LABOR MARKET SEARCH, ILLNESS, AND THE VALUE OF EMPLOYER-SPONSORED HEALTH INSURANCE

Pyoungsik Kim

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Approved by:
Luca Flabbi
Donna B.Gilleskie
Stanislav Rabinovich
Qing Gong
Fei Li
ABSTRACT

PYOUNGSIK KIM: Labor Market Search, Illness, and the Value of Employer-Sponsored Health Insurance
(Under the direction of Luca Flabbi)

Through the lens of a search model of the labor market with bargaining, I investigate both the employee- and employer-side mechanisms underlying the less-explored value of employer-sponsored health insurance (ESHI) in reducing costs of acute illnesses causing absenteeism. The model takes into account medical treatment and ESHI provision decisions when healthy individuals are at risk of contracting an acute illness. I evaluate the magnitude of acute illness costs, such as deteriorated productivity, increased medical expenses, fewer job opportunities, and reduced utility. The equilibrium proportion of firms providing health insurance is a function of labor market frictions, match-specific productivity, endogenous illness conditions, and the cost of insuring its workforce. I estimate the model using the Medical Expenditure Panel Survey (MEPS). I find that a relatively large portion (3%) of the value of production is lost due to acute illness over six months. Counterfactual simulations show that removing the acute illness shocks increases wages by 2% and workers’ welfare by 4%. ESHI serves to enhance productivity by directly or indirectly reducing illness costs. In my counterfactual policies, I study the impacts of mandatory health insurance and employer mandate penalties on illness costs, labor market outcomes, and welfare. Higher ESHI coverage rates can reduce illness costs and improve some labor market outcomes, and there is a redistribution of welfare from firms to workers.
My project aims to study how ex-ante identical individuals are dynamically sorted into different labor and health states as a result of their endogenous decisions and exogenous events. Sometimes people mistakenly believe that what they have achieved is only stems from their own decision. However, I would instead focus on the latter. All the achievements would not have been possible without unexpected exogenous encounters with others that they hardly control. Similarly, my economic model teaches me that what I have achieved at Chapel Hill can be possible thanks to the help of the following people rather than my sole efforts.

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1. INTRODUCTION

Even a healthy group of individuals might contract acute illnesses that appear suddenly and last for a short time at some point in their careers. Such illnesses incur observable costs (e.g., medical expenditures) and unobservable costs (e.g., deteriorated productivity, fewer job opportunities, or reduced utility). Over 700,000 US male workers were absent from work and lost 1.3% of their working hours due to illness in 2020. Illness-related absenteeism costs the average employer $1,685 per employee every year (Stewart et al., 2003). In such circumstances, employer-sponsored health insurance (hereafter, ESHI) is at the heart of the US healthcare system; it covers approximately 160 million Americans, and its annual social value is about 1.5 trillion dollars (Mulligan, 2021).

Although around 70% of illnesses are classified as acute, the economics literature has rarely quantified the relative importance of the associated costs that employees and employers face, compared to catastrophic chronic illnesses. Therefore, relationships between acute illness and labor market outcomes are rarely known.\(^1\) Furthermore, a large body of empirical literature only focuses on the values of ESHI as a device to reduce observable financial burdens.\(^2\) Considering that employees and employers demand ESHI to protect themselves from multiple sources of acute illness costs, the understanding of the values of ESHI is still insufficient. ESHI can reduce the costs of acute illnesses that are difficult to observe for patients and improve labor market outcomes and social welfare. For instance, ESHI might lower medical expenditures and promote medical treatment, thereby shortening the period of acute illnesses and reducing acute illness costs. Due to the COVID-19 pandemic, interest in acute illnesses and consequent absenteeism has grown in the

\(^1\)A few papers structurally study acute illness costs and how those affect labor market outcomes (see: Gilleskie (1998, 2010); Khwaja (2010); Cronin (2019)). However, these models do not explicitly consider the labor market decisions of firms, and therefore analysis is limited to only employees’ burdens.

\(^2\)See Currie and Madrian (1999); Gruber and Madrian (2002) for an excellent review.
U.S. health care system. Consequently, the following three questions that are not well answered so far become essential to design efficient health care policies:

1. How and by how much does ESHI insure against sources of acute illness costs?

2. What are the employee- and employer-side mechanisms through which ESHI provision and medical treatment decisions affect illness conditions, labor market outcomes, and social welfare?

3. What are the welfare effects of policy interventions to encourage the provision of ESHI?

To answer these questions, I develop and estimate a search model of the labor market with bargaining where ESHI provision and medical care consumption are endogenized in the presence of acute illnesses causing absenteeism. I am able to derive a number of implications from the model that have been rarely considered in the existing literature along three dimensions. First, I quantitatively study the relative importance of monetary and non-monetary costs of acute illnesses: deteriorated productivity, increased medical expenses, fewer job opportunities, and reduced utility. I also document the potential interactions of such illness costs with labor market outcomes and social welfare. Because of the absence of matched employer-employee data and the short nature of acute illnesses, it is often challenging to quantify the magnitude of unobserved acute illness costs, such as the loss of productivity borne by employers. Using the model and standard distributional assumptions, I separately identify unobserved acute illness costs. Second, I show that ESHI can be a productive factor in an employment match by extending job tenure, reducing medical costs, and shortening the duration of acute illness. In particular, I document the importance of ESHI in reducing unobserved acute illness costs through the productive effects of medical care on illness conditions. As a result, I complement less-explored economic principles that ESHI is productivity-enhancing, compared to other rationales such as risk pooling among a large group of relatively

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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).
healthy individuals or tax exemptions of ESHI premiums. Understanding such productivity-enhancing features of ESHI is required to answer why employers are the leading providers of health insurance coverage in the US. Finally, I study the welfare implications of the counterfactual experiments that are designed to increase the ESHI coverage rates (such as the employer mandate under the Affordable Care Act). The impacts of such policies on the welfare of employees and employers are ambiguous since they may already determine the optimal level of health insurance coverage. Therefore, I jointly study how health care policies affect acute illness costs, labor market outcomes, and social welfare. I am the first to provide such extensions to the best of my knowledge.

In the model, workers and employers search to establish a job relationship. Search frictions make job turnover costly to both sides of the market; it supports different types of jobs in equilibrium. Values of match-specific productivity and the bargaining process generate wage distributions over different insurance provisions. Optimal decision rules based on reservation values and the presence of different shocks (e.g., termination, job arrival, and health transition shocks) govern labor demand and supply, insurance provision, and medical treatment decisions endogenously. Even if all individuals are healthy, they are at risk of contracting an acute illness that temporarily prevents them from being in the labor market. Ill workers cannot contribute to production, and ill searchers cannot search for a job while illnesses directly involve a non-pecuniary disutility. They also might seek medical treatment to enjoy the benefits of investment in medical treatment. As a result, acute illnesses can lead to loss of productivity, medical care expenditures, fewer job opportunities, and lost utility. A novel feature of the model is to provide a rationale for both employees and employers to value ESHI in three ways: first, workplace providing ESHI lasts longer because insured workers are likely to be healthy, therefore it directly improves the value of the surplus in an employment match; second, it reduces the financial burdens of insured ill workers; third, it may shorten the period of acute illness by allowing treated ill individuals to recuperate quickly. The latter effects

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4Firms 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.
stem from the mechanism that ESHI decreases the marginal costs of medical care utilization; thereby, ill-insured workers are more likely to use medical care to treat the illness than uninsured ill individuals. Therefore, equilibrium ESHI provision decisions depend mainly on search frictions, match-specific productivity, endogenous illness conditions, and the cost of insuring their workforce.

I estimate the model using the Method of Simulated Moments (MSM) with individual-level data from the nationally representative Medical Expenditure Panel Survey (MEPS). In addition to labor market information, MEPS provides unique health-related information, such as insurance coverage, medical care expenditures, and illness conditions. I recover the model’s structural parameters by utilizing the search model’s equilibrium conditions with parametric assumptions. In an attempt to better fit the data, I augment the model with unobserved heterogeneity in the illness shocks parameters. I find 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 is estimated to be around one-third of those unemployed. Employees lost 3% of their working days due to acute illness, resulting in around 1,200 dollars loss of the value of production over six months. When I compare the current model with the re-solved model in which acute illnesses are not assumed, I find that acute illness decreases wages by around 2% and workers’ welfare by around 4%. Estimated unobserved types reflect the severity of illness: individuals with severe illnesses show a lower probability of recovery and higher medical care expenditures. All healthy individuals may contract an acute illness unexpectedly, but illness episodes can be shortened by more than half if they seek medical care. It shows the productivity effects of medical care utilization on illness conditions. Also, employment matches with ESHI last approximately three times longer than jobs without ESHI, increasing the overall value of the match. These empirical results support that ESHI acts as a productivity factor. ESHI and productivity complement earnings since productive individuals have a high marginal return to holding ESHI. As a result, wages of insured employees are higher than wages of uninsured employees on average. The model also does a reasonably good job of fitting the sample moments.
I use the estimated model to assess two counter-factual policy experiments by comparing the estimated model with a new environment in which agents re-optimize in response to new policies. First, I study the mandatory health insurance that forces all firms to provide health insurance in the economy. This policy lowers absenteeism rates, productivity loss rates, and medical care expenditures, thanks to the positive effect of medical care utilization. Insured workers have a longer job tenure, but fewer searchers are matched because the reservation values for accepting a job with ESHI is relatively high. Since the former has a more substantial influence, unemployment rates decrease. Firms cannot use the option of providing health insurance, so the policy decreases firms’ profits significantly. Next, I study the policy that imposes penalties on firms that do not provide ESHI. Specifically, total penalties that firms without ESHI pay get distributed to firms providing ESHI in the form of subsidies. Once equilibrium effects are taken into account, it redistributes the profits between firms, leading to changes in the ESHI coverage rate. The effect of the policy on the ESHI rate is found to be monotonic. Thus, it decreases overall illness costs and increases workers’ welfare. Also, similar to the mandatory health insurance policy, it has a similar effect on the length of employment and unemployment. The distortions of firms’ decisions also decrease firms’ profits at different rates; however, the reduction amount is less than in the case of mandatory health insurance. These policy experiments suggest that ESHI can increase workers’ welfare since it reduces individuals’ out-of-pocket medical care expenditures, encourages more frequent medical care utilization, and shortens episodes of acute illness. Overall, these policy results imply that it is essential to consider both the ESHI rate and other equilibrium effects to evaluate healthcare policies.

**Related literature.** The current paper makes several contributions to distinct areas of economic literature. First and foremost, 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. My model tries to bridge the structural medical treatment choice models and the job search models. In regards to the interaction between health insurance and health problems, 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
In particular, 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). My paper resembles work in this literature in which endogenized health outcomes depend on medical treatment choices or labor market outcomes. Though insightful, this literature is limited by its reliance on a competitive labor market where ESHI decision is exogenously given. Relative to these papers, ESHI coverage is jointly determined in equilibrium by labor demand and supply decisions and joint ESHI provision decisions in my model. Also, I introduce search frictions to guarantee the presence of different types of jobs in equilibrium since these make it costly for both employees and employers to change health insurance status frequently.

A growing structural search literature states that firms determine health insurance provision, and workers sort themselves into different jobs by adding equilibrium elements to the search framework. Dey and Flinn (2005) examine whether the ESHI system generates inefficiencies in mobility decisions using a search-matching-bargaining model. Using the equilibrium search framework of Burdett and Mortensen (1998), Aizawa and Fang (2020) additionally consider firm size, health status, and medical care expenditure to incorporate the main features of the US health insurance market. This framework is also extended by Aizawa (2019) to analyze the optimal social insurance program and by Fang and Shephard (2019) to incorporate household decisions.

A substantial difference between my model and the existing literature is that I explicitly study

5 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 treatment decisions to capture the positive relationship between medical treatment and health outcomes.

6 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.
acute illness conditions causing absenteeism and the consequent observed and non-observed costs that are relevant but overlooked or treated as latent variables in this literature. Considering that individuals with the same underlying health capital stock might face different health shocks, not incorporating specific illness conditions may bias the value of ESHI. Moreover, most of the existing literature does not explicitly allow individuals to respond to unexpected health shocks by making medical treatment decisions. Medical care consumption that improves workers’ health conditions generates more utility for individuals and more productive time at work for employers. Therefore, the understanding of the productivity-enhancing feature of ESHI is limited without considering medical care utilization decisions and subsequent health outcomes.

Second, this article relates to structural works estimating search models where workers have heterogeneous preferences for non-wage benefits. 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), health insurance provision (Dey and Flinn, 2008), and non-wage amenities of a job offer (Sullivan and To, 2014; Hall and Mueller, 2018). Previous studies estimate one aggregate parameter of the marginal willingness to pay for exogenous non-wage benefits. I contribute to this body of research by building a readily available model where workers and firms endogenously determine discrete non-wage job packages. In particular, I capture multiple channels through which health insurance affects workers.

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7One 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 and incorporate medical care utilization decisions.

8Only Aizawa (2019) introduces medical care utilization decisions, although the model does not explicitly include health problems and subsequent costs.

9Other 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.

10Other relevant equilibrium frameworks study decisions of firms to locate in the formal or informal sectors (Meghir et al., 2015; Bobba et al., 2021) or provide ESHI or not (Aizawa, 2019; Fang and Shephard, 2019; Aizawa and Fu, 2020; Aizawa and Fang, 2020). Only a few papers specify workers’ and firms’ joint job
employers, and social welfare through employee- and employer-side mechanisms. Understanding the relative contributions of both mechanisms and their relationships with labor market outcomes sheds light on inferring the true value of job amenities.

Third, this paper complements the relatively small literature quantifying the unobserved costs of illness-related absenteeism to firms in the workplace (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. In this paper, I suggest an identification strategy to quantify the effects of acute illness by structurally recovering unobserved illness-related productivity loss that has rarely been studied. With a quantified value of absence days, I assess the benefits of health insurance policies that reduce the number of absent days.

Outline. The rest of the paper proceeds as follows. Section 2 constructs a search-matching-bargaining model and 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.

amenity decisions, but they focus on estimates of workers’ marginal willingness to pay (Dey and Flinn, 2005; Flabbi and Moro, 2012).
2. THE MODEL

2.1 Environment

The stationary model is constructed for infinitely lived workers and firms in continuous time.\textsuperscript{11} Workers have one of the health conditions $i \in \{H, A, S\}$: $H$ if individuals are healthy, $A$ if they have a moderate acute illness, and $S$ if they have a severe acute illness. I introduce unobserved differences in illness to distinguish between illnesses that are differently affected by medical treatment and recuperation.\textsuperscript{12} I only consider acute illnesses that are severe enough to cause an individual to be absent from the labor market during acute illness. Health conditions are perfectly observable and verifiable by all the agents in the economy.\textsuperscript{13} Severe acute illness is indicated with a probability $p$ assigned by nature. 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 stock. Firms make health insurance decisions $d \in \{0, 1\}$, taking the value of 1 for firms providing ESHI and 0 for firms that do not. I do not allow the uninsured to be insured through other sources, such as savings, private health insurance, spousal insurance coverage, national health insurance programs, or charity care (or uncompensated care). All agents discount the future at the common rate $\rho$, 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, and a firm can fill a job vacancy or not. A healthy unemployed searcher meets an employer at the Poisson rate $\lambda$, but people with an illness rest at

\textsuperscript{11} In the empirical analysis, one firm refers to one job or employer, so the terminologies jobs, employers, and firms are used interchangeably.

\textsuperscript{12} Following Gilleskie (1998), Khwaja (2010), and Cronin (2019), I specify that illness types distinguish unobserved acute illness conditions such as severity, duration, and discomfort that the specific ICD-9 code cannot capture. Details are explained in Section 4.

\textsuperscript{13} See Gilleskie (1998), Arcidiacono et al. (2007), Khwaja (2010), and Darden (2017) for examples of the rational expectations assumption.
home and do not engage in the job search process. I exclude the possibility of receiving job offers while working as an employee. 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 $G(x)$. Upon observing the productivity, firms and employees engage in a Nash bargaining process to determine wages and ESHI provisions by sharing the total surplus with workers. If a searcher rejects this offer, she searches for a potential employer again. At any moment, a formed match can be exogenously terminated at an insurance-specific termination rate $\eta_d$. I allow the worker-firm pair to change the destruction rate through the purchase of health insurance. Specifically, ESHI provision reduces the rate of an exogenous termination from a match (i.e., $\eta_0 > \eta_1$). This specification fits the empirical results, as summarized in Section 3, and captures the health-enhancing feature of ESHI. The magnitude of a particular Poisson shock $\eta_0$ is written here as being greater than that of others $\eta_1$, but they are allowed to be freely estimated.

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14 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. Even though they do not search for a job during a short period of illness, they are still in the labor force because I do not consider persons who are neither employed nor unemployed are not in the labor force. Details are explained in Appendix D.

15 Ruling out on-the-job search may eliminate an important source of observed wage growth (see: Topel and Ward (2006); Cahuc et al. (2006); Yamaguchi (2010); Liu (2019)). However, identifying job-to-job transitions requires employer-employee matched data, which is unavailable. My data source, MEPS, does not collect information on continuous labor market histories that a unique job ID defines every worker’s job through the sample period. Therefore, it is challenging to model job-to-job transitions and job-specific wage growth on the job.

16 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.

17 I assume that health insurance improves unobserved general health conditions through frequent medical services. Healthy individuals maintain a better relationship with the employer than others and show good job performance. Therefore, ESHI results in lower destruction rates of jobs at which the worker becomes incapable of continuing to work. My assumption of the effect of ESHI on health is consistent with a thorough survey of empirical research examining the relationship between health insurance coverage and health outcomes (Levy and Meltzer, 2008). Also, this assumption is supported by the 2006 Massachusetts health care reform (Zapata, 2014) and the 2008 Oregon randomized health insurance experiment (Amy Finkelstein, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P. Newhouse, Heidi Allen and Group, 2012).
Poisson recovery shocks capture the effects of medical treatment on potential biological health transitions in a reduced form fashion. A healthy individual faces a probability of getting a moderate or severe acute illness at the Poisson rate $\nu$. If individuals contract a moderate illness, their recovery rate is $\zeta_{A,c}$ which depends on medical treatment decisions $c \in \{0, 1\}$, with 1 indicating the utilization of medical treatment. Seeking medical treatment reduces the period of illness but incurs medical costs $m \sim M(m)$ (i.e., $\zeta_{A,1} > \zeta_{A,0}$). 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:

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

(2.1)

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 the reduced utility associated with being ill $\kappa$ and the possibility of paying out-of-pocket medical expenses $o(d; cm)$. The out-of-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 function and the distribution of medical care expenditures. I do not consider preventive treatment, so healthy workers have no medical expenses.\(^{18}\) Employees receive

\(^{18}\)ESHI may improve health conditions of workers through preventive care, but limited evidence supports these claims, as mentioned in Jones et al. (2019); Song and Baicker (2019); Baicker et al. (2010).
the bargained wages $w(d; x)$ and pay their share $k$ of health insurance premiums $\phi$ if they work at a firm that offers health insurance. The remaining share of the premium $1 - k$ is covered by the employer, so an insurance holder pays only $k\phi$. Health insurance enters an individual’s utility through two channels: exogenous insurance premiums and protection against the financial loss associated with uncertain illnesses, medical care consumption, and medical prices.

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

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

(2.2)

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. This loss of productivity becomes another cost of acute illness. When an employee reverts to a healthy state, she becomes productive again. Firms pay labor costs $w(x, d)$ to their worker and, if they provide ESHI, they pay a portion of the insurance premium $(1 - k)\phi$. 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).

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19 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.

20 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.

21 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.

22 I assume workers to earn paid sick days to recover from a short-term illness because the average missed workdays are only around three days, and most workers are full-time workers. Whenever paid sick leaves are not available, it might cover a portion of a worker’s regular salary, but this is beyond the scope of my paper.
2.2 Medical treatment decision

Whether agents have a job or not, they are in danger of contracting an acute illness. If their acute illness condition is severe, medical treatment is necessary, and if the condition is moderate, medical treatment is optional. 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 $U_{A,c}(m)$ and the value of being employed and having a moderate acute illness by $E_{A,c}(w, d; x, m)$. Unemployed or employed individuals with a moderate acute illness make the medical treatment decisions by comparing the values of seeking medical treatment or not. The endogenous medical treatment status $c$ is determined as:

$$c \equiv c(w, d; x, m) = \begin{cases} 
1 & \text{if } E_{A,1}(w, d; x, m) \geq E_{A,0}(w, d; x) \\
0 & \text{otherwise}
\end{cases} \quad (2.3)$$

$$c = \begin{cases} 
1 & \text{if } U_{A,1}(m) \geq U_{A,0} \\
0 & \text{otherwise}
\end{cases} \quad (2.4)$$

I simplify notation by dropping the dependence of $c$ on $(w, d; x, m)$ 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
The firm’s value of the current employment contract is expressed by the sum of the flow profit and corresponding values:

\[
F_H(w, d; x) = (\rho + \eta_d + \nu)^{-1}\left[x - w(x, d) - (1 - k)\phi d\right] + \nu\left\{(1 - p)\left\{(1 - c)F_{A,0}(w, d; x) + cF_{A,1}(w, d; x)\right\} + pF_S(w, d; x)\right\}
\]

\[
F_{A,c}(w, d; x) = (\rho + \eta_d + \zeta_{A,c})^{-1}\left[-w(x, d) - (1 - k)\phi d + \zeta_{A,c}\right] F_H(w, d; x)
\]

\[
F_S(w, d; x) = (\rho + \eta_d + \zeta_S)^{-1}\left[-w(x, d) - (1 - k)\phi d + \zeta_S\right] F_H(w, d; x)
\]

Once a vacancy is filled, firms receive the flow profits defined in the equation (2.2) while being subject to the health shock \(\nu\), the recovery shocks \(\{\zeta_{A,c}, \zeta_S\}\), or the termination shock \(\eta_d\). After the match is realized, the health shock \(\nu\) results in the value function of firms matched with the ill worker, and the recovery shocks \(\{\zeta_{A,c}, \zeta_S\}\) result in the value functions of firms matched with the healthy worker. If the employee contracts an acute illness, they are absent from work, so their hourly productivity becomes zero over the duration of 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.

Both the employer and the worker simultaneously make health insurance provision choices based on the value of the match-specific productivity \(x\). I define the support for match-specific productivity that makes workers and firms choose the provision of health insurance as \(\Delta\). Formally, the decision to initiate an employment contract with ESHI is equivalent to the following inequalities:

---

23I 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).

24Cooperative 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.
\[
\Delta \equiv \{ x : E_H(w, 1; x) \geq E_H(w, 0; x) \} = \{ x : F_H(w, 1; x) \geq F_H(w, 0; x) \}
\]

(2.8)

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

### 2.3.2 Workers

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

\[
U_H = (\rho + \nu + \lambda)^{-1} \left[ b + \lambda \left\{ \int_{-\Delta} \max\{E_H(0; x), U_H\} dG(x) \right\} + \int_{\Delta} \max\{E_H(1; x), U_H\} dG(x) \right] + \nu \left\{ (1 - p) \int \max\{U_{A,0}, U_{A,1}(m)\} dM(m) + p \int U_S(m) dM(m) \right\}
\]

(2.9)

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

(2.10)

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

(2.11)

While the searcher receives the flow utility defined in equation (2.1), they might receive three possible Poisson shocks: the health shock \( \nu \), the recovery shocks \( \{\zeta_{A,c}, \zeta_S\} \), or the job arrival shock \( \lambda \). The first term refers to the option value of changing the employment status when meeting an employer at the rate of \( \lambda \). The firm and the worker decide the wage and health insurance status upon a meeting. Given the negotiated wage and health insurance outcomes, 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 \( 1 - p \) or a severe acute illness with a probability \( p \) when they receive the health shock. 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. Ill searchers cannot engage in job search activities because
acute illnesses cause absenteeism. Inability to search for a job might lead to fewer job opportunities. Recovery shocks $\{\zeta_{A,c}, \zeta_{S}\}$ send the ill searchers back to healthy conditions, and they enter the searching states again.

For the employee without or with an acute illness, the value of employment at a current match $x$ and wage and health insurance provision status $(w, d)$ is described by:

$$
E_H(w, d; x) = (\rho + \eta_d + \nu)^{-1}[w(x, d) - k\phi d] + \eta_d U_H + \nu \left\{ (1 - p) \max\{E_{A,0}(w, d; x), E_{A,1}(w, d; x, m)\} dM(m) + p \int E_S(w, d; x, m) dM(m) \right\}
$$

(2.12)

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

(2.13)

$$
E_S(w, d; x, m) = (\rho + \eta_d + \zeta_{S})^{-1}[w(x, d) - \kappa - k\phi d - o(d; m)] + \eta_d U_S(m) + \zeta_{S} E_H(w, d; x)
$$

(2.14)

An employee is subject to the same Poisson shocks $\{\nu, \zeta_{A,c}, \zeta_{S}, \eta_d\}$ as firms with filled positions. All workers receive wages even though they are ill, although they do not contribute to the total output. Health transition shocks change workers’ health conditions in the same way as the searcher. If employees receive the destruction shock $\eta_d$, 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{2.15}

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 \(\alpha\) 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 \(d:\)

\[\tilde{w}(x, d) = \arg \max_{w|d} S(w, d; x)\] \tag{2.16}

The equilibrium wage schedules of the jobs with or without ESHI \(\tilde{w}(x, d)\) are uniquely determined from the optimum equations (2.16). Analytical solutions to the maximization can be complex, so they are reported in Appendix B. There are important features of the wage schedules: first, wages are a convex combination of the match-specific productivity \(x\) and the worker’s outside option. The higher a worker’s bargaining coefficient \(\alpha\), the more weight that is given to the match productivity \(x\). Second, insured employees receive a lower net wage than uninsured employees with the same productivity because ESHI compensates for wages with higher non-wage benefits. Finally, the benefits and costs of ESHI and illness costs are partially transferred to wages. For instance, the contribution rate of ESHI premium and out-of-pocket costs shift wage schedules. More importantly, the wage is indirectly affected by the possibility of contracting an illness because value functions include discounted future variations of health conditions. I preclude the possibility that firms can use observable health conditions to negotiate with workers. This assumption is justified because illness-specific wage negotiations are not allowed by law, including the Equal Pay Act prohibiting discrimination or wage negotiation based on individuals’ health conditions. Wages are increasing in productivity \(x\), with the others held constant.

For the proof, see Appendix B. Under Lemma 1, the higher productivity drawn, the higher wage densities are generated. This property is a source of different accepted wage densities conditional on ESHI. By inserting optimal wages given the productivity, health insurance, and workers’ outside...
options into the total surplus, I can derive the maximum value of the Nash bargaining problem given health insurance status $S(\tilde{w}(x, d), d; x)$. Both firm and worker arrive at the same optimal decision thanks to the no disagreement result implied by Nash bargaining. As a result, they agree on the following optimal contract to achieve the maximum output:

$$\begin{align*}
\{w^*, d^*\}(x) = \begin{cases} 
\{\tilde{w}(x, 0), 0\} & \iff S(\tilde{w}(x, 1), 1; x) < S(\tilde{w}(x, 0), 0; x) \\
\{\tilde{w}(x, 1), 1\} & \iff S(\tilde{w}(x, 1), 1; x) \geq S(\tilde{w}(x, 0), 0; x)
\end{cases}
\end{align*}$$

## 2.4 Optimal decision rules and a steady-state equilibrium

### 2.4.1 Optimal decision rules

Ex-ante identical individuals and firms may end up in different states by the 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. However, when conditioning on health insurance provision, the optimal decision rule becomes similar to a reservation value property. 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. Individuals’ value functions are updated whenever health and employment status changes, leading to the new reservation values.

**Medical treatment decisions.** Medical care choices affect the extent of illness costs. A moderately ill individual compares the costs and benefits of seeking medical treatment. More specifically, medical care utilization might reduce the length of illness 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 status, 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 values $m^{**}$ and $m^*(x, d)$ that make the agent indifferent between $c = 1$ and $c = 0$: 
Following a reservation value property, medical treatment 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., \( c = 0 \)). Figure 2.1 contains graphs of two critical values of medical care expenditures under the value of unemployment and employment, holding other values fixed except for medical care expenditures. It is clear that when \( m \) is low enough, the values of medical treatment utilization are larger than the values of no medical care utilization.

Figure 2.1: 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.

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.\footnote{This theoretical result is also consistent with the empirical results of other literature (see: Manning et al. (1987); Dafny and Gruber (2005); Dey and Flinn (2005); Finkelstein and McKnight (2008); Cronin (2019)).} 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 $\bar{x}$ characterizes such decisions:

$$\bar{x} : S(\bar{w}(\bar{x}, 1), 1; \bar{x}) = S(\bar{w}(\bar{x}, 0), 0; \bar{x})$$

(2.19)

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

$$\bar{x} : \{x : E_H(\bar{w}(\bar{x}, 1), 1; \bar{x}) = E_H(\bar{w}(\bar{x}, 0), 0; \bar{x})\} \iff \{x : F_H(\bar{w}(\bar{x}, 1), 1; \bar{x}) = F_H(\bar{w}(\bar{x}, 0), 0; \bar{x})\}$$

(2.20)

For simplicity, I study ESHI decisions from the firms’ side. If the match value is greater than the cut-off value $\bar{x}$, a firm provides health insurance ($d = 1$); otherwise, a firm does not ($d = 0$).\footnote{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. In this sense, both take-up and ESHI decisions are modeled from the worker’s side as well.}

Existence and uniqueness of $\bar{x}$ is guaranteed from the different elasticities of the value functions of different types of filled jobs with respect to $x$: $F_H(\bar{w}(x, 1), 1; x)$ is increasing in $x$ faster than $F_H(\bar{w}(x, 0), 0; x)$ since there are complementarities between ESHI and the productivity of the match. 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 medical care expenditures. Insured moderately ill workers, who are likely to become healthy, contribute more to the total surplus as productivity increases.

**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 functions 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:

\[
x^*(d) : \{ x : E_H(\bar{w}(x^*(d), d), d; x^*(d)) = U_H \} \iff \{ x : F_H(\bar{w}(x^*(d), d), d; x^*(d), d) = 0 \}
\]

(2.21)

A match is realized for any $x \geq x^*(d)$ because both the worker and the employer know the value of the match and the bargaining process. Health insurance has two opposite effects on $x^*(d)$: it increases the reservation value because employees and employers need to share insurance premiums $\phi$, 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.
Proposition 1 Given a set of vectors \( \{\rho, b, \kappa, \lambda, \eta_d, \phi, k, \nu, \zeta_S, \zeta_A, p, a_m\} \) and probability distribution functions \( \{G(x), M(m)\} \), there exists a unique set of reservation productivity values \( \{\hat{x}, x^*(0), x^*(1)\} \) that determines the following optimal decisions rules:

(Case 1) \( x^*(0) < x^*(1) < \hat{x} \)

\[
\begin{align*}
& x < x^*(0) \quad \iff \quad \text{reject the match} \\
& x^*(0) < x < \hat{x} \quad \iff \quad \text{accept the match without ESHI} \quad d = 0 \\
& \hat{x} \leq x \quad \iff \quad \text{accept the match with ESHI} \quad d = 1 
\end{align*}
\]

(Case 2) \( \hat{x} < x^*(1) < x^*(0) \)

\[
\begin{align*}
& x < x^*(1) \quad \iff \quad \text{reject the match} \\
& x^*(1) \leq x \quad \iff \quad \text{accept the match with ESHI} \quad d = 1 
\end{align*}
\]

The proof and the predicted critical values are provided in Appendix B. The optimal decision rule is characterized by the support of match-specific productivity, which is divided into three regions in relation to the reservation values \( \{\hat{x}, x^*(0), x^*(1)\} \). In the first case, 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 \( \hat{x} \), or offers ESHI if \( x \) is higher than \( \hat{x} \). The second case 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 2.2 draws the cutoff values defined in proposition 2 as a function of the match-specific productivity \( x \), using two present discounted values of filled jobs that either provide ESHI or not.

The theoretical model derives some important empirical features characterizing the US labor market. First, ESHI is the primary source of insurance coverage for workers. Different optimal decision rules generate a significant measure of workers in each state as a result of drawn values of
Figure 2.2: DIFFERENT EQUILIBRIUM OUTCOMES DEPENDING ON THE CRITICAL MATCH VALUES

NOTE: The figures report the critical values of match-specific productivity \( \{x^*(0), x^*(1), \hat{x}\} \). \( x^*(d) \) is the cut-off value for a firm to hire an employee, and \( \hat{x} \) 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 \( x^*(0) < x^*(1) < \hat{x} \) and case 2 is based on the inequality \( \hat{x} < x^*(1) < x^*(0) \). It generates different equilibrium outcomes that are defined in Proposition 2. For the definitions of \( F(1) \) and \( F(0) \), see section 2.

match-specific productivity. As seen in the first case of Proposition 2, if the critical value \( \hat{x} \) is low enough, the model generates a high percentage of firms providing ESHI in an economy.

Second, observed wage differentials between two types of jobs 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. As seen in the second case of Proposition 2, 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. In Lemma 1, individuals who are likely to be matched to productive jobs with ESHI receive relatively higher wages on average. As a result, the differences in reservation productivity generate wage differentials that reflect productivity differences. On
the other hand, given the same productivity $x$, insured employees receive lower net wages than uninsured employees. Following the theory of compensating differentials, a firm and a worker agree on the wage that reflects the net value of ESHI conditional on the same productivity. For example, workers are willing to accept a lower wage in exchange for non-wage benefits of ESHI compensating for wage losses.\footnote{Han and Yamaguchi (2015) build 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.}

Third, the model captures the channel that acute illnesses can be costly to both employers and employees. When individuals contract a severe illness, they seek medical treatment and pay medical care expenditures. Individuals with a moderate acute illness choose to consume medical services to increase the hazard rate out of illness episodes. Such medical care expenditures also indirectly decrease the accepted wages by shrinking the present discounted values of the workers’ future surplus. Also, acute illnesses directly affect the worker’s productivity, with absenteeism corresponding to the zero marginal product in the period of acute illnesses.

Finally, my model captures the channel that workers and firms respond to updated labor market states by changing ESHI provisions. It explains the transitions between different job types from the workers’ and firms’ sides over the period. Ex-ante identical workers and firms need to optimize available insurance options in a different period since health shocks or the exogenous termination shock change their reservation value. Employment contracts do not only belong to segmented labor markets where barriers restrict access to two types of jobs. Therefore, whenever a new match is formed, they can make new ESHI provision decisions by responding to the firm’s updated optimal decision rules.

### 2.4.2 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 2 since other cases are straightforward specializations of these expressions. Given a set of parameters $\{\rho, b, \kappa, \alpha, \lambda, \eta_d, \phi, k, \nu, \zeta_S, \zeta_{A,c}, p, a_m\}$
and probability distribution functions \( \{G(x), M(m)\} \), a \textbf{steady-state equilibrium} in an economy is a vector of value functions of unemployment \( \{U_H, U_{A,0}(m), U_{A,1}(m), U_S(m)\} \) that solves the equilibrium equations (2.22), (2.23), (2.24) and (2.25).

\[
(\rho + \nu)U_H = \left[ b + \frac{\lambda \alpha B}{A} \left\{ \int_{x^*(0)}^{\bar{x}} [x - x^*(0)] dG(x) \right. \right. \\
\left. \left. + \int_{\bar{x}}^{\infty} [x - x^*(1)] dG(x) \right\} \right] \\
+ \nu \left\{ (1 - p) \left\{ U_{A,0} \int_{m^*}^{\infty} U_{A,1}(m) dM(m) \right\} \right. \\
\left. + p \int U_S(m) dM(m) \right\} \\
U_{A,0}(m) = (\rho + \zeta_{A,0})^{-1} [b - \kappa + \zeta_{A,0} U_H] \\
U_{A,1}(m) = (\rho + \zeta_{A,1})^{-1} [b - \kappa - o(0; m) + \zeta_{A,1} U_H] \\
U_S(m) = (\rho + \zeta_S)^{-1} [b - \kappa - o(0; m) + \zeta_S U_H]
\]

where:

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

A set of value functions uniquely identifies different reservation values that characterize the optimal behavior. I also characterize steady-state balance flow conditions using the Poisson process, parametric assumptions, and stationarity of the infinite horizon model. As described in Section 4, equilibrium and flow conditions are exploited for identification purposes. Details on derivations of such conditions are explained in Appendix B.

\subsection*{2.5 Discussion of the model}

The theoretical model endogenizes a richer set of employers’ and employees’ decisions compared to the existing literature and describes important features of the US labor market. Nevertheless, I made some assumptions in order to estimate the structural parameters of the optimization problem and evaluate counter-factual policies.
The first limitation of the framework is the lack of firm-size effects, although the provision of health insurance can be correlated with firm size in data. This limitation is common to all search-matching-bargaining models, and ex-post heterogeneous match-specific productivity parsimoniously captures size-dependent wage densities since firm size and productivity are positively correlated (Bobba et al., 2018, 2020). Similarly, it captures an additional source of heterogeneity, resulting from employers’ specific features, with exogenous termination rates in a reduced form fashion. An extension in this direction is the equilibrium search model based on Burdett and Mortensen (1998) that incorporates 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, 2000), one caveat of this model is that predicting reasonable accepted wage distribution requires posted wages to be a function of heterogeneous permanent firm productivity. As a result, in wage posting models, wages and ESHI contracts do not depend upon the productivity loss driven by the arrival of an acute illness at the workplace. These features are not appropriate for studying how short-term acute illness affects labor market outcomes, particularly the distribution of wages. Also, in the Burdett and Mortensen model, the estimated distribution of firm productivity has an exceedingly long right tail, which is hardly observed in data. This limitation will make identifying productivity distribution harder.

Second, I do not incorporate many 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. In terms of the assumption of no saving or borrowing, it is known that the amount of saved wealth held by the uninsured and by those insured through non-group health insurance is small. Also, modeling consumption bundles with non-linear budget constraints creates the difficulty of establishing global concavity of the value functions in the job search model. Uncompensated care and Medicaid arise when people cannot

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28 Matched employer-employee data can make progress to recover offered wage densities, but it is not available in the US (Postel-Vinay and Robin, 2002).

29 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.
afford medical care expenditures, but I have excluded relatively poor people from the sample. Finally, ESHI can be treated as a public good at the household level since employees with ESHI might have the option to cover spouses. A worker who cannot access a spouse’s health insurance coverage puts a much higher value on health insurance than others. 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 only one year. Household members are less likely to jointly change their labor supply, medical treatment, and health insurance provision, responding to such events.

Third, I do not capture the dynamics decisions associated with absenteeism. Even if the duration of acute illness is short, the correlation between absence decision and the probability of recovery is relevant, leading to biases of medical treatment effect. Gilleskie (1998, 2010) and Hirsch et al. (2017) show that the determination of illness-related absences is affected by changes in the extensive margin of medical treatment through improvements in access to health insurance. Although it is an interesting extension, modeling this decision in an equilibrium model increases the size of the problem exponentially. This extension would also require data on the entire history of the accumulated illness-related absences, which is not possible. In particular, MEPS does not provide daily illness behavior and exact dates of absences.

Fourth, there is a possibility that the moral hazard associated with health insurance leads to a non-efficient amount of medical care consumption. A possible way forward is to model risk-aversion parameters with well-defined consumption bundles and information on health insurance contracts. Unfortunately, there is little prior information on the initial health risks, so that introducing the concave utility function makes the identification strategies on the link between acute illness, productivity, and medical care utilization weaker. For similar reasons, other search-matching-bargaining frameworks also have the same parsimonious but tractable utility function with wages and job amenities entering separably without risk-aversion parameters (e.g., Dey and Flinn (2005); 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.
Flabbi and Moro (2012)). 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 decisions about care utilization. Therefore, the moral hazard issue is relatively not relevant in my model.

Fifth, due to the lack of firm-side or health insurance data and tractability of the model, I decided not to consider the intensive margins of medical treatment, illness conditions, and health insurance. Specifically, I ignore alternative forms of medical care (e.g., preventive or 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 or maximum deductible amounts), and health plan types (e.g., self-insured or fully insured plans).\textsuperscript{31} Modeling more states would lead to an increasing and unmanageable number of states to estimate the model. 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). Incorporating all possible alternatives into the model is beyond the scope of this paper, so I only consider the extensive margins of treatment, acute illness, and health insurance.

\textsuperscript{31}Different group health insurance plans, such as self-insured or fully 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 only pay a fixed premium to an insurance carrier if their plan is a fully-insured plan. According to the Employee Benefit Research Institute (EBRI), around 33\% of the total participants in private employment-based plans are insured through self-insured group health plans. However, I do model such different health insurance plans because of the lack of insurance data.
3. DATA

3.1 Description of the MEPS

The primary data source 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. MEPS has selected a new panel of sample households every year since 1996, drawn randomly from the previous year’s National Health Interview Survey sample. The survey interviews the same individual five times over the two full calendar years. I use the full-year consolidated data files from the Household Component (HC) section, which collects detailed information on each individual’s demographic characteristics, health status, medical care utilization, and health insurance coverage together with labor market outcome variables such as wages, working hours, and employment status. I also use the Medical Conditions (MC) files, which provide detailed information on illness conditions at the event level for each survey round. Each illness condition can be linked to medical care utilization data, including dates of the medical care use and sources of medical care expenditures.

MEPS data is well-suited for the analysis. First, it has detailed illness conditions accompanied by medical treatment use and disability days. Having accurate illness information is required to capture the effects of acute illness on the primitive labor market parameters and to understand the costs of health shocks over the limited sample period. Illness conditions are initially self-reported when health problems have bothered an individual over the survey period. Participants’ medical conditions are finally recorded as the verbatim text is coded to 3-digit ICD-9-CM codes by professional coders after verifying some of the previously obtained information. The ICD-9-CM codes in the Medical Conditions files include either conditions linked to medical events or conditions that bother the respondent during the reference period. Therefore, illness condition is collected...
even the individual sought no medical treatment, making it possible to minimize the censoring problem. Second, it 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. This information in other data sets, often documented at an annual frequency, understates illness episode distribution, which is severely problematic for acute illness. Also, it allows for identifying the medical care expenditures and the number of days missed work driven by physical or mental health problems. This feature helps to estimate the monetary and non-monetary costs of each illness condition correctly.

### 3.2 Determination of the sample

I focus on 2012 since it is a period of relative stability in terms of institutional parameters associated with the US medical care system before the implementation of the Affordable Care Act. To fully use the panel structure of the MEPS in a relatively short period, I stack together two cohorts of individuals surveyed in 2011 and 2012 into one data set. To satisfy the steady-state assumption, I only use one year of data, which still contains enough variation for identification. To guarantee relative homogeneity over observables, I impose several important restrictions on the final sample for estimation. The limitations focus on relatively homogenous individuals regarding health conditions, labor market experience, and steady-state positions assumed by the model. I restrict the sample to white males between the ages 30 and 55 with at least a high school education and who participated in all interviews. I exclude any individual who reports being self-employed, military service, or are

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32 Gilleskie (1998, 2010) explicitly account for this censoring problem by constructing the likelihood function allowing for the estimation of the illness probability parameters when there is no information on illness conditions not associated with medical treatment use.

33 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 the January of 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 E.
with either public or non-employer sponsored health insurance during the reference period. I also rule out the samples which are covered by the spouse’s ESHI coverage.\textsuperscript{34} To obtain a population of healthy individuals, I drop those who report unhealthy conditions and have had a chronic illness before.\textsuperscript{35} I limit the maximum number of missed workdays linked to specific ICD-9 codes to 31 days. The respondent’s hourly wage is directly reported or calculated by dividing the salary by the number of hours worked per period, depending on the data provided by the respondent. When a person indicates a change in hourly wage between rounds, the updated wage is imputed, accurately tracking down the wage dynamics. Wage distributions are trimmed at the bottom 1% because hourly wages greater than or equal to 75.76 dollars are top-coded for confidentiality. The definitions and construction of each variable are described in appendix E.

Splitting the observed heterogeneity of individuals into discrete values is necessary because of the state space’s size in the equilibrium model. I differentiate labor market status in the model, making the unique combination of employment transitions, the provision of ESHI, health states, and medical treatment.\textsuperscript{36} 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. MEPS does not distinguish between unemployed workers and those out of the labor force. In order to exclude the non-working population, I drop unemployed individuals who are retired, are unable to work because of disability or illnesses, need to take care of their family members, go to a school, and take time off. If the worker holds ESHI at the current main job, the employment match is identified as the job providing health insurance. Second, I define ill individuals as those absent from work due to an acute illness at least once during the

\textsuperscript{34} I do not model industry-specific characteristics in the model. First, the sample size of each industry is small. Second, in the data, absenteeism rates are relatively the same across the industry.

\textsuperscript{35} Health status is defined as five integer values of self-reported health, corresponding to the excellent/very good/good/fair/poor health categories. In this model, individuals who report fair or poor health conditions more than two times are treated as unhealthy. Overall, healthy individuals are assumed to experience health shocks while holding the same amounts of initial health capital. By controlling for general health status, I also solve the issue that unobserved lagged illness conditions might affect current individuals’ decisions, associated with omitted biases.

\textsuperscript{36} MEPS collects other types of employment states such as they had a job to return to or did not work at the interview date, although they did work during the reference period. I only consider employed workers as those who had a job at the interview date.
reference period. Acute 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. It is suited to the analysis of the model.37 Unfortunately, the information on daily illness behavior and exact dates of illness episodes does not exist in the survey.38 In particular, I use the accumulated number of absent days from work associated with specific ICD-9-CM codes to measure the length of the acute illness episode in the model. This is possible because the file contains indicator variables for whether a specific condition is associated with absenteeism at the workplace.39 In the model, acute illnesses directly affect match productivity since it induces ill workers to be absent from work. Therefore, although it might understate the actual illness episode, it is helpful to identify how unexpected and short-term absences cause damage to the employers, given the lack of data. Third, I define ill individuals consuming medical care as those who visit medical providers or take prescribed medicines at least once during the reference period. More specifically, five different medical events refer to prescription medication purchases, emergency room visits, outpatient visits, office-based medical provider visits, and hospital inpatient stays. The details on the medical event files are explained in Appendix E. The medical care 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. I do not include dental visits, home health care, or optical care, which are usually not covered by ESHI plans. Medical care expenditures are defined as the sum of payments for each medical care utilization. I measure the medical care expenditures by using the treatment price and the amount paid by an individual who consumes medical care. I measure the medical care

37ICD-9-CM codes characterize the types of illness conditions in the data. A chronic illness, such as heart disease and diabetes, lasts 12 months or longer and is 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. I explain how to interpret ICD-9-CM codes as discerning acute ailments in Appendix E.

38Gilleskie (1998, 2010) use the 1987 National Medical Expenditure Survey to use the information on a daily illness behavior; but MEPS does not have such information.

39MEPS directly asks the question, What are the health problems that caused you to miss work on those days? so that I can link each health problem to the number of missed workdays.
expenditures by using the treatment price and the amount paid by an individual who consumes medical care. Conditional on having health insurance, out-of-pocket expenditures paid by different individuals may be different due to cost-sharing features of their insurance plans. The out-of-pocket expenditure function is defined in the identification section.

The final estimation sample comprises three data sets: cross-sectional moments, dynamic moments, and illness-related moments. A cross-sectional sample is extracted from the intermediate round of Panel 16 and Panel 17, covering the middle of 2012. Since the statistics are stable across time, this sample can build moments characterizing the model’s main steady-state features. Mainly, 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. This information is helpful to fully capture the labor market dynamics for both covered and uncovered individuals over the same period. The illness-related moments capture statistics on individuals who had at least one acute illness causing absenteeism during six months in the intermediate round of Panel 16 and Panel 17. When they are observed to have acute illnesses, I can observe key statistics in different illness episodes. The final estimation sample consists of 1,269 males (representing 3,807 individual-round observations). Appendix E 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 3.1, 3.2 and 3.3. The reported patterns are broadly in line with the main empirical features in the literature.

Table 3.1 describes the cross-sectional features of the labor market states by comparing insured and uninsured individuals. First, there is a significant mass in each state, and most of the workers are covered by ESHI: the percent of males covered by ESHI (70%) is much larger than that of the uninsured (24%). The unemployment rate is around 6%. Second, insured individuals tend to report having higher wages ($27 an hour), while the average hourly wage for others without ESHI is $15
an hour. This suggests that an employment match with ESHI is derived from the upper support of the productivity distribution. This might be interpreted as an indication of a productivity-enhancing effect of health insurance. As seen in Figure 3.1, the empirical densities of the hourly wages for insured and uninsured employees share an overlapped support area. Wage densities of the insured employees first-order stochastically dominate the other one.

Table 3.1: CROSS-SECTIONAL MOMENTS: LABOR MARKET STATES

<table>
<thead>
<tr>
<th></th>
<th>Unemployed</th>
<th>Insured Employee</th>
<th>Uninsured Employee</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion (%)</td>
<td>6.03</td>
<td>69.79</td>
<td>24.19</td>
</tr>
<tr>
<td>Hourly Wages: Mean</td>
<td>26.65</td>
<td>15.14</td>
<td></td>
</tr>
<tr>
<td>Hourly Wages: SD</td>
<td>13.66</td>
<td>8.33</td>
<td></td>
</tr>
</tbody>
</table>

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

Figure 3.1: OBSERVED WAGE DENSITY FUNCTIONS

Note: Cross-sectional data obtained from the intermediate round of Panel 16 and Panel 17 of MEPS survey data (N=1,269). The insurance status of the job is defined according to whether or not workers have employer-sponsored health insurance through their employers.
Table 3.2 reports transition probabilities of individuals’ employment states at the beginning of the period and their states one year later. There are a number of transitions between labor market states and ESHI provisions. The evidence on these transitions shows 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 two types of jobs. As described in the first row of Table 3.2, I observe that around half of the unemployed become employed after a year. Over one year, only 12% of the unemployed transit to jobs with ESHI, and around 39% of them are sorted into jobs not offering ESHI. Also, employment and insurance changes for uninsured workers are more frequent than the insured. In particular, after a year, about 20% of uninsured employees become either unemployed or insured, but the opposite is not taking place that much: only around 2% of insured employees change their labor market states. These observations support the assumption made in the model that job tenure is longer for workplaces providing insurance.

Table 3.2: Dynamic Moments: Yearly Transition Rates

<table>
<thead>
<tr>
<th>Employment States at t</th>
<th>Unemployed</th>
<th>Uninsured Employed</th>
<th>Insured Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployed</td>
<td>47.95</td>
<td>39.73</td>
<td>12.33</td>
</tr>
<tr>
<td>Uninsured Employed</td>
<td>10.07</td>
<td>79.48</td>
<td>10.45</td>
</tr>
<tr>
<td>Insured Employed</td>
<td>0.57</td>
<td>1.13</td>
<td>98.30</td>
</tr>
</tbody>
</table>

NOTE: The stacked panel of individuals was followed for one year over 2012 of the MEPS. The table shows yearly transitions probabilities across the labor market states and insurance coverage 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 3.3 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%. Of those contracting acute illnesses over this period, the insured are more likely to seek medical treatment during an episode of acute illnesses. About 64 percent of insured workers seek medical treatment but only 39 percent of uninsured workers do. The insured consume more medical care than the uninsured since...
a large portion of medical treatment expenditures appear to be covered by health insurance.\textsuperscript{40} Ill individuals miss three workdays on average. The average cost of medical treatment is 37 dollars per hour and does not vary across the illness episode.

Table 3.3: ILLNESS-RELATED MOMENTS

<table>
<thead>
<tr>
<th></th>
<th>No Medical Treatment</th>
<th>Medical Treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td>At least one acute illness (%)</td>
<td>14.99</td>
<td></td>
</tr>
<tr>
<td>Average missed work days</td>
<td>3.24</td>
<td></td>
</tr>
<tr>
<td>Proportion: (%) If insured</td>
<td>64.29</td>
<td>35.71</td>
</tr>
<tr>
<td></td>
<td>38.62</td>
<td>61.38</td>
</tr>
<tr>
<td>Medical payments: Mean</td>
<td></td>
<td>37.58</td>
</tr>
<tr>
<td>Medical payments: SD</td>
<td></td>
<td>67.85</td>
</tr>
</tbody>
</table>

\textbf{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 medical treatment states are defined according to whether or not individuals have consumed any curative care during an illness episode.

\textsuperscript{40}The different patterns of consuming medical care utilization, depending on ESHI, also might be evidence of adverse selection. For example, it provides some private demand for health insurance by ill workers who want to consume more medical treatments. However, this is beyond the scope of the paper.
4. IDENTIFICATION

I need to identify the following set of parameters for agents of health conditions $i \in \{H, A, S\}$:

$$\Theta = \left\{ \rho, b, \alpha, \lambda, \eta_d, \mu_x, \sigma_x \right\}$$

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 describing the nontraditional features of the search model in the second row, and the unobserved acute illnesses 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 $\rho$ can only be jointly identified with the flow of unemployment utility $b$ through the equilibrium conditions. In particular, once the discount rate $\rho$ is set to 5% a year, the flow of unemployment utility $b$ can be identified. It is challenging to identify the bargaining power parameter $\alpha$ because of the lack of demand-side information 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 $\alpha = 0.5$ (See: Flinn (2006); Flabbi (2010b); Flabbi and Moro (2012)).

A recoverable match-specific productivity distribution needs to be assumed to estimate the entire wage offer distribution; these parameters are non-parametrically non-identified, as seen in
Flinn and Heckman (1982). The truncated observed wages in the data can be used to recover the unobserved productivity distribution parameters \( \{ \mu_x, \sigma_x \} \) in the following steps. First, accepted wages in the model measured by observed wages in the data correspond to accepted match-specific productivity \( x \) through the bargained wage schedules. Second, I make a parametric assumption on the match-specific productivity distribution \( G(x) \) to satisfy a recoverability condition (Flinn and Heckman, 1982). This condition is essential to recover the original wage distributions having truncation points. 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 (see, e.g., Eckstein and van den Berg (2007); Flabbi (2010a)).

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

(4.2)

where function \( f \) denotes a standard normal density function. Finally, I can recover the primitive parameters \( \{ \mu_x, \sigma_x \} \) from the truncated accepted productivity distribution.

The transition probabilities across labor market states and the steady-state proportion of workers in each state identify the mobility parameters \( \{ \lambda, \eta_d \} \). Following flow equations defined in Appendix B, the transition probability across labor market states is equal to the exogenous mobility parameters times the endogenous probability characterizing optimal decision rules for each agent. Once the productivity distribution belongs to a recoverable distribution, accepted wage densities with flow equations defined in Appendix B are enough to identify the transition probabilities with reservation values. Therefore, transitions between unemployment and employment with or without ESHI identify the job arrival rates and job destruction rates.\(^{41}\)

\(^{41}\)Flinn and Heckman (1982) use unemployment duration to describe the labor market dynamics. Using transitions across labor market states over one year express the same identification strategy in a different way.
4.2 Health-related parameters

The second set of parameters is a set of health-related parameters \( \{ \kappa, \nu, \zeta_S, \zeta_{A,c}, \mu_m, \sigma_m, \phi, k \} \). I identify the disutility from being ill \( \kappa \) by using the same argument I used to identify \( b \). Once \( \rho \) is fixed, the equilibrium equations (2.22), (2.23), (2.24) and (2.25) jointly identify \( \kappa \).

I can apply a similar identification strategy as the strategy I used to identify job mobility parameters in order to identify both the health shocks \( \nu \) and the recovery shocks \( \{ \zeta_{A,c}, \zeta_S \} \). Using the information on missed workdays by medical treatment utilization, I can identify the hazard rate out of the “healthy state” or “illness state.” Through the reparametrization of the model, I can separately recover health-related shocks \( \{ \nu, \zeta_{A,c}, \zeta_S \} \) from the hazard function with the information of \( G(x) \) and \( M(m) \) in the steady-state flow equations as defined in Appendix B.

Ill individuals might consume medical treatment, and each medical care utilization incurs medical expenses. I impose additional parametric assumptions to identify the primitive distribution of medical care expenditure \( M(m) \) since I can observe a truncation point of the primitive distribution. Each ill individual is assigned potential medical care expenditures \( m \) drawn from \( M(m) \). Conditional on a positive medical care expenditure, I assume log-normality and denote location and scale parameters for the distribution function of medical care expenditures:

\[
M(m) = \frac{1}{m\sigma} f \left( \frac{\ln(m) - \mu_m}{\sigma_m} \right), \quad m > 0
\]  

(4.3)

\( M(m) \) ensures the recoverability condition. Depending on the medical care utilization decision, positive medical care expenditures may be realized, and the amount of expenses suggests the severity of illness. 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 21%, according to statistics from the MEPS-IC. If hourly medical care expenditure is positive \( o(1; m) = m \times 0.21 \); otherwise \( o(0; m) = m \). Additional details are in Appendix A.

I exploit the Insurance Component of the 2012 MEPS (MEPS-IC) to calibrate the total premium and the employee contributions for single coverage. The fixed value of the premium of providing
ESHI $\phi$ is 2.59 dollars per hour, which captures the total costs of providing ESHI from the firms’ side and individuals’ direct payment to have ESHI. I divide the total employee contribution for single coverage by the total single premium per employee, and I set the employees’ contribution of the premium to 20.8 percent. Additional details on the calculation are in Appendix A.\textsuperscript{42}

Finally, thanks to the equilibrium framework, illness-related absenteeism costs on the total surplus can be identified and estimated, using supply-side labor information. The production function is assumed to capture the impact of acute illness conditions on the worker’s productivity. When a worker is absent at the workplace because of the illness, productivity becomes zero in that period, while healthy individuals can be productive all the time as usual. Therefore, the impact of adverse health shocks on labor productivity is reflected in the number of missed workdays due to illness. The missing match productivity due to absenteeism can be recovered using the mapping between the productivity and the bargained wage schedules.\textsuperscript{43}

### 4.3 Unobserved heterogeneity

The estimation procedure assumes that each illness can be described by an unobserved type that allows for a correlation between the unobserved determinants of medical treatment choices and health outcomes in the model. The intuition behind the identification of the unobserved heterogeneity is the optimal decision rules that are characterized in the model. Considering the productive effects of medical treatment, moderately ill individuals optimally choose to consume medical care to

\textsuperscript{42}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 the expected medical care costs of the risk pool at a workplace. Also, given that employees’ health conditions can affect ESHI premiums, calibrated premiums adverse selection do not capture adverse selection biases. Because of the lack of firm-size effects in the model, I cannot incorporate the risk pool of insured employees. Instead, I minimize this problem by having relatively homogenous healthy agents.

\textsuperscript{43}In the previous version, I recover the negative productivity shock with the empirical fraction of non-productive days over reference periods. For example, the marginal flow product of a worker with acute illness is given by $\delta x$, where $\delta$ discounts the match-specific productivity. I use the average proportion of missed workdays over the illness period to identify it. This strategy does not fit the definition of absenteeism since absences are recorded on a daily basis in the MEPS, and I use hourly accepted wages to recover hourly productivity loss.
recuperate quickly and stay productive at the workplace; otherwise, they are not willing to seek medical treatment because of medical expenditures. In the sample, as described in the health economics literature (see: Gilleskie (1998); Khwaja (2010); Cronin (2019)), the positive effects of medical care on illness episodes are difficult to estimate. Individuals with severe illnesses are more likely to consume medical care, leading to endogenous unobserved selection biases. If this were the case, the regression of illness on medical consumption would reveal a negative relationship. As a result, in the sample, individuals who consume medical treatment have more missed workdays than those who do not because there are different types of acute illnesses (observed by the individual but unobserved by the econometrician during the illness episode). The severity of acute illness is identified by how much a utility-maximizing search model fails to explain the empirical moments. I utilize information on the duration of illness episodes conditional on medical treatment decisions to distinguish the unobserved heterogeneous types. By introducing unobserved heterogeneity over acute illnesses, I can improve the fit of the model and lend more credibility to the estimated parameters.

I introduce two different types of unobserved acute illnesses, which capture more than the clinical classification codes (e.g., influenza or respiratory infections) or the specific three digits ICD-9 codes in order to capture the severity of the acute illness.44 It indicates that moderately ill patients are willing to pay medical care expenditures in the hope of recuperating quickly, which can be the underlying mechanism to identify the positive medical treatment effect. Moreover, the illness types capture the extensive margin of the medical treatment. Conditional on the ill sample, medical treatment may be correlated with its severity. If they are severely ill, medical treatment is not of choice but a necessity. Also, an individual who receives an exceptionally severe acute illness is likely to have high medical care expenditures.

---

44Gilleskie (1998, 2010) show that introducing additional unobserved heterogeneity does not improve the model’s fit.
Following the method proposed by literature, my model allows for both of these theoretical predictions to control for these potential sources of unobserved heterogeneity.\textsuperscript{45} I assume that there are two types of time-invariant illness types that approximate unobserved heterogeneity. There is a severe acute illness and its proportion in the population is $p$. Severe illnesses are associated with exogenous medical treatment, different recovery rates $\zeta_S$, and positive scalar for medical care expenditures $a_m$. Medical care price shocks are likely to be correlated with the unobserved acute illnesses as well. Positive scalar $a_m$ represents scale factors similar to TFP parameters to increase the overall distribution of medical care expenditures. In this economy, individuals with severe illnesses $i = S$ have a higher direct cost of medical treatment on average, comparable to moderate illnesses $i = A$. Specifically, I introduce the following specification that $m|S = a_m m$ where $a_m > 1$ and $m|A = m$. Due to data limitations, I am able to estimate the model with only two types of unobserved illnesses. I normalize the parameter associated with moderate illnesses to one so that there are only two free parameters $\{\zeta_S, a_m\}$.

\textsuperscript{45}Keane and Wolpin (1997, 2010) show how to introduce unobserved heterogeneity in the labor literature. There are similar examples in the search literature (see: Eckstein and Wolpin (1995); Sullivan (2010); Bobba et al. (2020)) and in the health economics literature (see: Gilleskie (1998); Khwaja (2010); Cronin (2019)) as well.
5. ESTIMATION

5.1 Estimation method

I estimate the model using the method of simulated moments (MSM).\textsuperscript{46} MSM minimizes a weighted average distance between sample moments and simulated moments from the model. A set of the parameters $\Theta_{MSM}$ in the space $\Omega$ are estimated by minimizing the following quadratic distance function:

$$\hat{\Theta}_{MSM} = \arg \min_{\Theta \in \Omega} |M_{N,R}(\Theta) - m_N|^T W_N^{-1} [M_{N,R}(\Theta) - m_N] \tag{5.1}$$

where $M_{N,R}(\Theta)$ is the vector of the simulated moments evaluated at $\Theta$ based on $R$ simulations for $N$ sample observations. I set the number of simulated samples $R$. $m_N$ is the vector of 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 $m_N$.\textsuperscript{47} 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.

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 moments in the estimation procedure to exploit the identification strategy in Section 4. I use four groups of

\textsuperscript{46}The method is commonly used to estimate nonlinear models numerically in other search literature (see: Dey and Flinn (2008); Flabbi and Moro (2012); Flinn and Mullins (2015); Bobba et al. (2020)). In principle, using a maximum likelihood approach is difficult since medical care expenditures generate different supports of outside options. It violates a standard regularity condition, as suggested by Flinn and Heckman (1982).

\textsuperscript{47}Under the assumption, I use the population value of the sample moments (i.e., $\lim_{N \to \infty} m_N = m$). Also, Del Boca et al., 2014 shows that consistency of MSM estimators for positive definite matrix $W_N$ is obtained under standard conditions (i.e., $\lim_{N \to \infty} \hat{\Theta}_{MSM} = \Theta$).
moments in the quadratic form: the first moments are cross-sectional, related to employment and insurance coverage. I build moments derived from the proportions in each labor market state and the wages at jobs conditional on ESHI provisions. The second set of moments summarize the yearly transition probabilities across employment status and health insurance coverage status. The third set of moments pertains to the mean and standard deviation on the accepted wage distributions for two types of jobs. The final set of moments captures the health-related features: medical care expenditures, the proportion of individuals who seek medical treatment during an illness episode, and missed workdays conditional on medical treatment.

### 5.2 Parameter estimates

Table 5.1 presents the parameter estimates of the model, together with the bootstrapped standard errors. The first set of parameters are search, matching, and bargaining parameters. Durations are measured in a month so that the point estimate of the job offer arrival rate $\lambda$, 0.11, implies that a healthy unemployed worker meets a firm on average every nine months. 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 jobs. The estimated parameters of the job destruction rates $\eta_d$ 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.\(^{48}\)

I speculate that ESHI might improve the unobserved health conditions of workers as a result of an increase in the chance of maintaining the current employment match. It involves in part a positive impact of ESHI on the productivity of the match. The productivity distribution parameters $\{\mu_x, \sigma_x\}$ generate the distributions of match values. In Table 5.3, I compute predicted values of the primitive distributions to interpret these parameters. The flow value of unemployment $b$ is estimated to be negative, which commonly generates enough wage variation in the search literature (see: Hornstein et al. (2011)).

\(^{48}\)Although I do not directly observe employment durations in the sample, those estimates are comparable to other estimates in the structural search literature (e.g., Dey and Flinn (2005)). It is common that the estimated rate of job separations for the uninsured is greater than the rate for the insured.
The second set of parameters characterize the health-related parameters. The estimates for the arrival rate of an acute illness $\nu$ imply 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 illness $\zeta_s$ show that they take around ten days to recover with medical care. The differences in the estimated values for the recovery shocks $\zeta_{A,c}$ generate the returns to seeking medical treatment. Moderate ill workers who consume medical care tend to have shorter illness episodes than those who do not: for individuals who seek medical treatment, it only takes less than one day to recover from illnesses, but about two days if they do not seek it. Medical care utilization alleviates the effect of moderate sickness by shortening episodes, although the size of medical care expenditures partially offsets the marginal benefit. It also becomes another motivation for workers to value ESHI since insurance decreases the marginal cost of medical treatment. Figure 5.2 plots the estimated Weibull survivor functions for ill workers based on the duration of each illness type and medical care use. It clearly shows the effect of medical treatment on shortening the number of sick days in the case of moderate illness. The disutility parameter associated with illness conditions $\kappa$ is similar to other health economics literature, such as Gilleskie (1998); Khwaja (2010); Cronin (2019). It appears that contracting an illness costs 3 dollars per hour (in psychic terms). In other words, individuals are willing to pay 3 dollars to recover from acute illnesses, on top of other benefits such as productivity gain, more job opportunities, and no medical care expenditures. Or the average disutility of being ill is estimated to be around one-third of the average disutility of being unemployed. As was discussed in the previous section, I introduce unobserved heterogeneity in illness conditions. Conditional on the same expected arrival time of an acute illness, individuals have a 27% chance of getting severe illnesses, and it incurs 20% 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.
Table 5.1: Parameter Estimates

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Estimates</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor market:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment utility</td>
<td>$b$</td>
<td>-9.1579</td>
</tr>
<tr>
<td>Job arrival rate</td>
<td>$\lambda$</td>
<td>0.1060</td>
</tr>
<tr>
<td>Separation rates</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\eta_{d=0}$</td>
<td>0.0159</td>
<td>0.0023</td>
</tr>
<tr>
<td>$\eta_{d=1}$</td>
<td>0.0065</td>
<td>0.0004</td>
</tr>
<tr>
<td>Match specific productivity</td>
<td>$\mu_x$</td>
<td>3.4273</td>
</tr>
<tr>
<td></td>
<td>$\sigma_x$</td>
<td>0.5088</td>
</tr>
<tr>
<td>Health:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>medical care expenditures</td>
<td>$\mu_m$</td>
<td>3.2169</td>
</tr>
<tr>
<td></td>
<td>$\sigma_m$</td>
<td>1.2125</td>
</tr>
<tr>
<td></td>
<td>$\zeta_{A,c=0}$</td>
<td>14.9997</td>
</tr>
<tr>
<td></td>
<td>$\zeta_{A,c=1}$</td>
<td>40.4067</td>
</tr>
<tr>
<td></td>
<td>$\zeta_S$</td>
<td>3.0964</td>
</tr>
<tr>
<td>Recovery rates</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Health shock</td>
<td>$\nu$</td>
<td>0.0302</td>
</tr>
<tr>
<td>Disutility of being ill</td>
<td>$\kappa$</td>
<td>2.9515</td>
</tr>
<tr>
<td>Proportion of Severe illnesses</td>
<td>$p$</td>
<td>0.2697</td>
</tr>
<tr>
<td>Scale factor of severe illnesses</td>
<td>$a_m$</td>
<td>1.2128</td>
</tr>
</tbody>
</table>

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. The complete set of sample moments, the corresponding simulated moments, and their used weights are reported in Appendix C.

5.3 Predicted values

Table 5.3 reports the predicted labor market and health-related values recovered from the structural model. The values are computed by simulating the labor market histories of each individual based on the corresponding estimated parameters in Table 5.1. In Table 5.3, 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); Mullins (2019)) assume that the primitive match-specific productivity explains the total value of the employment match
Table 5.2: 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.

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. Although match-specific productivity is drawn from the same primitive distribution \( G(x) \), it makes a stark difference in the predicted realized productivity for the two jobs. It supports the first case of Proposition 2 that searchers are pickier in accepting jobs providing ESHI, considering that \( x^* (1) \) is higher than \( x^* (0) \).

The second group of variables presented in Table 5.3 report average offered wages.\(^{49}\) Average offered wages when insured are 40% higher than wages when not insured. These wage differentials are slightly smaller than those of observed wages in the data. It demonstrates that accepted wages

\(^{49}\) 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.
are affected from the selection over labor market states within the model. Table 5.3 reports unemployment information. Considering the endogenous acceptance probability in the flow equations mentioned in Appendix B, the job arrival rate in Table 5.1 predicts that unemployed searchers accept a job offer on average every nine months.

Table 5.3: Estimation Results: Predicted Values

<table>
<thead>
<tr>
<th></th>
<th>Predicted Values</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Labor market:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average hourly realized productivity:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employees</td>
<td>41.017</td>
<td>3.514</td>
</tr>
<tr>
<td>Uninsured employees</td>
<td>20.888</td>
<td>1.427</td>
</tr>
<tr>
<td>Insured employees</td>
<td>46.734</td>
<td>3.724</td>
</tr>
<tr>
<td>Variance of hourly realized productivity:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employees</td>
<td>377.817</td>
<td>27.135</td>
</tr>
<tr>
<td>Uninsured employees</td>
<td>19.712</td>
<td>1.142</td>
</tr>
<tr>
<td>Insured employees</td>
<td>331.742</td>
<td>24.242</td>
</tr>
<tr>
<td>Average hourly offered wages:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Uninsured employees</td>
<td>15.853</td>
<td>1.245</td>
</tr>
<tr>
<td>Insured employees</td>
<td>26.133</td>
<td>1.432</td>
</tr>
<tr>
<td>Average duration to receive a job offer:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployed searcher</td>
<td>9.438</td>
<td>0.785</td>
</tr>
<tr>
<td><strong>Health:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average total months of illness episode:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Severe illness</td>
<td>9.430</td>
<td>0.653</td>
</tr>
<tr>
<td>Moderate illness with medical treatment</td>
<td>0.693</td>
<td>0.047</td>
</tr>
<tr>
<td>Moderate illness without medical treatment</td>
<td>2.068</td>
<td>0.103</td>
</tr>
<tr>
<td>Absenteeism rate: (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employees</td>
<td>3.231</td>
<td>0.135</td>
</tr>
</tbody>
</table>

**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 wages are measured in dollars per hour.
Table 5.3 also reports predicted health-related outcomes. I see large differences in the number of illness days across heterogeneous illness types and medical treatment 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 recovery. Consequently, those who consume medical care are exposed less to illness-related monetary and non-monetary costs. To calculate absenteeism rates 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:

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

Following the formula, I calculate an absenteeism rate of 3% as the rate of unplanned absences due to acute illnesses. I set the number of available workdays over six months at 122 days. This is close to the average values found in the US Bureau of Labor Statistics (BLS) in 2012, suggesting the absence rate for all full-time wage workers is around 2%. The absenteeism rates are linked to the productivity losses, and I can approximate the unobserved productivity by hourly wages or by primitive hourly productivity mentioned in Table 5.3.\(^{50}\) A simple back-of-the-envelope cost analysis suggests that productivity losses linked to absenteeism due to illness in one year are between 790 dollars (based on hourly wages) and 1,200 dollars (based on productivity) per employee.

### 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. Table 5.4 presents the fit of the cross-sectional moments, and Table 5.5 and 5.6 present the fit of the dynamic and illness-related moments,\(^{50}\) In a perfectly competitive labor market, the wage rate is equal to the marginal productivity of labor. Although I introduce search frictions, this statistic shows the lower bound of productivity loss due to absenteeism.
respectively. 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 5.4 replicates well the statistics of observed wages by insurance status and the proportions describing labor market states. The mean of wage distributions for different insurance states fits well, though it is less distributed. The estimated proportion of the unemployed is higher compared to the data because I try to match the high persistency of unemployment in the transition probabilities as reported in Table 5.5. In the model, match-specific values from the same support of \( G(x) \) generate sizable measures of the insured and the uninsured. 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 providing ESHI and the shape of wage densities of the insured.\(^{51}\) 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.

Table 5.4: THE FIT OF THE CROSS-SECTIONAL MOMENTS

<table>
<thead>
<tr>
<th></th>
<th>Unemployed</th>
<th></th>
<th>Insured Employee</th>
<th></th>
<th>Uninsured Employee</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data</td>
<td>Model</td>
<td>Data</td>
<td>Model</td>
<td>Data</td>
<td>Model</td>
</tr>
<tr>
<td>Proportion (%)</td>
<td>6.03</td>
<td>10.20</td>
<td>69.79</td>
<td>71.72</td>
<td>24.19</td>
<td>17.93</td>
</tr>
<tr>
<td>Hourly Wages: Mean</td>
<td>26.65</td>
<td>27.78</td>
<td>15.14</td>
<td>15.97</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hourly Wages: SD</td>
<td>13.66</td>
<td>8.71</td>
<td>8.33</td>
<td>2.11</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Cross-sectional data 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 employer-sponsored health insurance through their employers.

Table 5.5 shows that the model replicates important features of the dynamic moments. The model successfully generates a significant number of transitions between labor market states, but sometimes it overestimates or underestimates the persistency in some labor market states. For

\(^{51}\)The only relatively higher productivity matches are associated with the jobs with ESHI; higher wages should compensate the cost of having insurance through the utility gain. Given that the support of the wage densities depends on the reservation values, changing reservation values generate a mismatch over the proportion of states or mean accepted wages.
example, the model’s implications are less satisfactory for the transitions out of unemployment. This mismatch comes from the trade-off between fitting the transition probabilities and the steady-state portion of labor market states. The parsimonious specifications of the equilibrium model with relatively higher reservation wages for jobs with ESHI fail to replicate the move from unemployed to insured. When I improve the fit of this movement, it comes at the cost of having a higher ESHI rate and higher mean wages of the insured. In a similar sense, matching the high persistency in the insured produces a poor fit of the accepted wage distributions of the insured.

Table 5.5: The Fit of the Dynamic Moments

<table>
<thead>
<tr>
<th>Employment States at $t$</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment States at $t + 1$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemp.</td>
<td>47.95</td>
<td>12.33</td>
</tr>
<tr>
<td>Ins.</td>
<td>0.57</td>
<td>98.30</td>
</tr>
<tr>
<td>Unins.</td>
<td>10.07</td>
<td>10.45</td>
</tr>
</tbody>
</table>

Note: The stacked panel of individuals was followed for one year over 2012 of the MEPS. The table shows yearly transitions probabilities across the labor market states and insurance coverage 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 5.6 shows that the model is successful in replicating illness-related moments. The illness-related moments fit well the proportion of ill workers who decide to utilize medical treatment conditional on access to health insurance. It generates the productive effect of medical treatment, and the insured are more likely to seek treatment, as predicted in the model. The model also delivers a reasonably good replication of the portion of individuals who have had an acute illness during six months and the duration of the patient’s acute illnesses. The introduction of the unobserved heterogeneity over acute illness acts to smooth away differences between the model’s predictions and the data.
## Table 5.6: 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 work days | 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.

Figure 5.1 plots the actual and predicted wage distributions by insurance and cumulative distributions of hourly medical care expenditures. The model is able to predict the essential features of wage and medical care expenditure distributions.
Figure 5.1: Predicted and Empirical Wage Earnings and Medical Care Expenditures

Note: A simulated sample of 2,000 individuals is based on the estimates reported in Table 4. The predicted wage and medical care expenditures distribution are based on the parameter estimates presented in Table 4. The empirical wage distribution and empirical cumulative medical care expenditure are based on the MEPS.
6. COUNTERFACTUAL EXPERIMENTS

Given model estimates, I provide economic costs of acute illnesses and conduct two policy counterfactuals. I first measure acute illness costs with the help of counterfactual simulations. Next, I conduct several policy experiments to assess the value of ESHI when acute illnesses are present. I impose the mandatory health insurance policy that all employers must provide ESHI. I then implement a policy where employers receive a flow subsidy if they provide ESHI but a flow penalty if they do not provide ESHI.

6.1 Costs of acute illness

Recently, the COVID-19 pandemic increases absenteeism rates while simultaneously increasing the need for access to ESHI. This section aims to highlight the effects of acute illness on labor market outcomes and welfare. For each value of acute illness shocks $\nu$, I find and compute the new equilibrium with the structural parameters at the point estimates reported in Table 5.1. I highlight costs of acute illness as the relative difference between the wages, the total value of production, and workers’ welfare that agents realize in the benchmark model and those they would realize if there is no acute illness counterfactually. One should keep in mind that impacts of acute illness costs on key statistics might be biased by ESHI provision. To isolate the net effects of ESHI, I only consider jobs without ESHI.\footnote{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 main qualitative results do not change.}

Figure 6.1 displays relevant costs of acute illness computed at the various acute illness shocks over the range. I denote the benchmark value of $\nu$ with a vertical dotted line in all panels. Panel (a) shows that as the acute illness shock $\nu$ increases, the share of individuals who experience at
least one acute illness over six months increases proportionally. It is a straightforward result of
an increase in the 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) reports.\footnote{The value of lost production refers to the extent of the forgone productivity loss since ill workers do not contribute to the output. It can be calculated by multiplying the time absent from work by the hourly productivity over six months.} Also, the selection impact through the reservation values generates the non-linear relationship between
the size of lost production due to illness and the acute illness shock. Panel (c) and (d) show that
the acute illness shock decreases average wages and workers’ welfare. Increases in various acute
illness costs measured by productivity loss, medical expenditures, fewer job opportunities, and
reduced utility are indirectly taken into account in the form of lower total surplus. Considering that
I use the present discounted value of participating in the labor market as a workers’ welfare, these
illness costs directly enter into workers’ welfare. Through a Nash-bargaining process, firms can
partially share illness costs to the worker. As a result, acute illness costs lower workers’ wages
either. Additionally, I measure acute illness costs in the benchmark model. I only allow acute illness
shocks $\nu$ 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. These results also show
that absenteeism costs are much higher than labor costs, giving employers incentives to provide
ESHI to increase their profits.
Figure 6.1: COSTS OF ACUTE ILLNESS

NOTE: For each value of the health shock parameters, I derive various costs of acute illness from a simulated sample of 2,000 individuals, fixing the other estimates reported in Table 4. The vertical lines are set at the estimated values of the health shock in the benchmark model. Panel (a) shows the share of individuals who have 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 mean wages of all workers. Panel (d) includes workers’ present discounted values of the searching state.
6.2 Policy experiments

I use the estimates presented in the previous section to compute the equilibrium effects of policy interventions on illness costs, labor market outcomes, and welfare. I focus on counterfactual experiments to give a quantitative assessment of the role of ESHI coverage since the welfare impact of these policies is propagated through the equilibrium effects. I simulate labor market histories for each new value of the policy parameters. From the simulated samples, I calculate three sets of criteria by which one might reasonably evaluate the policy experiments. The first set measures the cost of illness for employees and employers by calculating absenteeism rates, productivity loss rates, and medical care expenditures. The second set represents important features of unemployment states and two types of jobs: average accepted wages, unemployment duration, and unemployment rate. The final set measures welfares by exploiting the steady-state equilibrium results of the model. For workers, their welfare is measured by the Present Discounted Values (PDV) of lifetime utility of participating in the labor market. For employers, I calculate the average of firms’ per-worker profits. More detailed explanations of the definitions of each criteria are presented in Appendix D. Table 6.1 and 6.2 show the statistics of the policy’s results and their percentage changes with respect to the results of the benchmark model reported in Table 5.1.

6.2.1 Mandatory health insurance

I study the effects of mandatory health insurance policy on key statistics at the estimated parameters. All firms must provide health insurance, and searchers now only receive job offers with ESHI.

The top panel in Table 6.1 shows that the policy reduces the costs of illnesses in several ways. As the hourly medical cost is reduced by 15 percent, the medical treatment utilization rate for ill...
individuals increases by 8 percent, compared to the benchmark model. It implies that ESHI reduces the marginal costs of medical treatment, and more individuals consume medical care. Thanks to the positive effects of medical care utilization, the policy helps moderately ill individuals quickly recuperate from illness conditions. As a result, overall absenteeism rate and productivity loss rates decrease by around 18 percent. These results show that the channel through which health insurance reduces illness costs is through the frequent use of medical services. Without taking medical care utilization decisions into account in the model, the productivity-enhancing effects of ESHI might be overestimated.

The middle panel in Table 6.1 reports the simulation results on labor market outcomes after the policy. The implications for the distribution of accepted wages are ambiguous. On the one hand, following Proposition 2, matching with jobs providing ESHI requires the productivity to be large enough to compensate the cost of ESHI. On the other hand, the flow profits of employers with lower preferences for ESHI might become reduced because their employers are forced to provide health insurance. Following the Nash-bargained wage equations, lower surplus decreases offered wages on average. As a result, the policy decreases accepted wages by around 2%, which is relatively small. A Higher ESHI coverage rate reduces the number of transitions between unemployment status and employment status in the post-policy regime: unemployment and employment duration increase by around 5 percent. The lower unemployment duration is driven by relatively higher critical match values of accepting jobs with ESHI \( x^*(1) \). After the policy, unemployed workers are pickier in accepting job offers, leading to a higher average duration in unemployment, given that reservation wages closely linked to the critical value \( x^*(1) \) become larger for them. The lower estimates of job destruction rates associated with ESHI explain the longer tenures of jobs with ESHI. Considering that all workers are insured, the effect of long job tenure on the unemployment rate dominates the effect of long unemployment duration on those searching. Therefore, the unemployment rates decrease by 16 percent since a sizable proportion of unemployed individuals optimally adjust to the new equilibrium environment and work for a longer duration in a job providing ESHI.
The bottom panel of Table 6.1 shows that firms’ welfare becomes significantly lower, but workers’ welfare does not when policy is imposed. This experiment shrinks the support of productivities corresponding to acceptable job matches. As seen in Figure 2.1, after the policy, the productivity within the support of \([x^*(0), \bar{x}]\) were previously matched with jobs without ESHI becomes unfilled.\(^{56}\) Mandatory health insurance removes the steady-state flow values of firms without ESHI; therefore, their profits decrease. More interestingly, the channel through which these effects arise is that firms can no longer utilize first-mover advantages in the bargaining process. In particular, firms are prevented from extracting redundant benefits from workers when proposing the job amenity offers. They had optimally chosen, so they are not the first-mover anymore. The impacts on workers’ welfare are very modest: workers’ ex-ante welfare increases by 5 percent. The main reason for these results is that the overall welfare of labor market participants depends on the transition probabilities between states and the duration in each state. Health insurance increases the probability of receiving job offers and maintaining employment relationships longer through the channel that insured individuals are more healthy, improving workers’ welfare. At the same time, the searchers who have a lower reservation value of accepting a job offer now become unemployed. It is accompanied by a loss in overall welfare due to negative unemployment flow utility.

In conclusion, the policy implies that ESHI can be valuable to employees who might receive health shocks. However, medical care policies only targeting higher ESHI coverage rates can be burdensome to firms because they might distort the ESHI provision decisions that the firm already made optimally. Therefore, it is essential to look at the ESHI coverage rate and other equilibrium effects when evaluating the policy.

\(^{56}\)The interval \([x^*(0), \bar{x}]\) 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.
Table 6.1: The Equilibrium Effects of the Mandatory Health Insurance

<table>
<thead>
<tr>
<th></th>
<th>Benchmark</th>
<th>Mandatory ESHI</th>
<th>% Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Health-related outcomes:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Absenteeism rate (%)</td>
<td>3.23</td>
<td>2.62</td>
<td>-18.91</td>
</tr>
<tr>
<td>Productivity loss rate (%)</td>
<td>3.40</td>
<td>2.75</td>
<td>-19.00</td>
</tr>
<tr>
<td>Hourly medical expenses</td>
<td>40.99</td>
<td>34.79</td>
<td>-15.14</td>
</tr>
<tr>
<td>Medical treatment rate (%)</td>
<td>59.19</td>
<td>63.00</td>
<td>7.79</td>
</tr>
<tr>
<td>Labor market outcomes:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean wages</td>
<td>23.07</td>
<td>22.71</td>
<td>-1.54</td>
</tr>
<tr>
<td>Employment duration</td>
<td>49.87</td>
<td>51.88</td>
<td>4.04</td>
</tr>
<tr>
<td>Unemployment duration</td>
<td>13.76</td>
<td>14.49</td>
<td>5.28</td>
</tr>
<tr>
<td>Unemployment rate (%)</td>
<td>8.32</td>
<td>7.01</td>
<td>-15.67</td>
</tr>
<tr>
<td>Welfare outcomes:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workers’ PDV of the search</td>
<td>215.82</td>
<td>226.75</td>
<td>5.07</td>
</tr>
<tr>
<td>Firms’ flow profits</td>
<td>12.83</td>
<td>9.83</td>
<td>-23.40</td>
</tr>
</tbody>
</table>

Note: A simulated sample of 2,000 individuals is based on the estimates reported in Table 4. The Benchmark is based on the estimates in Table 4. The PDV denotes present discounted values. Mandatory insurance means firms can only offer a contract with health insurance. 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 absenteeism. For a more detailed description of the policy, see Section 6.

6.2.2 Employer mandate penalties

Under the Affordable Care Act (ACA), if an employer does not offer ESHI coverage, they are required to pay penalties.\textsuperscript{57} I study the policy that collects a penalty from firms that do not provide

\textsuperscript{57}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 pre-ACA period.
ESHI. More precisely, I assume that a firm that does not provide ESHI receives a flow penalty of one dollar for each worker and 2,080 dollars annually. All taxes collected are redistributed to firms providing ESHI in the form of the flow subsidy. The subsidy becomes endogenous to balance a total amount of penalties at its estimated value in equilibrium. The penalty gives firms an incentive to provide ESHI by lowering the marginal cost of providing health insurance.

As expected, the top panel in Table 6.1 shows that penalties closely encouraging ESHI reduce illness costs. For example, the hourly medical cost was reduced by 10 percent, and the absenteeism rate and productivity loss rates decreased by around 15 percent. These outcomes are results of the productive effect of medical treatment through improved access to ESHI. For example, there is a transfer of uninsured workers and unemployed searchers to jobs with ESHI because providing ESHI is cheaper, and the reservation productivity value at which workers will accept a job with ESHI is lower. The result in the middle panel in Table 6.1 shows that the proportion of the employed in jobs with ESHI increases by 4 percent.

The middle panel in Table 6.1 reports the results of the policy on labor market outcomes. The equilibrium impact on accepted wages is ambiguous because accepted productivity may either increase or decrease. The transitions from jobs without ESHI to jobs with ESHI increase the reservation value \( x^*(1) \) but decrease the reservation value \( x^*(0) \). Therefore, deficient productive workers lose their jobs without ESHI, but slightly less productive workers are inflowed to jobs with ESHI. Moreover, the extent of subsidy and penalty on wages depend on how employed workers value ESHI. If many workers prefer to have ESHI, the increased workers’ outside option leads to higher accepted wages. Because the last channel dominates, average accepted wages increase by around 2 percent. Reduction of the cost of ESHI generates a similar impact on employment and unemployment duration as mandatory health insurance. They both increase after the policy on average since more workers are matched with firms with ESHI. As a result, the unemployment rate increases by 7 percent.

The bottom panel of Table 6.1 shows welfare measures for firms and workers. The impacts on employers’ welfare are ambiguous. There is an increase in welfare for firms because 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 and overall decrease in the value function of the filled job without ESHI decrease firms’ welfare. These channels lead to decrease in firms’ welfare: average firms’ profits become 16 percent lower in the post-policy environment than those in the pre-policy regime.

The increase in workers’ welfare is due to the provision of ESHI at a lower cost: workers who value ESHI enjoy a portion of additional subsidies with the employers providing ESHI through the bargaining process and uninsured workers who do not value ESHI do not accept a job offer from the employers without ESHI. On top of reduced illness costs, this setting improves workers’ welfare at the cost of a reduction in firms’ welfare, although this cost in part is transferred to workers.

To summarize, this policy implies a redistribution of welfare from firms to workers, but its impacts on overall welfare are minor. 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, leaving employers’ welfare reduced slightly, comparable to mandatory health insurance. If more workers put a higher value on ESHI, this policy becomes more efficient.
Table 6.2: The Equilibrium Effects of the Employer Mandate Penalties

<table>
<thead>
<tr>
<th></th>
<th>Benchmark</th>
<th>Penalties</th>
<th>% Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Health-related outcomes:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Absenteeism rate (%)</td>
<td>3.23</td>
<td>2.76</td>
<td>-11.44</td>
</tr>
<tr>
<td>Productivity loss rate (%)</td>
<td>3.40</td>
<td>2.86</td>
<td>-13.76</td>
</tr>
<tr>
<td>Hourly medical expenses</td>
<td>40.99</td>
<td>36.97</td>
<td>-14.18</td>
</tr>
<tr>
<td>Medical treatment rate (%)</td>
<td>59.19</td>
<td>61.54</td>
<td>3.97</td>
</tr>
<tr>
<td><strong>Labor market outcomes:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESHI coverage rate</td>
<td>71.49</td>
<td>81.48</td>
<td>13.96</td>
</tr>
<tr>
<td>Mean wages</td>
<td>23.07</td>
<td>23.44</td>
<td>1.62</td>
</tr>
<tr>
<td>Employment duration</td>
<td>49.87</td>
<td>51.23</td>
<td>2.73</td>
</tr>
<tr>
<td>Unemployment duration</td>
<td>13.76</td>
<td>15.29</td>
<td>11.13</td>
</tr>
<tr>
<td>Unemployment rate (%)</td>
<td>8.32</td>
<td>8.89</td>
<td>6.84</td>
</tr>
<tr>
<td><strong>Welfare outcomes:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workers’ PDV of the search</td>
<td>215.81</td>
<td>228.64</td>
<td>5.94</td>
</tr>
<tr>
<td>Firms’ flow profits</td>
<td>12.83</td>
<td>10.78</td>
<td>-15.96</td>
</tr>
</tbody>
</table>

**Note:** A simulated sample of 2,000 individuals is based on the estimates reported in Table 4. The Benchmark is based on the estimates in Table 4. 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 absenteeism. The employer mandates penalties mean 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 in the form of subsidies. For a more detailed description of the policy, see Section 6.
7. CONCLUSION

Most individuals are on the verge of experiencing a potentially significant loss in welfare in the event of unexpected illness. Considering that ESHI is the primary source of insurance coverage in the US, I study how employees and employers benefit from ESHI through the reductions in acute illness costs. Studying the value of ESHI to reduce acute illness costs requires an equilibrium search model of the labor market that considers rich forms of endogenous decisions of workers and firms. It also needs to be consistent with the empirical features of US labor markets to generate credible parameter estimates and conduct relevant policy experiments.

In this paper, I develop and estimate an equilibrium search model of the labor market where firms make ESHI provision decisions and workers exposed to acute illnesses make medical treatment decisions. The model allows for match-specific, firm-specific, and worker-specific heterogeneity, emphasizing the equilibrium impact of health insurance on wage dynamics, job trajectories, and the sorting patterns between firms and workers. As a result, the model replicates the empirical patterns that ESHI is the primary source of insurance coverage for workers and wage differentials between two types of jobs with and without ESHI. The acute illness affects workers and employers through various costs, such as deteriorated productivity, increased medical expenses, fewer job opportunities, and reduced utility. I investigate whether and how employees and employers are against specific sources of illness costs with ESHI. Health insurance reduces the rate of job destruction rates, financial expenses, and the duration of illness. As a channel of mitigating the above costs, workers and firms value ESHI so that the possibility of illness shocks creates their private demand for ESHI.

I propose an identification strategy to estimate the model’s structural parameters, using the labor market and health-related sample moments of workers from MEPS. I can identify unobserved illness costs separately by exploiting equilibrium conditions and distribution assumptions. The method of simulated moments estimates is consistent with the empirical features of data: different
critical values sort individuals into different types of jobs. They differentiate jobs along with wage distributions and health insurance provisions. In particular, the estimates are unique along two dimensions: first, the estimated model assesses the quantitative importance of acute illness. For example, the rate of unplanned absence due to illness is 3%, so 3% of potential average productivity cannot be realized due to illness. I show that even a short period of acute illness poses significant illness costs for both employees and employers. Second, it uncovers the channel that ESHI can be valuable to employees and employers by introducing medical treatment decisions of individuals. I find that insured ill individuals extensively consume medical care more thanks to reductions in the marginal cost of medical care utilization. As a result, ESHI shortens the episode of acute illness, leading to reductions in illness costs for both individuals and firms. Moreover, exogenous job destruction rates are lower for jobs with ESHI than those without ESHI. It can be treated as a firms’ investment in individuals’ productivity against health shocks.

This structure allows me to measure how institutional changes affect the employee and employers’ welfare. I perform two counterfactual experiments considering health insurance policies: mandatory health insurance and employer mandate penalties. Two policies are related to the higher ESHI coverage rate that has equilibrium effects on illness costs, labor market outcomes, and welfares. Overall, higher ESHI coverage rates reduce illness costs thanks to frequent medical care utilization. They also improve some labor market outcomes, such as employment duration or unemployment rates. However, there is a redistribution of welfare from firms to workers because it shrinks firms’ decisions sets or distorts their decisions. A critical lesson from the policy is that a higher ESHI coverage rate can be beneficial in several ways. For example, first, it effectively reduces acute illness costs with the help of medical treatment. Second, it improves workers’ welfare since healthier workers keep their match longer. Nevertheless, the impact of both policies on welfares for firms can be negative when considering equilibrium effects. Therefore, choosing the ESHI coverage rate as the sole policy goal might be misleading. Also, firms and workers can benefit from getting access to health insurance or not. Instead of shutting down this channel, changing their marginal decision through subsidy and penalty might reduce welfare loss.
This paper can be extended in several directions. First, my conclusions are obtained by making a number of assumptions, as mentioned in Section 2.5. Although relaxing such assumptions adds more state variables in the model, it is promising to study other effects of ESHI coverage. Second, I only focus on relatively healthy individuals since modeling other chronic health conditions often requires dynamics over the life cycle. An exciting venue for future research is to quantify the costs associated with other health problems, including disability or chronic illness, and their relationships with other labor market outcomes. In that case, my model can assess other programs, such as Social Security Disability Insurance (SSDI) program. Finally, I ignore the channel that health capital can be accumulated by individuals who can invest time or money in their general health conditions (see: Becker (1962); Acemoglu and Pischke (1999); Fang and Gavazza (2011)). Once health capital can be treated as a form of general human capital in the model, firms cannot fully internalize the returns to providing wellness programs (e.g., on-site fitness centers, yoga classes, and smoking cessation programs). As a result, the extent of search frictions and how workers and firms split the surplus leads to the under-provision of such programs from the socially optimal level. A model of health capital accumulation is an interesting next step to evaluate wellness programs at the workplace.
A. APPENDIX: INSTITUTIONAL CONTEXT AND PARAMETERS

A.1 Institutional context

The advantages of employer-sponsored health insurance are straightforward, even though there are costs of providing it. On the employers’ side, health insurance coverage increases employees’ productivity through improvements in future health capital and helps the firm match more productive workers. On the employee side, ESHI reduces health-related costs associated with sudden health shocks. As interests of both sides coincide, ESHI has been the main source of health insurance coverage for workers and firms in the United States. For example, the fraction of working-age populations with ESHI was about 58% in 2018. Overall, the equilibrium search model in the paper is well suited to understand how ESHI reduces the costs of illnesses.

The US medical care system has been developed to make health insurance more accessible to those who change jobs. First, 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) use the implementation of COBRA with state-level variation in “continuation of coverage” mandates to estimate the effects of continuation coverage benefits. They find that one more year of continuation benefits increases mobility by 10%. Because of the features of MEPS, I do not model COBRA since I cannot track down labor market histories of individuals, which are necessary to model such options. Also, Dey and Flinn (2005) show that ESHI does not lead to significant inefficiencies in mobility decisions.

As seen in the following Figure A.1, the fraction of firms offering ESHI and workers covered by it has decreased over 20 years. To reverse this trend, the ACA passed in March 2010 was designed 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 data on firm size and interactions between family members that are not relevant in the search-matching-bargaining framework. As a result, I do not study the ACA with my model in detail.

Figure A.1: 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 have to calibrate some health insurance-related parameters outside of the estimation process, but these decisions are aligned with the institutional context. The percent of total premiums contributed by employees $k$ is determined by the institutional setting of the US labor market. To derive
the portion of the premium paid by an employee, I use the MEPSnet/IC tool, which calculates national statistics and trends about ESHI premium. MEPS-HC does not include variables on the exact cost of health insurance for employers and employees, which are available in the MEPS Insurance Component, which is only accessible in one of the data centers. I extract the average total single premium (in dollars) per enrolled employee at private-sector establishments that offer health insurance. This value can be divided by the average total contribution (in dollars) per enrolled employee for single coverage at the same establishments. Accordingly, the percent of total premiums contributed by employees enrolled in ESHI was 20.8% in 2012. Therefore, \( k \) is set to be 20.8% of ESHI premium, while \( 1 - k \) represents the remaining 79.2% paid by employers. From my calculations, employee contributions for single coverage in private sectors have remained relatively constant, from 20.1% in 2008 to 20.8% in 2012.

The coinsurance rate and hourly insurance premium are set to be 21% and 2.59 dollars per hour, respectively, following MEPS statistical brief examining 2012 MEPS. The coinsurance represents the percentage of medical expenses the insured worker pays after the deductible amount has been paid. I do not include deductibles in the model because of the limited health insurance information. For this reason, I let the deductibles be zero. I set the average percentage coinsurance of private-sector employees enrolled in a plan equal to 21%.58

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58 In an earlier version of this paper, I try to identify health insurance premiums \( \phi \) and employee contributions \( k \) builds upon 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 \( w(x, 0) \). To identify \( \phi \), I exploit the following wage difference between \( w(\hat{x}, 1) \) and \( w(\hat{x}, 0) \) around the reservation value \( \hat{x} \) at which firms are indifferent to providing jobs with ESHI or without.

\[
\Delta \equiv w(\hat{x}, 0) - w(\hat{x}, 1) > 0
\]

Intuitively, wages of jobs with health insurance are lower than jobs without health insurance when productivity is around \( \hat{x} \); workers have to bear the costs related to insurance provision in the form of low accepted wages \( w(\hat{x}, 1) \), generating positive \( \Delta \). This discontinuity \( \Delta \) represents the existence of the overlapped area in support of the accepted wage distributions. When ignoring equilibrium effects, an increase in premium \( \phi \) increases the firm’s marginal costs of offering ESHI, moving the location of the reservation value \( \hat{x} \) to the right. Given that \( \hat{x} \) governs the location of the overlap, the higher \( \phi \), the smaller the overlap. Such overlaps constitute the mixture distributions from a collection of wage distributions conditional on health insurance status. With the help of fixed parameters, I can replicate the entire support area of the productivity and associated wage densities.
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 total utility (or disutility) from unemployment and two main events that may happen after a period $\triangle t$: staying in the unemployment status, 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:

$$
U_H(m) = b + (1 + \rho \triangle t)^{-1} \times \left[ \nu U_S(m) \triangle t \right]_{\text{contract illness}} + \lambda_H \left\{ \int_{-\triangle H}^{\triangle H} \max\left\{ E_H(w, 0; x), U_H \right\} dG(x) \right\} \triangle t + \int_{\triangle H}^{\triangle H} \max\left\{ E_H(w, 1; x), U_H \right\} dG(x)_{\text{receive a job offer}} + (1 - \nu - \lambda_H) U_H \triangle t + o(\triangle t)
$$

(B.1)

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 wages

Conditional on the provision of insurance, the analytical expression for wages of employees who are matched with different types of jobs are:
\[ w(x, 0) = \alpha [x + \nu \left\{ (1 - p) \left\{ \int_{-\Phi} F_{A,0}(w, 0; x) dM(m) + \int_{\Phi} F_{A,1}(w, 0; x) dM(m) \right\} + p F_S(w, 0; x) \right\} ] \]  
\[ + (1 - \alpha) [(\rho + \nu) U_H] \]
\[ - \nu \left\{ (1 - p) \int \max \{ E_{A,0}(w, 0; x), E_{A,1}(w, 0; x, m) \} dM(m) \right\} ] \]

\[ w(x, 1) = \alpha [x - (1 - k) \phi + \nu \left\{ (1 - p) \left\{ \int_{-\Phi} F_{A,0}(w, 1; x) dM(m) + \int_{\Phi} F_{A,1}(w, 1; x) dM(m) \right\} + p F_S(w, 1; x) \right\} ] \]
\[ + (1 - \alpha) [(\rho + \nu) U_H + k \phi] \]
\[ - \nu \left\{ (1 - p) \int \max \{ E_{A,0}(w, 1; x), E_{A,1}(w, 1; x, m) \} dM(m) \right\} ] \]

Wages can be expressed as closed solutions conditional on all the possible outcomes defined by optimal decisions rules over medical care expenditures \( m \). Closed-form wage equations are described in the proof of lemma 1. 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, given the model’s set of parameter values and steady-state equilibrium conditions.

### B.3 Optimal decision rules

I only consider \( m^*(x, 0) < m < m^*(x, 1) \), meaning that the insured always seek medical care for moderate illness and the uninsured do not \( (c = 1 \text{ if } d = 1 \text{ and } c = 0 \text{ if } d = 0) \); other cases are similar but simpler. After inserting the wage equations in all the value functions, I can compare value functions for each possible status to derive the reservation values that define the agent’s
decision. The rearranged value function of a filled job becomes:

\[
\frac{A(d)}{(1 - \alpha)} F_H(w, d; x) = B(d)(x + \eta_d U_H - k\phi d)
\]

\[- A(d)U_H - C(d)(1 - k)\phi d
\]

\[+ \nu \left\{ (1 - p)(\rho + \eta_d + \zeta_S)(\eta_d U_{A,d}(m) - k\phi d - \kappa - m) \right\}
\]

\[+ p(\rho + \eta_d + \zeta_{A,c})(\eta_d U_{S}(m) - \kappa - m) \]

where:

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

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

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

\[C(d) = (\rho + \eta_d + \zeta_{A,1})(\rho + \eta_d + \zeta_S)\]

\[+ \nu(\rho + \eta_d + \zeta_S) + p\nu(\rho + \eta_d + \zeta_{A,1})\]

I express terms \(A(d), B(d), C(d)\) and recovery shocks \(\zeta_{A,d}\) as a function of ESHI. A critical match for being employed \(x^*(d)\) is expressed as:

\[x^*(d) = -(\eta_d U_H - k\phi d)\]

\[+ \frac{A(d)}{B(d)} U_H + C(d)(1 - k)\phi d\]

\[- \frac{\nu}{B(d)} \left\{ (1 - p)(\rho + \eta_d + \zeta_S)(\eta_d U_{A,d}(m) - k\phi d - \kappa - m) \right\}
\]

\[+ p(\rho + \eta_d + \zeta_{A,c})(\eta_d U_{S}(m) - \kappa - m) \]
Note that $F_H(x, d)$ can be also expressed with $x^*(d)$ such that:

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

where:

$$A(d) = (\rho + \eta_d + \nu)(\rho + \eta_d + \zeta)$$

$$= (1 - p)\nu \zeta(\rho + \eta_d + \zeta) - p\nu \zeta(\rho + \eta_d + \zeta_A)$$

$$B(d) = (\rho + \eta_d)(\rho + \eta_d + \zeta)$$

In the interest of space, I do not report other critical values in the paper, but they are available from the author upon request.

Estimated decision rules in Table B.1 present the implied reservation matches for transitions out of unemployment $x^*(d; m)$ and for the provision of ESHI $\hat{x}(m)$ at the productivity of the realized matches. It supports the second case of proposition 2, generating all three labor market outcomes in this economy. Also, I report optimal decision rules for medical care utilization.

Table B.1: Estimates of the Critical Values

<table>
<thead>
<tr>
<th>Estimated critical values over $x$</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$x^*(0)$</td>
<td>11.935</td>
</tr>
<tr>
<td>$x^*(1)$</td>
<td>17.548</td>
</tr>
<tr>
<td>$\hat{x}$</td>
<td>28.076</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Estimated critical values over $m$</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$E_x[m^*(x, 0)]$</td>
<td>49.619</td>
</tr>
<tr>
<td>$E_x[m^*(x, 1)]$</td>
<td>49.968</td>
</tr>
<tr>
<td>$m^{**}$</td>
<td>26.803</td>
</tr>
</tbody>
</table>

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 $\hat{x}$ 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 coverage and employment states. Details are explained in Section 2.
Figure B.1 plots the simulated density function of 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 $\tilde{x}$. It supports case 2 of the Proposition 2 in the paper.

![Optimal Decision Rules](image)

**Figure B.1: 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 $\tilde{x}$. The definition of critical values is explained in Section 2.

### B.4 Proof of lemma 1

I insert the rearranged value function of employment, and the rearranged value function of a filled job into the bargained wage equations as defined in (B.2) and (B.3). Then, I derive a closed-form solution for the wage equations after some algebra. When $m^*(x, 0) < m < m^*(x, 1)$, the closed
solution of Nash bargaining model is such that:

\[
w(x, d) = \frac{\alpha}{C(d)} [B(d)x - C(d)(1 - k)\phi d] \\
+ \frac{(1 - \alpha)}{C(d)} [A(d)U_H - B(d)(\eta U_H - k\phi d)] \\
- \nu \left\{ (1 - p)(\rho + \eta_d + \zeta_S)(\eta_d U_{A,1}(m) - k\phi d - k - m) \\
+ p(\rho + \eta_d + \zeta_{A,c})(\eta_d U_{S}(m) - k - m) \right\}
\]

where:

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

It is obvious that \(\frac{\partial w(x, d)}{\partial x} = \frac{\alpha B(d)}{C(d)} > 0\), which is enough to prove the lemma, given \(B(d)\) and \(C(d)\) are positive.

### B.5 Proof of proposition 2

I only report the expressions for case 2 of Proposition 2 since the other case is a specialization of these expressions with similar arguments. I must prove that the value functions satisfy a single-crossing condition for each reservation value. Following the theoretical model and empirical results, I assume that the following inequalities hold: \(\zeta_{A,\{e=1\}} > \zeta_{A,\{e=0\}} > \zeta_S\) and \(\eta_0 > \eta_1\).

First, I prove that the value functions for two types of filled jobs 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 \(x\):
\[
\frac{\partial F_H(w, d; x)}{\partial x} = \left( \frac{B(d)}{A(d)} \right) (1 - \alpha) > 0
\]

This guarantees that each value function crosses only once the firms’ outside options values over the support of productivity.

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 \( \hat{x}_i \). 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:

\[
B(1) A(0) - B(0) A(1) = (\rho + \eta_0 + \nu)(\rho + \eta_0 + \zeta_A, 1)(\rho + \eta_1 + \zeta_S)(\rho + \eta_0 + \zeta_S)
\]

\[
- (1 - p)\nu(\rho + \eta_1 + \zeta_A, 1)(\rho + \eta_1 + \zeta_S)(\rho + \eta_0 + \zeta_S)
\]

\[
- p\nu\zeta_S(\rho + \eta_0 + \zeta_A, 0)(\rho + \eta_1 + \zeta_A, 1)(\rho + \eta + \zeta_S)
\]

\[
- (\rho + \eta_1 + \nu)(\rho + \eta_1 + \zeta_A, 1)(\rho + \eta_0 + \zeta_A, 0)(\rho + \eta_1 + \zeta_S)(\rho + \eta_0 + \zeta_S)
\]

\[
+ (1 - p)\nu(\rho + \eta_0 + \zeta_A, 0)(\rho + \eta_1 + \zeta_S)(\rho + \eta_0 + \zeta_S)
\]

\[
+ p\nu\zeta_S(\rho + \eta_1 + \zeta_A, 1)(\rho + \eta_0 + \zeta_A, 0)(\rho + \eta_0 + \zeta_S)
\]

\[
= (\rho + \eta_1 + \zeta_S)(\rho + \eta_0 + \zeta_S)(\rho + \eta_1 + \zeta_A, 1)[(\rho + \nu)(\zeta_A, 1 - \zeta_A, 0)
\]

\[
+ \rho(\eta_0 - \eta_1) + \eta_0(\eta_0 - \eta_1) + (\zeta_{A,1}\eta_0 - \zeta_{A,0}\eta_1)] > 0
\]

\[
+ (1 - p)\nu(\rho + \eta_1 + \zeta_S)(\rho + \eta_0 + \zeta_S)[\rho(\zeta_A, 1 - \zeta_A, 0) + \zeta_{A,1}\eta_0 - \zeta_{A,0}\eta_1] > 0
\]

\[
+ p\zeta_S(\rho + \eta_1 + \zeta_A, 1)(\rho + \eta_0 + \zeta_A, 0)(\eta_0 - \eta_1)] > 0
\]

> 0

Finally, depending on a range of rankings between the three reservation values, all the cases of proposition can be realized for given a set of parameters. Moreover, based on those rankings, one
of the equilibrium cases can be realized after assigning values of \( x \) between the three reservation values.

B.6 Additional details on the equilibrium definition

Derivation of the equilibrium equations. By inserting the wage schedules and critical values, the equilibrium value functions of the employment states can be expressed in the following way:

\[
A(d)E_H(w, d; x) = C(d)w_0 
+ B(d)(\eta U_H - k\phi d) 
+ \nu \left\{ (1 - p)(\rho + \eta_d + \zeta_S)(\eta_d U_{A,d}(m) - k\phi d - \kappa - m) 
  + p(\rho + \eta_d + \zeta_{A,1})(\eta_d U_S(m) - \kappa - m) \right\} 
= \alpha B(d)[x - x^*(d)] + A(d)U_H
\]

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

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

With the equilibrium value functions and the optimal decision rules described in Proposition 2, I can derive the following equilibrium conditions:
\[(\rho + \nu)U_H = \left[ b + \frac{\lambda d B(d)}{A(d)} \right] \int_0^{x^*} [x - x^*(0)]dG(x) + \int_0^\infty [x - x^*(1)]dG(x) \]
\[
+ \nu \left\{ (1 - p)U_{A,0} + (1 - p) \int_0^\infty U_{A,1}(m)dM(m) \right\} + p \int U_S(m)dM(m) \]
\]
\[
U_{A,0} = (\rho + \zeta_{A,0})^{-1} [b - \kappa + \zeta_{A,0}U_H] \]
\[
U_{A,1}(m) = (\rho + \zeta_{A,1})^{-1} [b - \kappa - o(d; m) + \zeta_{A,1}U_H] \]
\[
U_S(m) = (\rho + \zeta_S)^{-1} [b - \kappa - o(d; cm) + \zeta_SU_H] \]

where:
\[
A(d) = (\rho + \eta_d + \nu)(\rho + \eta_d + \zeta_{A,d})(\rho + \eta_d + \zeta_S) - (1 - p)\nu\zeta_{A,d}(\rho + \eta_d + \zeta_S) - p\nu\zeta_S(\rho + \eta_d + \zeta_{A,d}) \]
\[
B(d) = (\rho + \eta_d + \zeta_{A,d})(\rho + \eta_d + \zeta_S) \]

**Steady-state balance flow conditions.** The equilibrium measures of workers occupy all possible illness conditions \( i \in \{H, A_0, A_1, S\} \). I impose the steady-state conditions, which equate flows into and out of each state. Note that \( A_0 \) refers to a moderate acute illness without medical care utilization, and \( A_1 \) is an acute illness with utilization. \( u_i, e_i(0), \) and \( e_i(1) \) denote the measures of searchers, employees without ESHI, and employees with ESHI, respectively. In the steady-state, the total measure of workers with the illness conditions of all states should add up to 1, as in the case for workers with illness:

\[
u u_i + e_i(d = 0) + e_i(d = 1) = 1 \quad (B.4)\]

The model determines the distribution as a result of both inflows and outflows in equilibrium. The flows are governed by the optimal decision rules with Poisson shocks, and inflows and outflows from each state should balance:
\[ \lambda[1 - G(\tilde{x})](u_H + u_{A,0}\zeta_{A,0} + u_{S}\zeta_{S}) = \eta_0 e_H(0) \]

Flows into \( e_H(0) \)  

Flows out of \( e_H(0) \)

\[ \lambda[G(\tilde{x}) - G(x^*(0))](u_H + u_{A,1}\zeta_{A,1} + u_{S}\zeta_{S}) = \eta_1 e_H(1) \]

Flows into \( e_H(1) \)  

Flows out of \( e_H(1) \)

\[ \nu p[1 - M(m^*(0))] e_H(0) = \zeta_{A,0} e_{A,0}(0) \]

Flows into \( e_{A,0}(0) \)  

Flows out of \( e_{A,0}(0) \)

\[ \nu p[1 - M(m^*(1))] e_H(1) = \zeta_{A,0} e_{A,0}(1) \]

Flows into \( e_{A,0}(1) \)  

Flows out of \( e_{A,0}(1) \)

\[ \nu p M(m^*) e_H(0) = \zeta_{A,1} e_{A,1}(0) \]

Flows into \( e_{A,1}(0) \)  

Flows out of \( e_{A,1}(0) \)

\[ \nu p M(m^*) e_H(1) = \zeta_{A,1} e_{A,1}(1) \]

Flows into \( e_{A,1}(1) \)  

Flows out of \( e_{A,1}(1) \)

\[ \nu(1 - p) e_H(0) = e_S(0)\zeta_{S} \]

Flows into \( e_S(0) \)  

Flows out of \( e_S(0) \)

\[ \nu(1 - p) e_H(1) = e_S(0)\zeta_{S} \]

Flows into \( e_S(1) \)  

Flows out of \( e_S(1) \)

The hazard rate out of each state is defined as the probability of leaving that state conditional on how long the worker has been in that state. The above twelve flow equations represent a vector of twelve equations with twelve unknown equilibrium measures of workers with illness conditions for each state \( u_i, e_i(0), \) and \( e_i(1), \) given the knowledge of a parametric assumption on the exogenous match-specific productivity and medical care expenditure distribution. Notice that adverse health shocks on one match do last even after employment is terminated. I assume that there are no multiple solutions in the context of non-linear systems of equations. Therefore, the above flow equations can characterize equilibrium unemployment and the employment rate of workers with illness conditions.
B.7 Welfare measures

I estimate the model assuming the moments are extracted from a steady-state. I conduct counterfactual experiments with estimates by comparing different steady-state at different parameters values. In these experiments, I explicitly use welfare measures representing the total output and utility of the labor market for workers and firms. In particular, I use averages over the equilibrium measures and distributions of each labor market state in equilibrium. Therefore, these welfare measures summarize not only wages and medical care expenditures but also labor market frictions, transition probabilities between states, the duration in each state, and the value of ESHI.

**Total output.** The total output refers to the total production by mass of workers that are currently in a job,

$$\int_{x^*(0)}^{\bar{x}} x dG(x) + \int_{\bar{x}}^{\infty} x dG(x)$$

I also propose a welfare measure averaging the flow values of each state in each acceptable match-specific productivity. Specifically, I derive the total output per worker by dividing the total production by mass of workers that are currently in a job.

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

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

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

This welfare measure is the average per-worker profits times the proportion of that type of worker hired in a steady state.

**Workers’ welfare** I use the discounted value of searching states to measure workers’ welfare $\rho U_H$. It can be interpreted as a measure of workers’ welfare because it is the present discounted value of participating in the labor market.
B.8 Additional background on the employer mandate penalties

B.8.1 New 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 need to express the subsidy \( s(c) \) as a function of all the model parameters; for the sake of simplicity, I focus on the dependence of penalties. The profit function of employers with ESHI can be expressed as:

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

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

\[
w(x, 0) = \alpha[x + s(p) + \nu\left\{ (1 - p)\left\{ \int_{\Phi} F_{A,0}(w, 0; x)dM(m) + \int_{\Phi} F_{A,1}(w, 0; x)dM(m) \right\} + pF_S(w, 0; x) \right\} \\
+ (1 - \alpha)((\rho + \nu)U_H] \\
- \nu\left\{ (1 - p)\int \max\{E_{A,0}(w, 0; x), E_{A,1}(w, 0; x, m)\}dM(m) \right\} ]
\]

\[
w(x, 1) = \alpha[x - p - (1 - k)\phi + \nu\left\{ (1 - p)\left\{ \int_{\Phi} F_{A,0}(w, 1; x)dM(m) + \int_{\Phi} F_{A,1}(w, 1; x)dM(m) \right\} + pF_S(w, 1; x) \right\} \\
+ (1 - \alpha)((\rho + \nu)U_H + k\phi] \\
- \nu\left\{ (1 - p)\int \max\{E_{A,0}(w, 1; x), E_{A,1}(w, 1; x, m)\}dM(m) \right\} ]
\]
B.8.2 Simulation

I compute the endogenous subsidies as a function of changes in penalties. The subsidy is distributed from all penalties collections, so I need to calculate the number of penalties from the equilibrium proportion of employers with and 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 \( e_i(d = 1) s(p) - e_i(d = 0) p \) of implementing this policy from the government’s point of view. As total expense converges to zero, the flow of subsidy for each employer with ESHI changes implicitly.

B.9 Summary of the model

Below, I summarize the value functions that consist of the theoretical search model.
### Table B.2: Summary of the Model

<table>
<thead>
<tr>
<th>State</th>
<th>Value Fns</th>
<th>Shocks</th>
<th>Flow Utility</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Unemployed workers:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$i = H$</td>
<td>$U_H$</td>
<td>$\lambda, \nu$</td>
<td>$b$</td>
</tr>
<tr>
<td>$i = A, c = 0$</td>
<td>$U_{A,0}$</td>
<td>$\zeta_{A,0}$</td>
<td>$b - \kappa$</td>
</tr>
<tr>
<td>$i = A, c = 1$</td>
<td>$U_{A,1}(m)$</td>
<td>$\zeta_{A,1}$</td>
<td>$b - \kappa - o(m, 0)$</td>
</tr>
<tr>
<td>$i = S$</td>
<td>$U_S(m)$</td>
<td>$\zeta_S$</td>
<td>$b - \kappa - o(m, 0)$</td>
</tr>
<tr>
<td><strong>Employed workers:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$i = H$</td>
<td>$E_H(w, d; x)$</td>
<td>$\eta_d, \nu$</td>
<td>$w(x, d) - k\phi d$</td>
</tr>
<tr>
<td>$i = M, c = 0$</td>
<td>$E_{A,0}(w, d; x)$</td>
<td>$\eta_d, \zeta_{A,0}$</td>
<td>$w(x, d) - \kappa - k\phi d$</td>
</tr>
<tr>
<td>$i = M, c = 1$</td>
<td>$E_{A,1}(w, d; x, m)$</td>
<td>$\eta_d, \zeta_{A,1}$</td>
<td>$w(x, d) - \kappa - k\phi d - o(m, d)$</td>
</tr>
<tr>
<td>$i = S$</td>
<td>$E_S(w, d; x, m)$</td>
<td>$\eta_d, \zeta_S$</td>
<td>$w(x, d) - \kappa - k\phi d - o(m, d)$</td>
</tr>
<tr>
<td><strong>Firms:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$i = H$</td>
<td>$F_H(w, d; x)$</td>
<td>$\eta_d, \nu$</td>
<td>$x - w(x, d)$</td>
</tr>
<tr>
<td>$i = M, c = 0$</td>
<td>$F_{A,0}(w, d; x)$</td>
<td>$\eta_d, \zeta_{A,0}$</td>
<td>$-w(x, d) - (1 - k)\phi$</td>
</tr>
<tr>
<td>$i = M, c = 1$</td>
<td>$F_{A,1}(w, d; x)$</td>
<td>$\eta_d, \zeta_{A,1}$</td>
<td>$-w(x, d) - (1 - k)\phi$</td>
</tr>
<tr>
<td>$i = S$</td>
<td>$F_S(w, d; x)$</td>
<td>$\eta_d, \zeta_S$</td>
<td>$-w(x, d) - (1 - k)\phi$</td>
</tr>
</tbody>
</table>

**Note:** The table summarizes the notations with value functions and shocks in the model. The definitions of notations are explained in Section 2.
C. APPENDIX: NUMERICAL ALGORITHM TO SOLVE AND SIMULATE THE MODEL

I summarize the computational methods and procedures to estimate sets of parameters. Closed-form solutions for the value functions are not available and therefore, I use simulation methods to solve for the equilibrium at given parameters values. For a numerical solution of a continuous-time model, the environment should be converted to a discrete-time model. I numerically solve the model by the following iterative procedures:

1. Setting guesses for parameters: we define an initial guess of sets of parameters in $\Theta$.

2. Discretization of productivity: To handle integration, I approximate the continuous distribution functions, taking the continuous 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. Also, medical care expenditures $m$ are spread out to 100 finite equally spaced points over the support of $[0, 10]$. The probability mass functions of $x$ and $m$ are derived from the difference between the cumulative distribution functions at the 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, using fixed point methods on each grid point of the individual states. I make an initial guesses for the set of value functions $\{U_i(m), E_i(w, d; x, m), F_i(w, d; x, m)\}$ 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 history for 360 months, where each labor market histories refers to a sequence of transitions between labor market and illness states for each individual. Through this process, I can generate an artificial data set of labor market histories and wage paths.

$^{59}$Although this choice is arbitrary, I experimented with a variety of finite points. My choice generates the simulated match-specific productivity and medical care expenditure distributions well.
1. **Interpolation method:** I can interpolate the solved individual value functions at specific grid points using linear interpolation. In particular, match-specific productivity, health insurance provision, and realized medical care expenditures pass through the original points of all the value functions and the Nash bargained wage equations.

2. **Optimal decision rules:** I model the optimal decision rules that can be characterized by reservation values for discretized state space by comparing all the potential value functions. The optimal decisions are updated, depending on the different states of the same individual.

   (a) **Searching state:** At the first stage, agents meet potential employers at a Poisson rate \( \lambda \) 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 option. Searchers also receive health shocks conditional on their insurance coverage status. 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.

   (b) **Employment state:** Agents may receive a termination shock or a health shock. By the same argument as above, the duration of these shocks is drawn from negative exponential distributions with rates \( \eta \) and \( \delta \), respectively. If the termination shock arrives, the agent moves back to the searching state. If an agent receives a health shock (but no termination shock), their health status changes but the match with the current employer continues.

   (c) **Unobserved heterogeneity:** A severe illness is chosen randomly from a uniform distribution, allowing different probabilities to contract different types of acute illnesses.

3. **Steady-state:** As time goes on in the simulation, the model converges to its steady state. To decide whether the model has reached the steady state, once enough event histories are made, I compare each individual's labor market states and wages over the period, check whether...
the ex-ante identical individuals are sorted into different states well, and check that their cross-sectional features do not change. 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 are used to generate a set of moments for use in the criteria function as defined.

Finally, I calculate 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 simulated moments. I mainly use the Nelder-Mead algorithm for multidimensional unconstrained optimization decision problems with the help of other algorithms, such as Particle swarm optimization and pattern search.
D. APPENDIX: 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.\(^{60}\)

D.1 Sample restriction

In the theoretical model, individuals are ex-ante identical, so I take the following steps to have a homogeneous sample. I select individuals between the ages of 30 and 55. I use this restrictive age criteria since labor market behaviors are quite different by age. Younger individuals are likely associated with human capital accumulation decisions and employment decisions characterized by higher turnover rates between labor market states. Older individuals near retirement may make different medical care decisions 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.\(^{61}\) I exclude individuals who have either public, non-employer-sponsored health insurance, or spousal ESHI. Including other sources of 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 characterized by joint household labor supply.

I also exclude unhealthy individuals who have bad health status and had chronic illness 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 treatment

\(^{60}\text{The data can be found at https://www.meps.ahrq.gov/mepsweb/}\)

\(^{61}\text{I describe how to eliminate individuals who do not have relevant insurance information in the following subsection.}\)
decisions. The model parsimoniously introduces a health capital production function in which health investment is positively related to healthier living. Therefore, it is necessary to exclude unhealthy individuals to assume that parameters of the health capital production function are time-invariant, except for the interaction between medical care consumption and acute illnesses. Additionally, I impose the following sample selection criteria to make an estimation 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 deleted some individuals who report variables for which inconsistencies occur (e.g., unemployed workers have ESHI). My final estimation sample that meets all of the selection criteria consists of 3,807 individual-round observations, as described in D.1.

Table D.1: Sample Selection Information

<table>
<thead>
<tr>
<th>Homogeneity criteria</th>
<th>Remaining Sample Size</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>2012 MEPS participants</strong></td>
<td>109,305</td>
</tr>
<tr>
<td>Having relevant insurance information</td>
<td>96,558</td>
</tr>
<tr>
<td>and aged 30-55 years</td>
<td>36,285</td>
</tr>
<tr>
<td>and white male</td>
<td>12,127</td>
</tr>
<tr>
<td>and at least a high school education</td>
<td>9,476</td>
</tr>
<tr>
<td>and not self-employed</td>
<td>8,344</td>
</tr>
<tr>
<td>and not in military or public services</td>
<td>7,855</td>
</tr>
<tr>
<td>and no government welfare program</td>
<td>7,146</td>
</tr>
<tr>
<td>and healthy and no chronic illness</td>
<td>6,174</td>
</tr>
<tr>
<td>and only covered by ESHI</td>
<td>5,139</td>
</tr>
<tr>
<td>Trimmed wages and medical care expenditures</td>
<td>5,088</td>
</tr>
<tr>
<td>Construct balanced panel</td>
<td>3,807</td>
</tr>
<tr>
<td><strong>Final Sample</strong></td>
<td>3,807</td>
</tr>
</tbody>
</table>
D.2 Sample construction

Among various data files in MEPS, I merge three types of data files: the full-year consolidated file, the medical condition files, and the medical event files. Medical event files contain information for five different types of medical consumption: prescription medicines, hospital inpatient stays, emergency room visits, outpatient department visits, and office-based medical provider visits. My model requires the following variables: a general set of demographic variables, illness conditions, insurance status, medical treatment variables, and labor market states. 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 in order to make it tractable for estimation.

D.2.1 Demographic variables

A set of demographic variables is assumed and 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 (race) 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. Below are the important variables that discern state vectors in the model.

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 status variable (empst). To neatly define workers, I exclude respondents who did not work at the interview date but have a job to return to and were employed during the reference period. 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). 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. Employment-sponsored health insurance is defined by health insurance held at a current main job (heldnnx), not health insurance offered through a current main job (offernnx). Self-reported health status captures the severity of current health conditions. 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 (5) Poor.

D.2.2 Medical treatment variables

Respondents report all medical care consumption that is linked to each illness condition during a reference period through the unique record IDs of medical care utilization. When an illness condition induces individuals to seek medical treatments, they provide the consumption date, the type of illness treated, and the total amount of medical care expenditures. For example, it consists of visit dates, diagnosis and procedure codes, charges, and payments. These linked files correspond to the full-year consolidated file. 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 the possibility respondents might not accurately provide it. This procedure improves the quality of all medical treatment variables.

I categorize ill individuals as seeking medical care if they sought 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. Dental visits, other medical expenses, and home health are excluded since ESHI typically does not cover these types of medical care utilization. Outpatient

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62 If the number of hours worked per time period was not available, a value of 40 hours per week was assumed.
63 The variables obnum, opnum, ipnum, ernum, and rxnum indicate the total number of medical events that is linked to each condition record on the current file (i.e., office-based visits, outpatient visits, inpatient hospital stays, emergency room visits, and prescribed medicines, respectively). All these events files are derived from separate event files (HC-152G, HC-152F, HC-152H, HC-152D, HC-152E, and HC-152A).
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. The prescribed medicine is recorded when respondents purchase at least once. Prescribed drugs are ordered by authorized medical personnel through written or verbal prescriptions for a pharmacist to fill for the patient.

I calculate the total medical care expenditures for illness conditions associated with the above medical treatment variables. The total medical care expenditures are the sum of the twelve sources of payment categories at the annual frequency. 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. Other than out-of-pocket prices, two more medical care prices exist in the United States. A list price refers to the theoretical market price of medical care, and a transaction price is the sum of insurance’s and insured individual’s payments for care provided. Out-of-pocket costs, which are lower than a list and transaction price, are directly associated with an individual’s behavior. Besides, it includes a variety of essential components of medical costs such as deductibles, coinsurance, co-payments for covered services, and all costs for services that aren’t covered. Therefore, I focus on out-of-pocket expenses to capture heterogeneous medical care expenditure risks.

Medical events associated with illness conditions include all healthcare utilization between January 1, 2012, and December 31, 2012.

Expenditures for medical care services consist of payments from all sources, such as direct payments from individuals, private insurance, Medicare, Medicaid, Workers’ Compensation, and miscellaneous other sources.
D.2.3 Illness conditions variables

This section explains the procedure to classify acute illnesses from all the medical conditions and their illness episodes. Before characterizing acute illness, I need to find current illness conditions from the MEPS Medical Conditions files. MEPS Medical Conditions files contain the current conditions of the respondents. It means that the individual had reported a medical event or a disability day for the condition in the reference period or reported that the condition 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 for the person during the interview reference period. Second, the condition can be recorded in the Medical Events (ME) section when any specific physical or mental health problems are associated with a particular medical event (medical provider office visits (MV), emergency rooms (ER), outpatient departments (OP), hospital inpatient stays (HS), prescribed medicine purchases (PM) or home health providers (HH). Third, a condition can be recorded in the Disability Days section (DD) if the condition causes respondents to miss school or work or spend more than half a day in bed. An individual’s description of the illness condition is recorded as verbatim text, later coded to 5-digit ICD-9-CM codes by professional coders. These illness conditions are recorded even if individuals do not consume any medical care. If a person has multiple events during the calendar year, each of these events will be represented with an event-level record.

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. The CCI defines a chronic condition when it lasts more than

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65 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.”

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

67 The Chronic Condition Indicator (CCI) is a software tool developed as part of the Healthcare Cost and Utilization Project (HCUP), sponsored by the Agency for Healthcare Research and Quality.
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 the MEPS public-use files collapse all ICD codes into 3-digits 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 the 5-digits ICD codes 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 in CCI). Regarding the remaining conditions, I label them as a chronic illness when more than half of 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. It is similar to the fully specified 5-digits ICD codes that 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 illnesses associated with the Herpes Simplex Virus (Genital Herpes). It is classified as a chronic illness because it cannot be fully cured. However, outside of periods when individuals seek medical treatment because it bothers them, it does not affect their lives. Therefore, I re-coded it as acute illness. In a similar sense, the clarifications for 14 illness conditions were changed to fit the definitions of acute or chronic illnesses.

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68 https://www.cdc.gov/std/herpes/STDFact-Herpes.htm

69 If the features of chronic illnesses are very similar to those of acute illnesses, they were re-coded as such. For example, 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.
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.

![Histogram of interview months in MEPS](image)

**Figure D.1: The Distribution of Period Lengths in MEPS**

One caveat of the MEPS is that the interview rounds are not necessarily evenly spaced, so some individuals are interviewed at different frequencies. Fig. D.1 shows that 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. I only include observations where the reference period is between four months and eight months for the cross-sectional moments. For example, individuals are asked about their labor market and health status covering March 2012 to July 2012. In this case, the reference period is five months from the intermediate rounds of Panel 16 and Panel 17, so I include this sample for the cross-sectional moments. Although the reference periods of the final cross-sectional sample vary in length, their average period length is 5.9 months, which is close to 6 months that the model targets. For the dynamic moments, I extract yearly transitions from individuals with interviews spaced 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 those in 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., round 1 and 2 or round 2 and 3) covers one year. As a result, my model captures the variant of changes in labor market states observed over the year at the interview dates.

Another caveat of the MEPS is that some variables are recorded at different frequencies, leading to timing problems. I have to clarify several variables in the following procedure. First, the medical care utilization and their expenditures variables are observed at the annual frequency in the data. Medical care utilization variables indicate the consumption date of medical care utilization linked to each illness condition. Thus, I can capture whether ill individuals consume medical care in each round for a specific source of illness. Medical care expenditures refer to the sum of all the spendings of 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 money they spend on medical care on an hourly basis on average. This is possible because medical care consumption variables and associated medical care expenditures from the multiple files are linked to medical conditions in the Medical Condition files. Second, I observe employment states, ESHI states, and health status illness states at the interview dates. I let the model’s composite states (e.g., workers with an illness or searchers without an illness) correspond to the sample’s observed variables. Then, based on the period lengths, I can generate cross-sectional and dynamic sectional moments for these variables, following the procedure I used to control for non-evenly spaced interview rounds. Third, I observe the health insurance status other than ESHI at the monthly frequency. This information is required to remove individuals who are covered by other types of health insurance such as Medicaid or Medicare. I assume that a monthly individual’s health insurance status other than ESHI corresponds to recorded variables in the same month as the interview date. With this classification, I classify different health insurance status for a given respondent in each round. Finally, I use the

70Demographic variables, such as education, ages, and race, are assumed to be time-invariant over the calendar. These variables do not change in any reference periods in my sample, so I do not need to clarify those variables.
number of missed workdays due to acute illnesses to measure the duration of illness episodes. I use this information only for different hazard functions, which take days into account. Therefore, there is no timing issue for this variable.


FLINN, C. J. (2006): “Minimum wage effects on labor market outcomes under search, matching, and endogenous contact rates.”


