = (\rho + \zeta_{A,0})^{-1}[b - \kappa + \zeta_{A,0}U_H] \tag{30}$$

$$U_{A,1}(m) = (\rho + \zeta_{A,1})^{-1}[b - \kappa - o(0;m) + \zeta_{A,1}U_H] \tag{31}$$

$$U_S(m) = (\rho + \zeta_S)^{-1}[b - \kappa - o(0;m) + \zeta_S U_H] \tag{32}$$

where:

$$A = (\rho + \eta_d + \nu)(\rho + \eta_d + \zeta_{A,c})(\rho + \eta_d + \zeta_S)$$
$$- (1-p)\nu\zeta_{A,c}(\rho + \eta_d + \zeta_S) - p\nu\zeta_S(\rho + \eta_d + \zeta_{A,d})$$
$$B = (\rho + \eta_d + \zeta_{A,c})(\rho + \eta_d + \zeta_S)$$

The equilibrium measures of workers occupy all possible illness conditions $i \in \{H, A_0, A_1, S\}$. u_i, $e_i(0)$, and $e_i(1)$ denote the measures of searchers, employees without ESHI, and employees with ESHI, respectively. I impose the steady-state conditions, which equate flows into and out of each state.[68] In the steady-state, the total measure of workers of all states should add up to 1:

$$u_i + e_i(d=0) + e_i(d=1) = 1 \tag{33}$$

The optimal decision rules govern the flows with Poisson shocks, and inflows and outflows from each state should balance in equilibrium:

$$\underbrace{\lambda[1 - G(\widehat{x})](u_H + u_{A,0}\zeta_{A,0} + u_S\zeta_S)}_{\text{Flows into } e_H(0)} = \underbrace{\eta_0 e_H(0)}_{\text{Flows out of } e_H(0)}$$

$$\underbrace{\lambda[G(\widehat{x}) - G(x^*(0))](u_H + u_{A,1}\zeta_{A,1} + u_S\zeta_S)}_{\text{Flows into } e_H(1)} = \underbrace{\eta_1 e_H(1)}_{\text{Flows out of } e_H(1)}$$

---

[68]Note that H refers to a healthy worker, A_0 refers to a moderately ill patient who does not consume medical care, A_1 refers to a moderately ill patient who consumes medical care, and S refers to a severely ill patient.

$$\underbrace{\nu p[1 - M(m^*(0))]e_H(0)}_{\text{Flows into } e_{A,0}(0)} = \underbrace{\zeta_{A,0}e_{A,0}(0)}_{\text{Flows out of } e_{A,0}(0)}$$

$$\underbrace{\nu p[1 - M(m^*(1))]e_H(1)}_{\text{Flows into } e_{A,0}(1)} = \underbrace{\zeta_{A,0}e_{A,0}(1)}_{\text{Flows out of } e_{A,0}(1)}$$

$$\underbrace{\nu p M(m^*)e_H(0)}_{\text{Flows into } e_{A,1}(0)} = \underbrace{\zeta_{A,1}e_{A,1}(0)}_{\text{Flows out of } e_{A,1}(0)}$$

$$\underbrace{\nu p M(m^*)e_H(1)}_{\text{Flows into } e_{A,1}(1)} = \underbrace{\zeta_{A,1}e_{A,1}(1)}_{\text{Flows out of } e_{A,1}(1)}$$

$$\underbrace{\nu(1 - p)e_H(0)}_{\text{Flows into } e_S(0)} = \underbrace{e_S(0)\zeta_S}_{\text{Flows out of } e_S(0)}$$

$$\underbrace{\nu(1 - p)e_H(1)}_{\text{Flows into } e_S(1)} = \underbrace{e_S(0)\zeta_S}_{\text{Flows out of } e_S(1)}$$

The hazard rate out of each state is defined as the probability of leaving the state, conditional on how long the worker has been in the state. The above eight flow equations represent a vector of eight equations with eight unknown equilibrium measures of workers u_i, $e_i(0)$, and $e_i(1)$, given the knowledge of a parametric assumption on the match-specific productivity and medical care expenditure distribution. There are no multiple solutions in the context of non-linear systems of equations. Therefore, the above flow equations can characterize unique equilibrium unemployment and employment rates of all workers.

The set of value functions uniquely identifies different reservation values that characterize the optimal behavior as a function of the exogenous parameters. I characterize steady-state balance flow conditions by equalizing flows in and out of each state. Those flow conditions determine the measure of labor market participants. I provide a detailed description of my procedure on equilibrium conditions

B.7 Welfare measures

I conduct counterfactual experiments by comparing different steady-state equilibrium values. In these experiments, I explicitly use welfare measures representing the total output and utility of workers and firms, respectively. These welfare measures consider labor market frictions, transition probabilities between states, the duration in each state, and the value of ESHI.

Total output. I compute a total flow output over the support of the realized match-specific productivity $\int_{x^*(0)}^{\widehat{x}} x dG(x) + \int_{\widehat{x}}^{\infty} x dG(x)$. Specifically, I derive the total output per worker by dividing the total production by the mass of workers that are currently in a job:

$$\frac{e_H(0)}{1 - u_H} \int_{x^*(0)}^{\widehat{x}} x dG(x) + \frac{e_H(1)}{1 - u_H} \int_{\widehat{x}}^{\infty} x dG(x)$$

Firms' welfare. I calculate firms' average instantaneous profits per worker at each match in order to measure firms' welfare:

$$\sum_{i=\{H,A_0,A_1,S\}} \left(\frac{e_i(0)}{1 - u_i} \int_{x^*(0)}^{\widehat{x}} (I_{\{i=H\}} x - w(x,0)) dG(x) + \frac{e_i(1)}{1 - u_i} \int_{\widehat{x}}^{\infty} (I_{\{i=H\}} x - w(x,1) - \phi) dG(x) \right)$$

This welfare measure is computed from the average per-worker profits times the proportion of hired workers at either job with ESHI or without ESHI in a steady state.

Workers' welfare. The overall welfare of labor market participants depends on the transition probabilities between states and the duration in each state. I use the discounted value of searching states to measure workers' welfare ρU_H. It can be interpreted as a measure of workers' welfare because it is the present discounted value of participating in the labor market. Average accepted wages at each acceptable match-specific productivity for workers are of particular interest when measuring the returns to each job type. The unemployment duration represents, in part, the welfare value of the unemployment state in equilibrium because it shows how the optimal decision rules sort searchers when the labor market converges to the new equilibrium.

B.8 Additional details on the employer mandate penalties

B.8.1 Wage equations

Once employer mandate penalties are implemented, the exogenously fixed penalty c is collected from firms without ESHI and their profits $\pi_i(x,0)$ will be:

$$\pi_i(x,0) = \mathbb{I}_{\{i=H\}} x - w(x,d) - c$$

Now, I express the subsidy $s(c)$ as a function of all model parameters; for the sake of simplicity, I focus on the dependence on penalties. This subsidy is collected from the sum of the penalties that firms without ESHI pay. The profit function of employers with ESHI can be expressed as follows:

$$\pi_i(x, 1) = \mathbb{I}_{\{i=H\}}x - w(x, d) - (1 - k)\phi + s(c)$$

Following the same Nash bargained process, the policy leads to the following wage equations:

$$
\begin{aligned}
w(x, 0) \; = \; & \alpha[x + s(p) + \nu\left\{ \begin{array}{c} (1 - p)\{\int_{\neg\Phi} F_{A,0}(w, 0; x)dM(m) + \int_{\Phi} F_{A,1}(w, 0; x)dM(m)\} \\ +pF_S(w, 0; x) \end{array} \right\}] \\
+ \; & (1 - \alpha)[(\rho + \nu)U_H \\
- \; & \nu\left\{ \begin{array}{c} (1 - p)\int \max\{E_{A,0}(w, 0; x), E_{A,1}(w, 0; x, m)\}dM(m) \\ +p\int E_S(w, 0; x, m)\}dM(m) \end{array} \right\}] \\
w(x, 1) \; = \; & \alpha[x - p - (1 - k)\phi + \nu\left\{ \begin{array}{c} (1 - p)\{\int_{\neg\Phi} F_{A,0}(w, 1; x)dM(m) + \int_{\Phi} F_{A,1}(w, 1; x)dM(m)\} \\ +pF_S(w, 1; x) \end{array} \right\}] \\
+ \; & (1 - \alpha)[(\rho + \nu)U_H + k\phi \\
- \; & \nu\left\{ \begin{array}{c} (1 - p)\int \max\{E_{A,0}(w, 1; x), E_{A,1}(w, 1; x, m)\}dM(m) \\ p\int E_S(w, 1; x, m)\}dM(m) \end{array} \right\}]
\end{aligned}
$$

B.8.2   Simulation

I compute the endogenous subsidies as a function of changes in penalties. The subsidy is distributed from all penalty collections, so I need to calculate the number of collected penalties from employers without ESHI. Once I set the initial value of subsidies corresponding to a certain level of penalty, I simulate the model to calculate the total expense $e_i(d = 1)s(p) - e_i(d = 0)c$ of implementing this policy. As total expense converges to zero, the sum of subsidies for employers with ESHI is the same as that of penalties from employers without ESHI.

B.9   Summary of the model

I summarize the value functions that consist of the theoretical model.

Table A2: SUMMARY OF THE MODEL

State	Value Fns	Shocks	Flow Utility
Unemployed workers:			
$i = H$	U_H	λ, ν	b
$i = A, c = 0$	$U_{A,0}$	$\zeta_{A,0}$	$b - \kappa$
$i = A, c = 1$	$U_{A,1}(m)$	$\zeta_{A,1}$	$b - \kappa - o(m, 0)$
$i = S$	$U_S(m)$	ζ_S	$b - \kappa - o(m, 0)$
Employed workers:			
$i = H$	$E_H(w, d; x)$	η_d, ν	$w(x, d) - k\phi d$
$i = A, c = 0$	$E_{A,0}(w, d; x)$	$\eta_d, \zeta_{A,0}$	$w(x, d) - \kappa - k\phi d$
$i = A, c = 1$	$E_{A,1}(w, d; x, m)$	$\eta_d, \zeta_{A,1}$	$w(x, d) - \kappa - k\phi d - o(m, d)$
$i = S$	$E_S(w, d; x, m)$	η_d, ζ_S	$w(x, d) - \kappa - k\phi d - o(m, d)$
Firms:			
$i = H$	$F_H(w, d; x)$	η_d, ν	$x - w(x, d)$
$i = A, c = 0$	$F_{A,0}(w, d; x)$	$\eta_d, \zeta_{A,0}$	$-w(x, d) - (1 - k)\phi$
$i = A, c = 1$	$F_{A,1}(w, d; x)$	$\eta_d, \zeta_{A,1}$	$-w(x, d) - (1 - k)\phi$
$i = S$	$F_S(w, d; x)$	η_d, ζ_S	$-w(x, d) - (1 - k)\phi$

NOTE: The table summarizes the notations of value functions and shocks in the model. The definitions of notations are explained in Section 2.

C   Numerical algorithm to solve and simulate the model

I explain the computational methods and procedures that estimate sets of parameters. Closed-form solutions for the value functions are unavailable; therefore, I use simulation methods to solve for the equilibrium at given parameter values. The environment should be converted to a discrete-time model for a numerical solution of a continuous-time model. I numerically solve the model by the following iterative procedures:

1. *Setting guesses for parameters:* I define an initial guess of sets of parameters in Θ.

2. *Discretization of productivity and medical expenditure*: To handle integration, I approximate the continuous distribution functions $G(x)$ and $M(m)$ over the grid points of x and m, taking the expected value as the weighted average with probabilities of x and m, respectively. Match-specific productivity x is discretized to 100 finite points over the support of $[0, 150]$, and its grids are equally

spaced. Medical expenditures m are spread out to 100 finite equally spaced points over the support of $[0, 10]$.[69] The probability mass functions of x and m are derived from the difference between the cumulative distribution functions at the different midpoints of the grid points of x and m.

3. *Solving individual value functions:* Given the parameters and discretized probability density functions of x and m, I can numerically solve a set of value functions by using fixed point methods at each grid point of the individual states. I make an initial guess for the set of value functions $\{U_i(m), E_i(w, d; x, m), F_i(x; d)\}$ over the grid points in the state space and jointly iterate the Bellman's equations and optimal wage equations until all the equations converge using typical tolerance criteria.

I randomly generate 2,000 labor market histories of workers for 360 months, where each labor market history refers to a sequence of transitions between the labor market and illness states for each individual. I can generate an artificial data set of labor market histories and wage paths through the following simulation process:

1. *Interpolation method:* I compute the value of the individual value functions at specific match-specific productivity, health insurance provision, and realized medical care expenditures using linear interpolation.

2. *Optimal decision rules:* I model the optimal decision rules over discretized state space can characterize by comparing all the potential value functions. The optimal decisions are updated depending on the different states of each individual:

   (a) Searching state: In the first stage, agents meet potential employers at a Poisson rate λ drawn from a negative exponential distribution. Once they meet, employers decide to provide health insurance when their values of a filled job are larger than the outside options. If a searcher receives a health transition shock, a new search process starts for the same individual but with different health conditions. Otherwise, a searcher continues to wait for a job offer in the same health state. If a searcher meets an employer and agrees on the job offer package, a match is realized, and the searcher moves to the employment state with his or her current illness state.

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[69]Although this choice is arbitrary, I experimented with a variety of finite points. My choice generates the simulated match-specific productivity and medical expenditure distributions well.

(b) Employment state: Agents may receive a termination or health shock. By the same argument as above, the duration of these shocks is drawn from negative exponential distributions with rates η and ν, respectively. If the termination shock arrives, the agent moves back to the searching state. If an agent receives a health shock, their health status changes but the match with the current employer continues.

(c) Unobserved heterogeneity: Once an individual contracts an illness, the probability of receiving severe illnesses is chosen randomly from a uniform distribution. It allows for probabilities of contracting different types of acute illnesses.

3. *Steady-state*: Individuals' value functions are updated whenever health conditions and employment states change, leading to new reservation values. As time goes on in the simulation process, the model converges to its steady state. To decide whether the model has reached a steady state, I check whether individuals' cross-sectional features do not change after they are sorted into different states. In the steady state, I construct a panel of quarters for each individual. Specifically, the panel data shows that individuals stay in the sample for three consecutive quarters given a set of parameters. The final set of simulated samples is used to generate a set of moments for use in the criteria function as defined.

Finally, I simulate a set of moments in the same way I select a set of sample moments from this simulated data. As a result, the labor market history of all individuals in the simulation maps well to a set of sample moments. I mainly use the Nelder-Mead algorithm for multidimensional unconstrained optimization problems with the help of other algorithms, such as Particle swarm optimization and pattern search.

D   Data overview

MEPS is a national representative longitudinal survey of medical care use, expenditures, sources of payment, and health insurance coverage for the US civilian non-institutionalized population since 1996. This section provides more details about sample restrictions and some variable definitions I have used in the paper.[70]

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[70]The data can be found at https://www.meps.ahrq.gov/mepsweb.

D.1 Sample restriction

In the theoretical model, individuals are identical, so I take the following steps to have a homogeneous sample. I select individuals between the ages of 30 and 55 because labor market behaviors differ by age. Younger individuals are more likely associated with general human capital accumulation decisions and employment decisions characterized by higher turnover rates. Older individuals may make different medical care decisions near retirement since they become eligible for Medicare at age 65. Also, they are more likely to leave the sample through death or retirement. I do not model the above complexities in employment, schooling, and medical care decisions, and therefore I exclude individuals in the affected age ranges. The type of health insurance is only limited to ESHI in the model. I exclude individuals with either public or non-employer-sponsored health insurance or spousal ESHI. Including other sources of health insurance makes the model richer, but the assumption that individuals are ex-ante identical can be weaker. In particular, omitting spousal insurance coverage might bias the workers' value of ESHI. I do this because it requires constructing a family search framework with a joint household labor supply.

I also exclude unhealthy individuals with bad health statuses and chronic illnesses over the life cycle. In the literature, individuals with lower health capital, approximated by bad self-reported health status and the severity of chronic illness, might make different medical care decisions. The model parsimoniously introduces a health capital production function in which health investment positively relates to healthier living. Therefore, excluding unhealthy individuals to introduce the health capital production function for homogeneous workers is necessary. Additionally, I impose the following selection criteria to make the sample homogeneous in skills. First, I restrict the sample to white males with at least a high school education. Second, I keep only individuals who are not students, are not self-employed, do not work in the public sector, do not engage in the military, and are not involved in government welfare programs (e.g., AFDC or food stamps) throughout the sample period.

Finally, I eliminate individuals who are non-respondents for key variables such as demographic features, educational information, medical care expenditures, health insurance, health status, wages, and illness conditions at any round of the survey. I also delete individuals who report variables for which inconsistencies occur (e.g., unemployed workers who have ESHI). My final estimation sample that meets the selection criteria consists of 3,807 individual-round observations, as described in A3.

Table A3: Sample Selection Information

Homogeneity Criteria	Remaining Sample Size
2012 MEPS participants	109,305
Having relevant insurance information	96,558
and aged 30-55 years	36,285
and white male	12,127
and at least a high school education	9,476
and not self-employed	8,344
and not in military or public services	7,855
and no government welfare program	7,146
and healthy and no chronic illness	6,174
and only covered by ESHI	5,139
Trimmed wages and medical care expenditures	5,088
Construct balanced panel	3,807
Final sample	3,807

D.2 Sample construction

I merged three data files in the MEPS: the full-year consolidated file, the medical condition file, and the medical event files. My model requires the following variables: demographic variables, illness conditions, insurance status, medical care consumption, and labor market outcomes. The following section serves two purposes. First, it explains how to construct variables used in estimation from the raw data since some variables are not directly taken from one data file but constructed from multiple data files. Second, it explains how to define key variables as used in the model; I strategically minimize the number of states in the model to make the theoretical model tractable for estimation.

D.2.1 Demographic variables

A set of demographic variables is observed to be time-invariant over one year. For example, I observe age (*dobyy*), industry group (*indcat*), education level (*educyear*), marital status (*marrynnx*), and race (*racex*) for each year from the full-year consolidated file. These variables are taken from the fourth round of Panel 16 and the second round of Panel 17. Also, Self-reported health status captures the amount of health capital. In particular, respondents answer the question asking how they rate their health status as

one of the five categories: (1) Excellent, (2) Very Good, (3) Good, (4) Fair, and (5) Poor.

I define labor market states and hourly wages in the following way. I define an individual as employed if they had a job at the interview date, using the employment state variable (*empst*).[71] If the person did not have a job at the interview date, did not work during the reference period, and did not have a job to which they could return, I define that person as unemployed. One caveat is that this classification might include persons who are not in the labor force. MEPS contains variables indicating the main reason a person did not work (*nwk*), so I can omit respondents who did not work because they are retired, unable to work due to illness or their disability, on maternity or paternity leave, go to school, or wanted some time off. Hourly wage (*hrwg*) is reported for respondents whose main job is not self-employment (*selfcm*). Employer-sponsored health insurance is defined as health insurance *held* at a current main job (*heldnnx*), not health insurance *offered* through a current main job (*offernnx*). Wages are either directly reported by the respondent or constructed based on their salary and the number of hours worked per week at their current main job.[72]

D.2.2 Medical treatment variables

Respondents report all medical care consumption linked to each illness condition during a reference period. When an illness condition induces individuals to seek medical treatments, the consumption dates of medical care and the total amount of medical care expenditures are recorded. Those and illness conditions variables can be linked to the full-year consolidated file through the individual IDs. Given the limit of retrospective questions, there might be measurement errors in medical treatment information. Therefore, survey administrators contact a sample of medical providers to verify the information to minimize measurement errors. This procedure improves the quality of all medical treatment variables.

I define ill individuals as those who seek medical care if they seek any of the following medical treatments: (1) outpatient visits, (2) office-based visits, (3) emergency room visits, (4) hospital inpatient stays, or (5) prescribed drugs.[73] Dental visits, other medical expenses, and home health care are excluded

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[71]To neatly define workers, I exclude respondents who did not work at the interview date but had a job to return to and were employed during the reference period.

[72]If the number of hours worked per time period was not available, a value of 40 hours per week was assumed.

[73]The variables *obnum*, *opnum*, *ipnum*, *ernum*, and *rxnum* indicate the total number of medical events that are linked to each condition recorded on the current file (i.e., office-based visits, outpatient visits, inpatient hospital stays, emergency room visits, and prescribed medicines, respectively). All these event files are derived from separate event files (HC-152G, HC-152F, HC-152H, HC-152D, HC-152E, and HC-152A). Medical events cover from January 1, 2012, to December 31, 2012.

since ESHI typically does not cover these types of medical care utilization. Outpatient visits are made when individuals visit a hospital outpatient department, and the facility does not require hospitalization overnight. Office-based visits occur in a variety of places such as a doctor's or group practice office, medical clinic, managed care plan or HMO center, neighborhood/family/community health center, surgical center, rural health clinic, company clinic, school clinic, urgent walk-in centers, VA facility, or laboratory/x-ray facilities. Emergency room visits occur when a respondent visits a hospital emergency room. The hospital inpatient stay occurs when respondents stay in a hospital, regardless of its length, and it ends within the calendar year. Prescribed drugs are ordered by authorized medical personnel through written or verbal prescriptions for a pharmacist to fill for the patient at least once. The total medical care expenditures are the sum of the twelve sources of payment categories at the annual frequency. Expenditures for medical care services consist of direct payments from individuals, private insurance, and miscellaneous other sources.[74] Note that the total charges are not used because they are too broad, and the common practice of discounting charges makes them an inaccurate measure of medical care expenditures.

D.2.3 Illness conditions variables

This section explains the procedure for classifying acute illnesses and their episodes. Before characterizing acute illness, I need to find current conditions from the MEPS Medical Conditions files. MEPS Medical Conditions files contain the "current conditions" of the respondents, which means that the individual had reported conditions that had "bothered" them in the reference period.

This information comes from three sources: first, a condition can be recorded in the Condition Enumeration (CE) section, in which respondents report any specific physical or mental health problems during the interview reference period.[75] Second, a condition can be recorded in the Medical Events (ME) section when any specific physical or mental health problems are associated with particular medical events, such as medical provider office visits (MV), emergency rooms (ER), outpatient departments

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[74]Other than out-of-pocket prices, two more medical care prices exist in the US. A list price refers to the theoretical market price of medical care, and a transaction price is the sum of the insurer's and insured individual's payments for provided care. Out-of-pocket costs, which are lower than a list and transaction price, are directly associated with an individual's behavior. Therefore, I focus on out-of-pocket expenses to capture heterogeneous medical care expenditure risks.

[75]Participants are asked to report all "health problems (experienced during the current interview period) including physical conditions, accidents, or injuries that affect any part of the body as well as mental or emotional health conditions, such as feeling sad, blue, or anxious about something."

(OP), hospital inpatient stays (HS), prescribed medicine purchases (PM) or home health providers (HH). Third, a condition can be recorded in the Disability Days (DD) section if the condition causes respondents to miss school or work or spend more than half a day in bed. Professional coders record an individual's descriptions of the illness condition as verbatim text, later coded to 5-digit ICD-9-CM codes. These illness conditions are recorded even if individuals do not receive medical care.[76] Each event is treated individually if a person has multiple events during the calendar year.

To estimate the model, I need to categorize all illness conditions into acute or chronic illnesses. Chronic conditions are defined using the specified ICD9-CM diagnosis codes and the Chronic Condition Indicator (CCI) program.[77] The CCI defines a chronic condition when it lasts more than twelve months, places limitations on self-care, independent living, and social interactions, or results in the need for ongoing intervention with medical products, services, and special equipment. One caveat is that MEPS public-use files collapse all ICD codes into 3-digit codes for confidentiality reasons. This can create difficulty using the MEPS data with the CCI that is originally based on fully specified 5-digits ICD codes. I find that 885 (86.8%) cases of 1,020 3-digits ICD-9-CM conditions have the same illness type as 5-digits ICD-9-CM so that those conditions can be fully identified. For example, 3-digits ICD code 047 (Meningitis due to enterovirus) is categorized as acute illness because all 5-digits ICD codes of Meningitis due to enterovirus are categorized as acute illness (i.e., Meningitis due to coxsackievirus 047.0, Meningitis due to echovirus 047.1, Other specified viral Meningitis 047.8, and Unspecified viral meningitis 047.9 are all labeled as acute illnesses. Regarding the remaining conditions, I label them as chronic illnesses when more than half of the 5-digits ICD codes in each category indicate chronic illness. Otherwise, it is labeled as an acute illness. As a result, 33% of 1,020 illness conditions are categorized as chronic illnesses in my sample. This ratio is similar to the case of fully specified 5-digits ICD codes, where 33% of 13,769 conditions refer to chronic illness. As described in Cronin (2019) and the CDC website, 17% of individuals aged 14 to 49 have the Herpes Simplex Virus (Genital Herpes).[78] It is classified as a chronic illness because it cannot be fully cured. However, I re-coded it as acute illness because it occasionally bothers them but does not affect their daily lives. In a similar sense, the

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[76]Since 2018, the medical conditions file contains only conditions respondents reported as linked to a medical event in the reference period. This is one reason why I use the 2012 MEPS.

[77]The Chronic Condition Indicator (CCI) is a software tool developed as a part of the Healthcare Cost and Utilization Project (HCUP), sponsored by the Agency for Healthcare Research and Quality.

[78]https://www.cdc.gov/std/herpes/STDFact-Herpes.htm

clarifications for 14 illness conditions were changed to fit the definitions of acute or chronic illnesses.[79] Acute illness conditions are considered when associated with how many days a person stays in bed for half a day or more. To follow the definition of illness conditions, I assume that the job-finding rate and production value of unhealthy workers become zero in the model.

D.3 Additional background on samples

Each panel consists of a set of five reference rounds over two calendar years. I generate yearly transitions over the year 2012 from stacked panel data sets of Panel 16 and Panel 17.

Figure A5: THE DISTRIBUTION OF INTERVIEW PERIOD LENGTHS IN THE MEPS
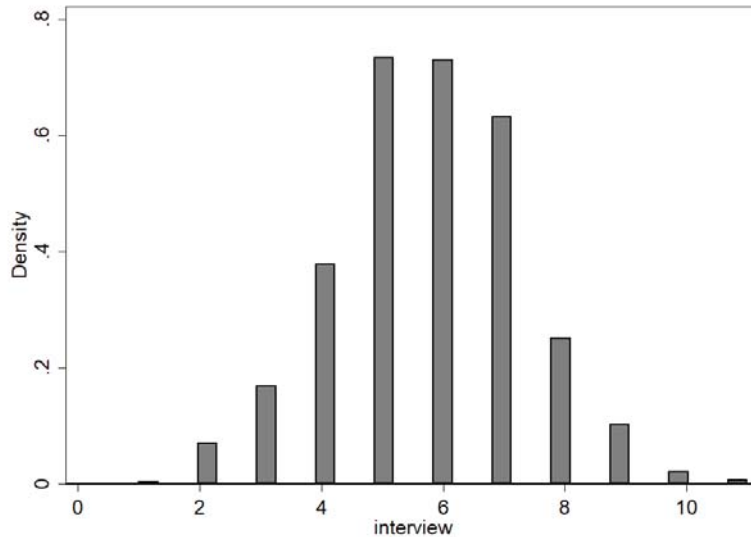
One caveat of the MEPS is that the interview rounds are not necessarily evenly spaced, so some individuals are interviewed at different frequencies. Figure A5 shows the histogram of interview months for each individual in the MEPS sample. I utilize individual-specific interview dates to match the sample moments with simulated moments. Specifically, I only include observations where the length of the interview period is between four months and eight months, and samples are from the intermediate rounds of Panel 16 and 17 for the cross-sectional moments. For example, individuals are asked about their labor

[79]If the features of chronic illnesses are very similar to those of acute illnesses, they were re-coded as such. Herpes simplex 054, acute reaction to stress 308, adjustment reaction 309, carpal tunnel 354, a disorder of the globe 360, acute cerebrovascular disease 436, chronic sinusitis 473, chronic disease of the tonsils and adenoids 474, diverticula of the intestines 562, premenstrual syndrome 625, unspecified osteomyelitis 730 are changed to acute illnesses. In a similar sense, some acute illnesses, such as unspecified cancer 239, respiratory disease 519, and past cancer V10 are re-coded to chronic illnesses.

market states and health status covering March 2012 to July 2012. In this case, the interview period length is five months, so I include this sample to capture the cross-sectional moments. Although the interview period lengths of the final cross-sectional sample vary in length, their average length is 5.9 months, which is close to the six months that the model targets. For the dynamic moments, I extract yearly transitions from interviews between 9 and 15 months long. For example, an individual was interviewed in January in round 1 and later in November in round 3 over the same calendar year. In this case, yearly transitions are extracted for this individual by comparing information in round 1 and round 3; because interview dates are spaced in 11 months. In the sample, round 1 and 3 of the panel captures around 93% of yearly transitions, although sometimes consecutive rounds (e.g., rounds 1 and 2 or round 2 and 3) covers one year.

Another caveat of the MEPS is that some variables are recorded at different frequencies, leading to timing problems.[80] I have to clarify several variables in the following procedure. First, the medical care utilization and expenditures variables are observed at the annual frequency in the data. Thanks to the information on the consumption date, I can capture whether ill individuals consume medical care each round for a specific source of illness. Medical care expenditures are the sum of all the spending on each medical care utilization over the year. Based on the assumption that ill individuals spend their medical care expenditures over illness episodes, I can measure how much they spend on medical care on an hourly basis. Second, I observe the employment, ESHI, and illness states of individuals on the interview dates. I can generate the model's composite states (e.g., workers with an illness or searchers without an illness) at each round from these variables by matching the interview dates of composite states to each round. Third, I observe the health insurance status other than ESHI at the monthly frequency. This information is required to remove individuals covered by other types of health insurance, such as Medicaid or Medicare, at any time. Finally, I use the number of missed workdays due to acute illnesses to measure the duration of illness episodes. I use this information only to identify different hazard functions outside the classic search model, so this variable has no timing issue.

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[80]Demographic variables, such as education, age, and race, are assumed to be time-invariant over the calendar year. These variables do not change in any reference periods in my sample, so I do not need to clarify those variables.

D.4 Additional background on the unobserved illness types

Ignoring this possibility might lead to biased estimates of medical treatment effects on the duration of illness. Therefore, I introduce unobserved illness types to consider other unobserved dimensions, such as the effectiveness of medical treatment and the severity of illness, and to improve the fit of the model significantly. I provide some observed characteristics of illnesses to explain why my specifications related to contraction of and recovery from unobserved types of illness are required in the model. Table A4 describes some observed characteristics of acute illnesses defined by ICD-9-CM codes, which is one dimension among many characterizations of illness types.[81] I focus on ICD-9-CM codes 8 (diseases of respiratory conditions) and 13 (diseases of the musculoskeletal system and connective tissue), which represent one of the most common acute illnesses in my sample.

The severity of acute illnesses differs in my sample. However, the duration of illnesses associated with respiratory conditions is shorter than those of illnesses associated with the musculoskeletal system and connective tissue. It means that illnesses that even are categorized as acute differ significantly in their severity because illnesses are considered severe if they have a longer duration than others. To consider this margin, I differentiate recovery rates among unobserved illness types.

Moreover, more severe acute illnesses will likely result in frequent medical treatment utilization. Patients with diseases of the musculoskeletal system and connective tissue having a longer duration seek about twice as much medical treatment as patients with respiratory conditions. It implies that unobserved illness severity that is partially captured by different duration may affect the decision to seek treatment. To consider the productive effects of medical treatment, I allow the medical treatment to affect the recovery probability by employing the model's optimization structure. Also, I assume that severe illnesses are treated with certainty to reduce the computational burden and have a better identification strategy.[82]

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[81]I observe 118,850 illness conditions in the MEPS. Among them, there are 72,116 acute illness conditions. Information on explanations of ICD-9-CM is available at https://www.cdc.gov/nchs/icd/icd9cm.

[82]I introduced medical care decisions for individuals with moderate acute illnesses and those with severe acute illnesses. Such additional recovery shocks in illness did not improve the fit of the model. More importantly, adding one more parameter weakens my identification strategies, given the lack of information on the severity of the illness. Consequently, I decided to assume that individuals with severe illnesses are treated with certainty.

Table A4: Features of Acute Illness Conditions

ICD9–CM code	1	2	3	4	5	6	7	8	9
$P(c)$	59.36	80.27	93.51	84.43	43.83	77.20	71.89	37.13	74.74
Duration	2.07	4.21	3.10	4.00	4.43	3.47	3.21	1.65	3.38
N	6,644	877	1,756	167	851	3,566	683	13,042	5,981
ICD9–CM code	10	11	12	13	14	15	16	17	V
$P(c)$	79.49	71.26	81.72	63.93	-	-	37.22	67.75	77.29
Duration	1.99	2.80	3.49	3.16	-	-	2.24	3.58	3.06
N	2,569	435	2,867	9,134	-	-	10,804	6,055	6,685

NOTE: Acute illness conditions are infectious or parasitic diseases, such as cold and flu, that appear suddenly and last at most 30 days. $P(c)$ refers to the fraction of medical care consumption associated with each acute illness. Illness duration is measured in days.

E Robustness analysis

This section of the appendix provides robustness checks for my specifications. I compare the estimated model with a new environment in which agents re-optimize in response to new settings. The first analysis concerns the paid sick leave coverages, and the second concerns the assumption of the utility function specifications.

E.1 Paid sick leave coverage

Unfortunately, MEPS does not have information on each firm's paid sick leave policies and the stock of sick leave days each absent ill worker has used. As a result, I cannot estimate the percentage of the wage replaced by sick leave coverages after depleting the stock of paid sick days. I assume that ill workers receive sick leave that replaces their wages 100%. Also, I do not model endogenous absenteeism decisions that might be affected by the insurance system for sick leave compensation. In this section, I assess the importance of different fractions of wages that an absent sick worker receives from the firm. In particular, I changed replacement rates, a portion of a worker's regular wages that can be covered by paid sick leave policies, from 60% to 100%.[83]

Panels (a) and (b) of Figure A6 report how changes in the replacement rates affect the proportion of insured workers and average hourly wages. As expected, the effect is minimal. Since ill individuals

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[83]Few papers estimate replacement rates using the 1987 National Medical Expenditure Survey (NMES). For instance, Gilleskie (1998) and Gilleskie (2010) estimate the replacement rate at 98.0% for the first absence of an illness episode.

do not negotiate with employers or get fired from the workplace due to exogenous absence, different replacement rates do not change labor market outcomes quantitatively. If sick workers change their absence behavior because of generous paid sick leaves, they will prefer to be absent more often and longer. Although it is an exciting extension, I do not consider such moral hazard effects. Panels (c) and (d) of Figure A6 report how replacement rate changes affect workers' welfare and firms' profits. As wage replacement rates increase, firms are worse off, and workers are better off. This outcome is not surprising since exogenous changes in replacement rates are a device to transfer profits from firms to ill workers during an illness period. Modeling firms' decisions to decide the replacement rates will change the results since my model does not capture the mechanism in which various sick play schemes have heterogenous effects on firms' costs.

Figure A6: ROBUSTNESS CHECKS FOR DIFFERENT VALUES OF THE REPLACEMENT RATES

(a) Fraction of Insured Employees

(b) Mean Wages

(c) Firms' Profits

(d) Workers' Welfare

NOTE: I simulate a sample of 2,000 individuals based on the estimates reported in Table 4 at different values of the replacement rates. The replacement rate refers to a portion of the hourly wage replaced by sick leave coverage for the absence of an illness episode.

E.2 Concave utility function

II assume that all individuals are risk-neutral to justify that there is no saving or borrowing in the model and interpret the disutility of contracting an illness in dollar terms. Because of the identification issue and the lack of data on subjective risk-aversion parameters, the provision of ESHI may induce moral hazard such that insured workers consume a non-efficient amount of medical care. A possible extension is to quantify the effects of moral hazard by studying a risk-averse individual's behavior over different types of medical care consumption. Although the linear utility is very common within a search-matching-

bargaining model, this specification may underpredict the value of ESHI.[84] Specifically, introducing risk-aversion parameters affect the marginal value of additional wages and ESHI, leading to different optimal decision rules associated with employment states. To test this possibility, I re-estimate the model under a concave utility function with one additional risk-aversion parameter. I assume the following Constant Absolute Risk Aversion (CARA) form that allows for risk aversion:

$$-\frac{\exp\left(-\delta w(x,d)\right)}{\delta}$$

where and $\delta > 0$ measures the degree of risk aversion. To avoid the identification issue, I fix the risk-aversion parameters at 0.05.

Table A5 reports the impact of the new utility function on two crucial moments of interest: the proportion of and dynamic transitions over labor market status. These two moments show well how the concavity of the utility function might affect labor market decisions through optimal decision rules. The proportion of covered employees increases by about 12 percentage points. Also, workers search for a job longer than the benchmark model. The mechanism is straightforward: workers now prefer ESHI to protect against future illness shocks. As a result, searchers need to search for a long period of time to receive job offers with ESHI, in which they have higher reservation values.

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[84]Some structural search papers identify the relative risk aversion coefficients using the following factors: consumption-leisure composite (Fang and Shephard, 2019), the dependence between spouses' labor market decisions (Flabbi and Mabli, 2017), and wealth effects (García-Pérez and Rendon, 2020). Their model is, however, not comparable to my model because they do not have a wage bargaining process. Having the above factors within a search-matching-bargaining model is known to be notoriously difficult (Flabbi and Moro, 2012).

Table A5: Robustness Checks for the Risk Aversion Parameter

	Baseline	Risk-averse
Proportions (%):		
Unemployed	10.20	11.24
Uninsured employees	17.93	6.47
Insured employees	71.72	82.28
Transition Probabilities (Yearly):		
Unemployment → Unemployment	37.19	51.11
Unemployment → Insured	38.69	40.44
Unemployment → Uninsured	24.12	8.44
Insured → Unemployment	5.10	10.19
Insured → Insured	93.92	84.26
Insured → Uninsured	0.98	5.56
Uninsured → Unemployment	12.82	4.89
Uninsured → Insured	2.56	0.60
Uninsured → Uninsured	84.62	94.51

NOTE: The results are computed using the constant absolute risk aversion utility function with a calibrated risk aversion parameter based on the estimates presented in Table 4.