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Accounting for Mismatch Unemployment

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Abstract

We investigate unemployment due to mismatch in the United States over the past three and a half decades. We propose an accounting framework that allows us to estimate the contribution of each of the frictions that generated labor market mismatch. Barriers to job mobility account for the largest part of mismatch unemployment, with a smaller role for barriers to worker mobility. We find little contribution of wage-setting frictions to mismatch.

Keywords: mismatch, structural unemployment, worker mobility, job mobility
JEL codes: E24 J61 J62

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1 Introduction

After the end of the Great Recession in December 2007, unemployment in the United States remained high for more than half a decade. One explanation that was suggested is a mismatch in the skills or geographic location of the available jobs and workers, a view that seemed to be supported by a decline in aggregate matching efficiency (Elsby, Hobijn, and Şahin (2010), Barnichon and Figura (2010)) and geographic mobility (Frey (2009)). Direct estimates using disaggregated data confirm that mismatch rose in the recession (Şahin, Song, Topa, and Violante (2014)). However, the literature offers little insight into the reasons for this increase.

In this paper, we estimate mismatch unemployment on the U.S. labor market from 1979 to 2015, and we explore what frictions caused mismatch to arise. To do so, we use a model to derive an accounting framework that puts just enough structure on the data to allow us to quantify the sources of mismatch unemployment.

The labor market in our model consists of multiple submarkets or segments. Mismatch is defined as inefficient dispersion in labor market conditions, in particular the job-finding rate, across labor market segments. Within segments, frictions prevent the instantaneous matching of unemployed workers to vacant jobs, resulting in search unemployment in the tradition of Diamond (1982), Mortensen (1982) and Pissarides (1985). Across segments, frictions generate dispersion in labor market conditions, which gives rise to mismatch unemployment.[1]

Three types of frictions generate mismatch: worker-mobility costs, job-mobility costs, and wage-setting frictions. Worker-mobility frictions prevent an unemployed worker in one submarket from taking up a job in a different submarket. For example, if we think of labor market segments as occupations, worker-mobility frictions might prevent an unemployed construction worker from finding a job as a retail sales representative, a displaced steelworker from filling a vacancy for a nurse, or an unemployed engineer to take up a job as a lawyer. In these examples, worker mobility frictions take the form of training costs and occupational licensing. If we think of labor market segments as states, regions or commuting zones, frictions may also take the form of moving costs, etc. Job-mobility frictions prevent firms from substituting positions (e.g., onsite technicians) in submarkets where labor is scarce with different positions (e.g., online customer support representatives) for which the supply of workers is more abundant. We think of

[1] The definition of mismatch as a deviation from an efficient allocation follows the recent empirical literature, in particular Şahin, Song, Topa, and Violante (2014). Although not directly related, this definition is also consistent with the theoretical literature. Shimer (2007) shows that mismatch between the distributions of workers and jobs over segments of the labor market gives rise to a relationship between the job-finding probability and labor-market tightness that is very similar to the relationship obtained if there are search frictions and an aggregate matching function. Stock-flow matching, as in Coles, Jones, and Smith (2010); rest unemployment, as in Alvarez and Shimer (2011); reallocation unemployment as in Carrillo-Tudela and Visschers (2013), Wong (2012) or Chang (2011); waiting unemployment as in Birchenall (2011); mismatch unemployment as in Wiczer (2013); and move unemployment as in Pilossoph (2014) are all closely related to this concept of unemployment due to mismatch. As opposed to these studies, the focus of our paper is empirical. One way to think about the contribution of this paper is to provide a set of facts that can be used to test the theoretical models of mismatch unemployment.

these frictions as rigidities in the production technology, or as barriers to entry in particular occupations or industries. Both of these frictions may explain why a situation of mismatch between the distribution of vacancies and unemployed workers over submarkets can persist. Wage-setting frictions prevent the wage from reflecting the relative abundance or shortage of workers in different submarkets. This type of friction, which we could think of as a type of wage rigidity, generates mismatch because (everything else equal) workers will prefer to look for jobs in submarkets where wages are relatively high, whereas firms are more inclined to try and recruit in submarkets where wages are relatively low. As an example, this type of friction might explain why many workers with engineering backgrounds work in finance, while manufacturing firms find recruiting engineers difficult.

Our approach to estimate the sources of mismatch unemployment uses data on job- and worker-finding rates, and worker and job surplus by labor market segments, which we operationalize as occupations, states, or industries. We construct these variables over the 1979-2015 period from the Current Population Survey (CPS) and the National Income and Product Accounts (NIPA).

We argue that mismatch is an important reason for unemployment. Our estimates show that mismatch across detailed occupations and states is responsible for about a fifth of fluctuations in, and for around 13% of the level of unemployment. The cyclical behavior of mismatch unemployment is very similar to that of the overall unemployment rate. This finding is driven by the fact that dispersion in labor market conditions across states and industries moves closely with the business cycle, similar to what Abraham and Katz (1986) documented over three decades ago.[2] The unemployment that derives from this dispersion is as cyclical as the overall unemployment rate, and no more persistent. As a corollary, the nature of the increase in unemployment in the Great Recession was no different from the increase in previous recessions, although it was, of course, more severe.[3] The absence of a secular trend in mismatch unemployment indicates that the increase in mismatch unemployment was not "structural", in the sense that it would not respond to stabilization policy.[4]

[2] In response to the "structural shifts view" of recessions put forward by Lilien (1982), which holds that recessions are periods of reallocation between industries, Abraham and Katz showed that aggregate shocks can give rise to countercyclical fluctuations in dispersion of employment growth across sectors.

[3] This result is not inconsistent with the observation that there was an outward shift in the Beveridge curve, the negatively sloped relationship between vacancies and unemployment, which indicates a decline in aggregate matching efficiency and provides much of the basis for the argument that there was an unprecedented increase in mismatch in the Great Recession (Elsby, Hobijn, and Şahin (2010), Lubik (2013)). While an increase in mismatch indeed reduces matching efficiency (Shimer (2007)), there are many other causes for shifts in the Beveridge curve as well, including changes in the separation rate and demographics. Controlling for these factors, the remaining role for mismatch is very small (Barnichon and Figura (2010)). For the same reason, our findings do not contradict the observation that exogenous shocks to mismatch are not an important as a source of unemployment fluctuations (Furlanetto and Groshenny (2016)).

[4] In the wake of the Great Recession, this was a widely held view, advocated most prominently by Narayana Kocherlakota (2010), the president of the Federal Reserve Bank of Minneapolis, who argued that "it is hard to see how the Fed can do much to cure this problem. Monetary stimulus has provided conditions so that manufacturing plants want to hire new workers. But the Fed does not have a means to transform construction workers into manufacturing workers." See Estevão and Tsounta (2011) and

Our most interesting and novel set of results concerns the sources of labor market mismatch. We find that almost all mismatch is caused by barriers to worker and job mobility, and that the latter are much more important than the former. Little or no mismatch is due to wage-setting frictions. These conclusions are based on testing the strong predictions generated by our framework for the patterns we should observe in the data in the absence of the various frictions that can give rise to mismatch. In particular, if there are no barriers to worker mobility, a no-arbitrage condition dictates that we should see a negative correlation between wages (measuring how attractive it is to have a job in a given state or industry) and job-finding rates (how hard it is to find these jobs). We indeed find this correlation in the data.

The early empirical literature on mismatch focused on shifts in the Beveridge curve, trying to use aggregate data to estimate matching efficiency (Lipsey (1965), Abraham (1987), Blanchard and Diamond (1989), Barnichon and Figura (2010)). Two more recent contributions use disaggregated data and are closely related to this paper. Şahin, Song, Topa, and Violante (2014) use data on unemployment and vacancies by counties, occupations, and industries (from the JOLTS and the HWOL data for the 2001-2011 and 2005-2011 periods, respectively), to construct indices of mismatch. Barnichon and Figura (2015) use the CPS to explore how much dispersion in labor market conditions contributes to movements in matching efficiency.[5] The contribution of this paper is the accounting framework that allows us to decompose mismatch into its sources, and to estimate the contribution of each of these sources to unemployment.

This paper is organized as follows: In the next section we define mismatch as any deviation from the allocation chosen by a planner who can freely allocate vacancies and unemployed workers across submarkets of the labor market; we also set up the model environment to implement this definition. In Section 3, we show how the competitive equilibrium of this model can be used to decompose mismatch into the different sources of inefficient dispersion in job-finding rates. We identify three sources of mismatch: worker-mobility costs, job-mobility costs and wage-setting frictions. Section 4 presents the details of our proposed "mismatch accounting" procedure and discusses some important caveats. Section 5 describes the data used in the estimation, and explains in detail how we construct the empirical counterparts of the variables that define a labor market segment in our model. Finally, Section 6 presents the empirical results and Section 7 concludes.

Groshen and Potter (2003) for versions of this argument. Early critics include Krugman (2010), DeLong (2010), P. and Spletzer (2012), and Peter Diamond (2011), who notes in his Nobel lecture that "there is a long history of claims that the latest technological or structural developments make for a new, long-term, high level of unemployment, but these have repeatedly been proven wrong." (p.1065). Kocherlakota later changed his views in light of the evidence (New York Times (2014)).

[5] Another related recent paper is Herz (2017), who examines the role of skill mismatch for unemployment using micro-data on displaced workers. If no vacancies matching a displaced worker's skill set are currently available, she can either fill a vacancy for a job she is not trained for, and suffer a wage loss as a result; or she can wait until until a more suitable vacancy opens up. Herz empirically examines this trade-off using a difference-in-difference approach, and finds that such "wait unemployment" accounts for a substantial part of aggregate unemployment.

2 Mismatch

We define mismatch, following Şahin, Song, Topa, and Violante (2014), as any deviation from the allocation of unemployed workers and vacancies over labor market segments that a social planner would choose. Mismatch unemployment is unemployment that arises due to this mismatch, i.e., the difference between actual unemployment and unemployment in the social planner allocation. We show that, under some conditions, a social planner would equalize job-finding probabilities across labor market segments. Under these conditions, mismatch unemployment can be equivalently defined as unemployment due to dispersion in job-finding rates.

2.1 Model Environment

Consider a labor market that consists of segments indicated by i. The idea is that each unemployed worker cannot match with each vacancy. A segment, or submarket, is defined as the subset of jobs that a given unemployed worker searches for, or the subset of unemployed workers that can form a match with a given vacancy.

There are n_{it} workers employed in segment i at time t, who produce output using a production technology that requires only labor $f(n_{it}; z_{it})$, where z_{it} is a production efficiency shifter, which may vary across segments. Each labor market segment is subject to frictions in the tradition of Diamond (1982), Mortensen (1982) and Pissarides (1985). Job matches are formed from u_{it} unemployed workers and v_{it} vacancies using a constant-returns-to-scale matching technology $m(u_{it}, v_{it}; \phi_{it}) = \phi_{it} u_{it}^{\mu} v_{it}^{1-\mu}$, with $0 < \mu < 1$ and where ϕ_{it} is a matching efficiency shifter, which determines the job-finding and vacancy-filling probabilities $p_{it} = m(u_{it}, v_{it}; \phi_{it}) / u_{it} = \phi_{it} (v_{it}/u_{it})^{1-\mu}$ and $q_{it} = m(u_{it}, v_{it}; \phi_{it}) / v_{it} = \phi_{it} (v_{it}/u_{it})^{-\mu}$. Matches are destroyed with an exogenous probability δ_i in each period, so that employment in each segment evolves as $n_{it+1} = (1 - \delta_i) n_{it} + m(u_{it}, v_{it}; \phi_{it})$.

Unemployed workers engage in home production in the amount of b_{it} and workers not participating in the labor force produce λ^u, which includes any unemployment and welfare benefits and utility from leisure. Vacancies cost $g(v_{it}; \kappa_{it})$ in each period, where κ_{it} is a vacancy cost shifter, and there is an additional opportunity cost λ^v of keeping a position open, whether filled or unfilled, which we may think of as the revenue from renting out the capital associated with the position if it is closed (set $\lambda^v = 0$ to represent free entry of vacancies). The segment-specific shocks z_{it}, ϕ_{it}, b_{it} and κ_{it} all follow exogenous Markov processes. Workers have linear utility over consumption only,[6] and discount future periods at rate $\beta = 1/(1 + r)$.

[6] For simplicity. The efficient and equilibrium allocations are unchanged if we assume instead that households consisting of many workers share risk between their members. Utility from leisure is included in home production b_{it} and λ^u.

2.2 Efficient Allocation of Unemployed and Vacancies

The social planner allocates unemployed workers and vacancies over labor market segments to maximize the expected net present value of utility of the representative worker, which is equivalent to maximizing the expected net present value of output net of vacancy costs $\sum_i f(n_{it}; z_{it}) + b_{it}u_{it} - g(v_{it}; \kappa_{it}) + \lambda^u (1 - n_{it} - u_{it}) + \lambda^v (1 - n_{it} - v_{it})$, subject to the evolution of employment in each segment under the matching technology.

In appendix A.1, we show that the social planner chooses an allocation that satisfies the following efficiency condition,

$$p_{it} = \phi_{it} \left(\frac{1-\mu}{\mu} \frac{\lambda^u - b_{it}}{\lambda^v + g'(v_{it}; \kappa_{it})} \right)^{1-\mu} \tag{1}$$

where $p_{it} = \phi_{it} (v_{it}/u_{it})^{1-\mu}$ is the job-finding probability in segment i at time t, and μ is the unemployment share parameter in the matching function, $m(u_{it}, v_{it}; \phi_{it}) = \phi_{it} u_{it}^{\mu} v_{it}^{1-\mu}$.

A version of efficiency condition (1) may be found in Şahin, Song, Topa, and Violante (2014), who assume the production function is linear but that vacancy posting costs increase with the amount of vacancies in a segment. If we set $f(n_{it}; z_{it}) = z_{it} n_{it}$ and $g(v_{it}; \kappa_{it}) = (1/(1+\varepsilon)) \kappa_{it}^{\varepsilon} v_{it}^{1+\varepsilon}$, then (1) reduces to (A36) in Şahin, Song, Topa, and Violante (2014), see appendix A.1.[7]

2.3 Dispersion in Labor Market Conditions and Mismatch

If home production, vacancy costs and matching efficiency are homogeneous, $b_{it} = b_t$, $g'(v_{it}; \kappa_{it}) = \kappa_t$ and $\phi_{it} = \phi_t$, then condition (1) prescribes that in the efficient allocation the job-finding probability must be equal in all labor market segments, $p_{it} = \bar{p}_t$. Furthermore, the planner allocates more vacancies and unemployed workers to segments where productivity is high, so that the expected net present value of the marginal product of labor is equal as well, see appendix A.1.4.[8] This is our benchmark allocation with full equalization of labor market conditions.[9]

[7] If the vacancy distribution is exogenous (not under the control of the planner), as in the baseline of Şahin, Song, Topa, and Violante (2014), condition (1) is replaced by,

$$m_u(u_{it}, v_{it}; \phi_{it}) S_{it} = \lambda^u - b_{it} \tag{2}$$

where S_{it} is the expected net present value of the marginal productivity of labor $f'(n_{it}; z_{it})$, which equals $(z_{it} - \lambda^u - \lambda^v)/(r + \delta_i)$ if we further assume that the production function is linear and productivity z_{it} follows a random walk (derivation in appendix A.1). This is condition (2) in Şahin, Song, Topa, and Violante (2014).

[8] We need decreasing returns in production function $f(n_{it}; z_{it})$ for this result. This is a reasonable assumption if production requires not only labor but also capital, which may be harder to adjust than employment.

[9] If vacancies are exogenous, but in addition to home productivity $b_{it} = b_t$ and matching efficiency $\phi_{it} = \phi_t$, market productivity and separation rates are homogeneous as well, $z_{it} = z_t$ and $\delta_i = \delta$ so that $S_{it} = S_t$, then (2) states that in the efficient allocation the marginal contribution of unemployment to job matches $m_{u,it}(u_{it}, v_{it}; \phi_{it})$ must be equalized. In this case, which is condition (1) in Şahin, Song, Topa, and Violante (2014), the job-finding probability is equalized as well.

There are two reasons for dispersion in labor market conditions: parameter heterogeneity and mismatch. Heterogeneity in the parameters b_{it} (productivity of home production of the unemployed), κ_{it} (vacancy maintenance costs), and ϕ_{it} (matching efficiency), generates efficient dispersion in job-finding rates. In the empirical part of this paper, we try to control for heterogeneity in these parameters, as described in Section 4.2 below. Mismatch is defined as deviations from condition (1), i.e., *inefficient* deviations from the benchmark of fully equalized labor market conditions.

3 Sources of Mismatch

In this Section, we solve for an equilibrium of the model described in Section 2.1 above, in which there are no frictions other than the search friction as in Diamond (1982), Mortensen (1982) and Pissarides (1985). We will show that the allocation of unemployed workers and vacancies in this equilibrium is the same as the efficient allocation and therefore refer to this equilibrium as the no-mismatch equilibrium. The equilibrium conditions can be used to decompose mismatch, i.e., deviations from the efficient no-mismatch equilibrium allocation, into the contribution of three different types of frictions: barriers to the mobility of workers between labor market segments, barriers to the mobility of vacancies between segments, and inefficient wage dispersion. Below, we describe the equilibrium conditions in words. The derivations may be found in appendix A.2.

3.1 Worker Mobility

If unemployed workers are free to move between labor market segments, then they must be indifferent about the labor market in which they will search for a job; this is described by the following equilibrium condition, see appendix A.2.1, which we call the "worker-mobility condition."

$$p_{it} S_{it}^{W} = \lambda^{u} - b_{it} \tag{3}$$

S_{it}^{W} is the surplus that is expected to realize for a worker who is allocated to segment i if she finds a job there in period t, i.e., the expected net present value of wages w_{it} in that segment. If wages follow a random walk, then $S_{it}^{W} = (w_{it} - \lambda^{u}) / (r + \delta_i)$ is the value of an infinite stream of (expected) wages w_{it}, net of home production of non-participants, discounted by the rate of time preference and the probability δ_i that the worker loses the job again.

Intuitively, worker-mobility condition (3) is a no-arbitrage condition. In the absence of parameter heterogeneity, $b_{it} = b_t$, it states that attractive jobs must be hard to find, and unattractive jobs easy to find.[10] If home productivity b_{it} differs across segments,

[10] The insight is the same as that of the Harris and Todaro (1970) model of rural-urban migration. In the context of worker mobility, it should not be surprising that some (urban) areas have much lower job-finding rates (higher unemployment) if wages are much higher there. Similarly, Montgomery (1991) proposes differences in job-finding rates as an explanation for persistent wage differentials across

then segments with high home productivity must have low job-finding rates or low worker surplus, or both.

3.2 Job Mobility

If firms can freely relocate vacancies across labor market segments, a no-arbitrage condition holds that is similar to the worker-mobility condition above. We call this condition the "job-mobility condition." Let $q_{it} = m(u_{it}, v_{it}; \phi_t)/v_{it}$ be the probability that a firm fills a vacancy in segment i in period t. Then, as derived in appendix A.2.2,

$$q_{it} S_{it}^F = \lambda^v + g'(v_{it}; \kappa_{it}) \tag{4}$$

where S_{it}^F is the surplus a firm realizes when its vacancy in segment i is filled in period t, i.e. the expected net present value of profits. If profits follow a random walk, then $S_{it}^F = (f'(n_{it}; z_{it}) - w_{it} - \lambda^v)/(r + \delta_i)$.

In the absence of heterogeneity, e.g., if $g'(v_{it}; \kappa_{it}) = \kappa_{it} = \kappa_t$, vacancies in segments where jobs are expected to generate large profits must be hard to fill, and vacancies in low-profit segments must be easy to fill. With heterogeneity, vacancies in segments with high vacancy-maintenance costs must be easy to fill or expected to generate high profits or both. As in the social planner problem, the opportunity cost of creating more vacancies in total λ^v equals zero if the firm is able to freely generate vacancies (i.e., if there is "free entry"). This does not change any of the predictions of the model for dispersion across segments.

3.3 Matching Technology

The job-finding probability p_{it} in worker-mobility condition (3) and the vacancy-filling probability q_{it} in job-mobility condition (4) are related to each other, because both depend on the vacancy-unemployment ratio through matching technology. For our Cobb-Douglas matching function, $m(u_{it}, v_{it}; \phi_{it}) = \phi_{it} u_{it}^{\mu} v_{it}^{1-\mu}$, we get that $p_{it} = \phi_t (v_{it}/u_{it})^{1-\mu}$ and $q_{it} = \phi_t (v_{it}/u_{it})^{-\mu}$, which implies

$$p_{it}^{\mu} q_{it}^{1-\mu} = \phi_{it} \tag{5}$$

Different from the optimality conditions (3) and (4), equilibrium condition (5) is a technological constraint, which plays the role of the market-clearing condition on a perfectly competitive labor market in connecting labor supply with labor demand.

In the absence of parameter heterogeneity, $\phi_{it} = \phi_t$, the job-finding probability and the job-filling probability are inversely related to each other. With heterogeneity, both probabilities are higher in segments with high matching efficiency, and lower in segments with low matching efficiency. If the elasticity of the matching function μ is not constant

industries.

across segments, then condition (5) still holds in first order approximation. In this case, dispersion around the condition reflects heterogeneity in ϕ_{it} as well as μ_{it}.

3.4 Wage Determination

Worker mobility depends on the surplus of a job that accrues to the worker S_{it}^W, see (3). Job mobility depends on the surplus that accrues to the firm S_{it}^F, see (4). Thus, to close the model we need to specify how the total surplus of a match is divided between worker and firm. In the no-mismatch equilibrium, we assume the wage is set such that the worker gets a share μ of total match surplus, where μ is the unemployment share parameter in the matching technology.

$$\frac{S_{it}^W}{\mu} = \frac{S_{it}^F}{1-\mu} \tag{6}$$

This surplus-sharing rule can be justified as the outcome of a Nash bargaining process, where the bargaining power of workers satisfies the Hosios (1990) condition. Under this wage-setting condition, the equilibrium is efficient, see below equation (11) in Section 3.5.

3.5 No-Mismatch Equilibrium

The equilibrium conditions are all log-linear in the endogenous variables of the model p_{it}, q_{it}, S_{it}^W and S_{it}^F. It is convenient, therefore, to write the equilibrium conditions in logs, using a tilde over a variable to denote its logarithm, $\tilde{X}_{it} = \log X_{it}$. Taking logs of conditions (3), (4), (5) and (6), we can summarize the equilibrium with the following four conditions,

$$\tilde{p}_{it} + \tilde{S}_{it}^W = \alpha_{it}^{WM} \tag{7}$$

$$\tilde{q}_{it} + \tilde{S}_{it}^F = \alpha_{it}^{JM} \tag{8}$$

$$\tfrac{\mu}{1-\mu}\tilde{p}_{it} + \tilde{q}_{it} = \alpha_{it}^{MT} \tag{9}$$

$$\tilde{S}_{it}^W - \tilde{S}_{it}^F = \alpha^{WD} \tag{10}$$

where $\alpha_{it}^{WM} = \log(\lambda^u - b_{it})$, $\alpha_{it}^{JM} = \log(\lambda^v + g'(v_{it};\kappa_{it}))$, $\alpha_{it}^{MT} = (1/(1-\mu))\log\phi_{it}$ and $\alpha^{WD} = \log(\mu/(1-\mu))$ so that heterogeneity in α_{it}^{WM}, α_{it}^{JM} and α_{it}^{MT} reflects heterogeneity in home productivity, vacancy costs and matching efficiency, respectively.

Solving this system of equations, we get an explicit expression for segment-specific job finding probabilities in equilibrium.

$$\tilde{p}_{it} = (1-\mu)\left(\alpha_{it}^{WM} - \alpha_{it}^{JM} + \alpha_{it}^{MT} - \alpha^{WD}\right) \tag{11}$$

Substituting the definitions of α_{it}^{WM}, α_{it}^{JM} and α_{it}^{MT} and α^{WD} into (11), it is straightforward to show that this equilibrium distribution of job-finding probabilities equals the efficient distribution as in (1).

As in the efficient allocation, the equilibrium job-finding probabilities are constant across labor market segments, even if productivity z_{it}, wages w_{it}, and separation probabilities δ_i vary across submarkets, if the crucial parameters home productivity, vacancy costs and matching efficiency are homogeneous, i.e., if $b_{it} = b_t$, $g'(v_{it}; \kappa_{it}) = \kappa_t$ and $\phi_{it} = \phi_t$ so that $\alpha_{it}^{WM} = \alpha_t^{WM}$, $\alpha_{it}^{JM} = \alpha_t^{JM}$ and $\alpha_{it}^{MT} = \alpha_t^{MT}$. It is straightforward to show that in this case the vacancy-filling probability q_{it}, and worker and firm surplus S_{it}^W and S_{it}^F are equalized as well, and the model effectively reduces to a standard search model with a single, unsegmented labor market.

3.6 Discussion

The no-mismatch equilibrium conditions for worker and job mobility can be interpreted in various ways. Our preferred interpretation is as no-arbitrage conditions, because that interpretation allows us to posit the conditions with very few assumptions. However, we also showed how these conditions can be derived as optimality conditions of, respectively, a household and a firm in a model of a segmented labor market subject to search frictions within each segment. Very similar conditions could be derived in the context of a directed search model as well.

The assumptions we need to derive conditions (7), (8), (9) and (10) are relatively uncontroversial, so that the framework so far is quite general (we will need to make many more assumptions to operationalize the procedure, which we discuss in the next section). One assumption in particular, which does not affect the equilibrium conditions, is worth mentioning explicitly. We assume that workers and firms can only search in one labor market segment at the same moment in time. The conditions would be unchanged if we relax this assumption and assume that workers and firms can distribute search effort over multiple segments, as long as the total amount of search effort is finite, so that more intensive search in one segment comes at the cost of reduced search intensity in another segment. However, in this case our approach will overstate the effect of deviations from the worker mobility conditions for unemployment, as pointed out by Marinescu and Rathelot (2016). We return to this issue when we discuss the robustness of our results in Section 6.4.

In the next section, we discuss our procedure to decompose mismatch unemployment into its sources using the no-mismatch equilibrium conditions. We want to emphasize that we are not taking a stance ex-ante on whether or not we expect these conditions to be satisfied in the data. These no-mismatch equilibrium conditions are just benchmark conditions; that is, they are conditions, under which labor market conditions are fully equalized across segments. Deviations from the benchmark conditions represent sources of labor market mismatch.

4 Mismatch Accounting

In general, the distribution of job-finding probabilities across labor market segments may deviate from the efficient equilibrium, generating mismatch. The equilibrium conditions allow us to decompose any deviations from the no-mismatch allocation into deviations from optimality condition (7) for workers, deviations from optimality condition (8) for firms, or deviations from the efficient surplus-sharing rule (10). We refer to these three sources of mismatch as worker-mobility frictions, job-mobility frictions, and wage-setting frictions, and to the decomposition exercise as mismatch accounting. Since condition (9) is a technological constraint rather than a behavioral equation, we do not anticipate deviations from this condition other than efficient deviations due to heterogeneity in matching efficiency.

In this section we describe the implementation of our mismatch accounting procedure. First, we show why it is not possible to identify mismatch from efficient dispersion in labor market conditions due to parameter heterogeneity without further assumptions. Then, we describe how we control for parameter heterogeneity by assuming it is time-invariant, similar to controlling for fixed effects in a regression. Third, we discuss how we can summarize the aggregate effects of labor market mismatch as mismatch unemployment, unemployment that arises due to mismatch or the difference between actual unemployment and the unemployment rate that would prevail in the social planner allocation. Finally, we put everything together and then discuss a few caveats and limitations.

4.1 Frictions and Wedges

If there are other frictions on the labor market than just within-segment search frictions, then there is no reason why the no-mismatch equilibrium conditions (7), (8) and (10) should be satisfied. We can therefore represent such frictions in terms of the deviations from these conditions observed in the data. We denote these deviations, which we call wedges following Chari, Kehoe, and McGrattan (2007), by γ_{it}^{WM}, γ_{it}^{JM} and γ_{it}^{WD}. Then, the equilibrium allocation observed in the data can be written as

$$\tilde{p}_{it} + \tilde{S}_{it}^{W} = \alpha_{it}^{WM} + \gamma_{it}^{WM} \tag{12}$$

$$\tilde{q}_{it} + \tilde{S}_{it}^{F} = \alpha_{it}^{JM} + \gamma_{it}^{JM} \tag{13}$$

$$\tfrac{\mu}{1-\mu}\tilde{p}_{it} + \tilde{q}_{it} = \alpha_{it}^{MT} \tag{14}$$

$$\tilde{S}_{it}^{W} - \tilde{S}_{it}^{F} = \alpha^{WD} + \gamma_{it}^{WD} \tag{15}$$

and the job finding rates across segments are

$$\tilde{p}_{it} = (1-\mu)\left(\alpha_{it}^{WM} - \alpha_{it}^{JM} + \alpha_{it}^{MT} - \alpha^{WD} + \gamma_{it}^{WM} - \gamma_{it}^{JM} - \gamma_{it}^{WD}\right) \tag{16}$$

The basic idea behind our proposed exercise of mismatch accounting is to measure the wedges γ_{it}^{WM}, γ_{it}^{JM} and γ_{it}^{WD} from equations (12), (13) and (15), and then use equation (16) to quantify the contribution of each of the three wedges to dispersion in job-finding rates. However, since not only wedges γ_{it}^{WM}, γ_{it}^{JM} and γ_{it}^{WD}, but also parameter heterogeneity, as measured by α_{it}^{WM}, α_{it}^{JM} and α_{it}^{MT}, generate dispersion in the observables $\tilde{p}_{it}$, $\tilde{q}_{it}$, $\tilde{S}_{it}^{W}$ and $\tilde{S}_{it}^{F}$, it is not possible to implement this procedure without more data or further assumptions on the parameter hetorogeneity.

4.2 Heterogeneity

Our identifying assumption is that parameter heterogeneity is constant over time, i.e., $b_{it} = b_i$, $\kappa_{it} = \kappa_i$ and $\phi_{it} = \phi_i$, so that $\alpha_{it}^{WM} = \alpha_i^{WM}$, $\alpha_{it}^{JM} = \alpha_i^{JM}$ and $\alpha_{it}^{MT} = \alpha_i^{MT}$, Under this assumption, we can control for parameter heterogeneity in a way that is similar in spirit to controlling for fixed effects in a regression: by removing the segment-specific time-series averages from our data.

Let a hat over a variable denote the deviation of its logarithm from the segment-specific time-series average, i.e. $\hat{X}_{it} = \tilde{X}_{it} - \frac{1}{T}\sum_{t=1}^{T}\tilde{X}_{it}$, where T is the final time period in the sample. Then, taking deviations from equations (12), (13), (14) and (15), the allocation observed in the data can be written as,

$$\hat{p}_{it} + \hat{S}_{it}^{W} = \hat{\gamma}_{it}^{WM} \tag{17}$$

$$\hat{q}_{it} + \hat{S}_{it}^{F} = \hat{\gamma}_{it}^{JM} \tag{18}$$

$$\tfrac{\mu}{1-\mu}\hat{p}_{it} + \hat{q}_{it} = 0 \tag{19}$$

$$\hat{S}_{it}^{W} - \hat{S}_{it}^{F} = \hat{\gamma}_{it}^{WD} \tag{20}$$

because $\hat{\alpha}_i^{WM} = \hat{\alpha}_i^{JM} = \hat{\alpha}_i^{MT} = \hat{\alpha}^{WD} = 0$, where $\hat{\alpha}_i^{XX} = \alpha_i^{XX} - \frac{1}{T}\sum_{t=1}^{T}\alpha_i^{XX}$ and $\hat{\gamma}_{it}^{XX} = \gamma_{it}^{XX} - \frac{1}{T}\sum_{t=1}^{T}\gamma_{it}^{XX}$.

Solving this system of equations, we get

$$\hat{p}_{it} = (1-\mu)\left(\hat{\gamma}_{it}^{WM} - \hat{\gamma}_{it}^{JM} - \hat{\gamma}_{it}^{WD}\right) \tag{21}$$

Under our identifying assumption that parameter heterogeneity is constant over time, all observed dispersion in segment-specific job-finding rates in deviations from their time-series averages $\hat{p}_{it}$ is due to dispersion in the wedges, i.e. to mismatch.

We treat parameter heterogeneity as unobservable, because it is not feasible to convincingly measure heterogeneity in the parameters of our model. Although some data on these parameters is available, it is likely to be of lower quality than data on p_{it}, q_{it}, S_{it}^{W} and S_{it}^{F}. For example, while there is information on unemployment benefits across states, which is informative about dispersion in b_{it}, we do not have information on unemployment benefits across industries, nor do we have estimates for the dispersion in the value of leisure across either states or industries. To the best of our knowledge,

there is no data at all on vacancy maintenance costs or matching efficiency by states or industries. Our solution is to assume that parameter heterogeneity is time invariant.

Our approach to deal with heterogeneity has advantages as well as disadvantages. The most obvious disadvantage is that we do not control for time variation in parameter heterogeneity. It seems reasonable to assume that there is more variation in parameters across states or industries than within segments over time.[11] Nevertheless, if there is heterogeneous time variation in unemployment benefits, vacancy maintenance costs or matching efficiency, then we will spuriously attribute the dispersion in labor market conditions that arises because of it to mismatch. In Section 4.4, we discuss to what extent this bias may affect our results.

A second disadvantage is that, in addition to dispersion due to heterogeneity, we may also remove dispersion due to mismatch. If differences across submarkets due to worker-mobility, job-mobility or wage setting frictions are persistent over time, then some of the dispersion in γ_{it}^{WM}, γ_{it}^{JM} and γ_{it}^{WD} will be removed if we take deviations from time-series averages. In that sense, our estimates should be viewed as a lower bound for the contribution of mismatch to aggregate job finding and unemployment.

Offsetting these disadvantages is an important advantage of our approach: in addition to parameter heterogeneity, the approach also controls for all other time-invariant heterogeneity, observable as well as unobservable, and across workers as well as across firms. Heterogeneity across workers and firms is a concern because we estimate the contribution of mismatch to unemployment from the dispersion in wages, profits, and finding probabilities. Heterogeneity generates dispersion that is unrelated to mismatch. Wages, profits and even job-finding rates may vary across workers not only because of deviations from the no-mismatch equilibrium conditions, but also because workers have different education, experience, and other characteristics. Failing to control for these differences would spuriously attribute the dispersion across labor market segments they generate to mismatch.[12] Residual wage differentials are due at least in part to compensating differentials: non-monetary job amenities such as flexible hours or safe working conditions, in return for which workers are willing to accept lower wages, see Rosen (1979) and Roback (1982).[13] These differences, which are completely unobservable in our dataset, also generate dispersion that is not inefficient, and, thus, should not be attributed to mismatch.

[11] For unemployment benefits across states, for which data are available, we find that 77% of the variance in the UI replacement ratio is due to variation between states, and the between-state standard deviation of 0.044 is close to the overall standard deviation of 0.050. Source: UI replacement ratios (definition 1) by state and year 1997-2017 from the US Department of Labor, available at https://oui.doleta.gov/unemploy/ui_replacement_rates.asp.

[12] In Section 6.4, we show that explicitly controlling for observable worker heterogeneity affects the results very little, indicating that this heterogeneity is already adequately controlled for in our baseline results.

[13] One of these compensating differentials is explicitly taken into account in our calculations, which is the separation probability. However, this is only one of many differences between jobs.

4.3 Effect of Mismatch on Unemployment

Mismatch unemployment is given by the difference between the actual unemployment rate and the counterfactual unemployment that would prevail if all wedges were zero. The wedges generate dispersion in labor market conditions over and above the counterfactual dispersion in the no-mismatch equilibrium. But how does dispersion in labor market conditions affect the aggregate unemployment rate?

The aggregate unemployment rate is determined by the aggregate separation rate $\bar{\delta}_t$ and the aggregate job-finding probability $\bar{p}_t$. Using the approximation that the aggregate unemployment rate is in steady state given these worker flows, and taking a first-order Taylor approximation, we can show that the effect of mismatch on unemployment is roughly proportional to its effect on the job-finding rate,

$$\bar{u}_t = \frac{\bar{\delta}_t}{\bar{\delta}_t + \bar{p}_t} \Rightarrow \log \bar{u}_t - \log \bar{u}_t^* \simeq \frac{\bar{p}_t}{\bar{\delta}_t + \bar{p}_t} \left(\log \bar{p}_t^* - \log \bar{p}_t\right) \tag{22}$$

where $\bar{u}_t^*$ and $\bar{p}_t^*$ denote the counterfactual unemloyment and job-finding rate in the absence of mismatch. The effect of mismatch on unemployment through the aggregate separation rate is negligible compared to the effect through the aggregate job-finding rate for two reasons. First, the first-order effect through $\log \bar{\delta}_t - \log \bar{\delta}_t^*$ is multiplied by $\bar{\delta}_t / \left(\bar{\delta}_t + \bar{p}_t\right)$, which is much smaller than the $\bar{p}_t / \left(\bar{\delta}_t + \bar{p}_t\right)$ factor multiplying the effect through the job-finding rate because $\bar{\delta}_t << \bar{p}_t$ in the US data. Second, the aggregate separation rate $\bar{\delta}_t = \sum_i \delta_i n_{it} / \sum_i n_{it}$ is not affected by reallocating unemployed workers and vacancies in the short run, and the long-run effect through changes in the steady-state distribution of employment n_{it} across segments is small compared to the change in the aggregate job-finding rate.[14]

The counterfactual job-finding rate in the absence of mismatch is higher than the actual job-finding rate, $\bar{p}_t^* > \bar{p}_t$, because job-finding rates are concave in vacancy-unemployment ratios, $p_{it} = \phi_t \theta_{it}^{1-\mu}$ with $0 < \mu < 1$, so that dispersion in labor market conditions lowers the average job-finding probability. To get a closed-form expression for the aggregate effect of mismatch, we assume that the distribution of p_{it} is log-normal. Under this assumption, the relative contribution of mismatch to the aggregate job-finding rate is proportional to the dispersion in job-finding rates across labor market segments,

$$\log \bar{p}_t^* - \log \bar{p}_t = \tfrac{1}{2} \frac{\mu}{1-\mu} V\left[\hat{p}_{it}\right] \tag{23}$$

where $V\left[\hat{p}_{it}\right] = \left(\sum_i u_{it} \left(\hat{p}_{it} - E\left[\hat{p}_{it}\right]\right)^2\right) / \sum_i u_{it}$ is the unemployment-weighted variance of $\hat{p}_{it}$. Equation (23) is very similar to comparable expressions in Şahin, Song, Topa, and Violante (2014) and Barnichon and Figura (2015). The derivation is given in appendix B.

The amount of mismatch unemployment will depend on the level of disaggregation.

[14] The segment-specific separation probabilities, unlike the segment-specific job-finding probabilities, are constant, and the weights are affected less simply because $n_{it} >> u_{it}$ for almost all i and t.

At higher levels of aggregation, we would expect to see substantial mismatch within segments, so that the observed mismatch across segments is a lower bound for the actual labor market mismatch. We return to this issue in detail when we discuss our estimates for mismatch unemployment in Section 6.1.

4.4 Accounting Procedure

The decomposition of mismatch unemployment into its sources is implemented in three steps. First, we estimate empirical equivalents of the wedges $\hat{\gamma}_{it}^{WM}$, $\hat{\gamma}_{it}^{JM}$, $\hat{\gamma}_{it}^{WD}$ from equations (17), (18) and (20) using data on the worker and firm surpluses and job-finding and vacancy-filling rates (see Section 5 below for how we obtain these data). Second, given these estimates, we use equation (21) to calculate what the distribution of job-finding probabilities over segments would be if one or more of the wedges were zero in all labor market segments. Finally, we use equations (22) and (23) to calculate the contribution of mismatch to the aggregate job-finding probability and unemployment rate.

The idea behind this procedure is that if we remove, for example, the worker-mobility frictions, setting $\hat{\gamma}_{it}^{WM}$ equal to zero, but leave the job-mobility and wage-setting frictions in place, then $\hat{\gamma}_{it}^{JM}$ and $\hat{\gamma}_{it}^{WD}$ would stay the same. A complication arises if the wedges are correlated. Then, removing a friction does not necessarily decrease mismatch and unemployment, but may increase it. This is simply because in a second-best environment, different frictions may reinforce or counteract each other, so that removing a friction may decrease efficiency.[15] Potentially, the correlations between $\hat{\gamma}_{it}^{WM}$, $\hat{\gamma}_{it}^{JM}$ and $\hat{\gamma}_{it}^{WD}$ are informative about the frictions that maintain labor market mismatch. Empirically however, we find very little correlation, see Section 6.2; we therefore focus on a simple variance decomposition between the three sources of mismatch.

Any correlation between the wedges means the variance decomposition of equation (23) will depend on the order, in which we shut down the various sources of mismatch in equation (21). To understand this point, it is important to realize that the contribution of a friction is always relative to a baseline. We can estimate the contribution of a particular friction to mismatch as the difference between the aggregate job-finding rate that would prevail without this friction, leaving all other frictions as they are in the data, and the actual aggregate job-finding rate. Or, we can estimate this contribution as the difference between the aggregate job-finding rate that would prevail if only this friction were present, and the aggregate job-finding rate in the no-mismatch allocation. In general, the two approaches will give different answers, because the first friction that is shut down will shut down the covariance terms as well. In appendix C, we show that

[15] As an example, consider two otherwise identical labor market segments, one with high wages and one with low wages. Suppose these wage differentials can exist because of wage-setting frictions, but that labor market tightness is nevertheless equal in both submarkets, because mobility costs prevent workers and jobs from moving from one submarket to the other. Now suppose we were to remove the mobility costs but leave the wage-setting frictions in place. Unemployed workers would move to the submarket where wages are high, whereas vacancies would move to the submarket where wages are low. The result would be a decrease in the aggregate job-finding rate and an increase in mismatch unemployment.

the contribution of a friction that we remove includes the contribution of the covariance of that friction with other frictions in place, whereas the contribution of a friction that we introduce does not. Therefore, we calculate the contribution of each friction in both ways and average it, attributing the covariance between two frictions in equal proportions to each of the frictions. This approach, which is similar to a Shapley-Owen decomposition, guarantees that our decomposition adds up to exactly 100% of mismatch unemployment.

The most important limitation of our approach is that we needed to assume that parameter heterogeneity is time-invariant, in order to be able to identify the contribution of mismatch to unemployment. If in reality there is time variation in unemployment benefits b_{it}, vacancy maintenance costs κ_{it} and/or matching efficiency ϕ_{it} then we will incorrectly attribute the dispersion due to this heterogeneity to mismatch. Substituting out for $\hat{q}_{it}$, which is not directly observable, in equations (12), (13) and (15) using (14), and taking deviations, we get the following expressions for the wedges we would measure in this case.

$$\hat{p}_{it} + \hat{S}_{it}^{W} = \hat{\gamma}_{it}^{WM} + \hat{\alpha}_{it}^{WM} \tag{24}$$

$$\hat{S}_{it}^{F} - \tfrac{\mu}{1-\mu}\hat{p}_{it} = \hat{\gamma}_{it}^{JM} + \hat{\alpha}_{it}^{JM} - \hat{\alpha}_{it}^{MT} \tag{25}$$

$$\hat{S}_{it}^{W} - \hat{S}_{it}^{F} = \hat{\gamma}_{it}^{WD} \tag{26}$$

The wage determination wedge is not affected, but time-varying heterogeneity in unemployment benefits $\alpha_{it}^{WM} = \log(\lambda^u - b_{it})$ biases the contribution of worker mobility frictions, and time-varying heterogeneity in vacancy maintenance costs $\alpha_{it}^{JM} = \log(\lambda^v + g'(v_{it};\kappa_{it}))$ and matching efficiency $\alpha_{it}^{MT} = (1/(1-\mu))\log\phi_{it}$ is spuriously attributed to job mobility frictions.

If we assume that the time variation in parameters is uncorrelated with the true wedges, then time-varying parameter heterogeneity will lead to an upward bias in the estimated overall amount of mismatch, and in the contribution of worker mobility and job mobility frictions, because $V\left[\hat{\gamma}_{it}^{WM} + \hat{\alpha}_{it}^{WM}\right] > V\left[\hat{\gamma}_{it}^{WM}\right]$ and $V\left[\hat{\gamma}_{it}^{JM} + \hat{\alpha}_{it}^{JM} - \hat{\alpha}_{it}^{MT}\right] > V\left[\hat{\gamma}_{it}^{JM}\right]$. If the heterogeneity in these parameters comoves with the business cycle, then the estimates for the cyclicality of total mismatch and the contribution of worker and job mobility frictions will be affected as well. Unfortunately, it is not possible to say much more about the bias we should expect without data on these parameters. However, in Section 6.4, we present estimates with additional controls for time-varying worker heterogeneity. To the extent that parameter heterogeneity is correlated with observable worker characteristics, we would expect that controlling for these characteristics would alleviate the bias due to time-varying parameter heterogeneity. We take the finding that controls for worker characteristics affect our results very little as suggestive evidence that time-varying parameter heterogeneity is not a great concern in practice.

5 Data and Measurement

To implement the mismatch accounting exercise described in the previous section, we need empirical measures of the job-finding rate p_{it}, the worker-finding rate q_{it}, worker surplus S_{it}^W, which is closely related to wages, and firm surplus S_{it}^F, closely related to profits, for submarkets of the labor market. In this section, we describe how we obtain these measures. In Section 5.1, we describe the micro-data we use to extract disaggregated measures for finding rates, wages, and profits. Then, in Sections 5.2 and 5.3, we describe how we use these data to calculate the theoretical measures we need for our accounting exercise. Here, we need to make some auxiliary assumptions, which we revisit after discussing our results in Section 6.4.

The first empirical difficulty is how to define a labor market segment or submarket. A submarket of the labor market is defined as a subset of unemployed workers or vacant jobs that are similar to each other but different from other workers or jobs, so that each unemployed worker and each firm with a vacant job searches in one submarket only. In our theoretical framework, we assumed that submarkets are mutually exclusive, so that two workers who are searching for some of the same jobs are searching for all of the same jobs, and if a worker is searching for a job, then that job is searching for that worker. In practice, these assumptions are likely to be violated, unless we define submarkets as very small and homogeneous segments of the labor markets, based on geographic location as well as the skill set required to do a job.

We use 51 U.S. states (including Washington, D.C.) to explore geographic mismatch and around 37 industries to explore skill mismatch.[16] This choice is driven by data limitations and follows other empirical contributions in this literature (Şahin, Song, Topa, and Violante (2014), Barnichon and Figura (2015)). Unfortunately, it is not possible to use very small submarkets, because we would have too little data about each submarket.[17] For our estimates of overall mismatch, we also use three-digit occupations, as Şahin, Song, Topa, and Violante (2014) do, which arguably better categorize similarly skilled jobs than do industry-oriented groupings; however, because data on profits by occupation are not available, we cannot use these data for our decomposition.

5.1 Data Sources

Our primary data sources are the January 1979 to December 2015 basic monthly files of the Current Population Survey (CPS) administered by the Bureau of Labor Statistics (BLS).[18] We limit the sample to wage and salary workers between 16 and 65 years of

[16] We have 37 industries based on the SIC classification for the 1979-1997 period and 38 industries based on the NAICS classification for the 1998-2015 period.

[17] Shimer (2007), for instance, suggests using the interaction of 800 occupations and 922 geographic areas (362 MSAs plus 560 rural areas), which gives a total of $740,000$ submarkets. In our dataset, we have information on about $150,000$ workers in a given year, so that we would have 1 datapoint for each 5 submarkets.

[18] We mostly rely on data provided by IPUMS (Flood, King, Ruggles, and Warren (2017)), but complement these with data provided by the NBER to add the variables unemployment duration (DURUNEMP) before 1994 and weekly earnings (EARNWEEK) before 1989.

age, with non-missing data for state and industry classification. From the basic monthly files we construct job-finding and separation rates. We aggregate the monthly data to an annual time series in order to increase the number of observations. Our estimates of finding and separation rates are based on about $750,000$ observations per year. From the outgoing rotation groups, we get wages, calculated as usual weekly earnings divided by usual weekly hours. Again, we aggregate the data to an annual time series, ending up with a sample of about $160,000$ workers per year. Table 2 in appendix F lists the states and industries we use and summarizes the number of observations used to calculate the job-finding and separation rates and the average wage for the state-year and industry-year cells. The average cell size for job-finding and separation rates is 858 per year for the state-level data, and 1124 per year for the industry-level data; the smallest cells have 159 and 15 observations, respectively.

Data on profits by state and industry come from the National Income and Product Account (NIPA) data collected by the Bureau of Economic Analysis (BEA). We use gross operating surplus per employee as our measure of profits. Gross operating surplus equals value added, net of taxes and subsidies, minus compensation of employees. Net operating surplus equals gross operating surplus minus consumption of fixed capital; it is the measure of business income from the NIPA that is closest to economic profits. Because data on net operating surplus are not available at the state and industry levels, we use gross operating surplus, thus effectively assuming that fixed capital does not differ much across labor market segments. Under the assumptions of a Cobb-Douglas production technology and perfect capital markets, profits per employee equal the marginal profits from hiring an additional worker.[19]

In 1998, the industry classification system changed from the SIC to the NAICS. Using a consistent industry classification over the entire sample period would force us to aggregate at a higher level. Instead, we use the SIC classification until 1997, and the NAICS from 1998 onwards, using approximately the same number of industries in both subsamples. This allows us to calculate comparable cross-industry variances for $\hat{p}_i$, $\hat{q}_i$, $\hat{S}_i^W$, and $\hat{S}_i^F$ over the full sample period. When adjusting for parameter heterogeneity, as described in Section 4.2, we subtract industry-specific time-series averages separately for the 1979-1997 and 1998-2015 periods.

We deflate nominal data on wages and profits using the CPI provided by the BEA (series CUUR00000SA0). Using an aggregate price deflator does not directly affect our results, because we use only the cross-sectional variation in the data, but it is important for the heterogeneity correction, which relies on subtracting the time-series mean for each segment. As a robustness check, we also show results for unemployment due to geographic mismatch using a state-specific deflator provided by Berry, Fording, and

[19] Let $Y = AK^{\alpha}L^{1-\alpha}$ be output, produced according to a Cobb-Douglas technology from capital K and labor L. Profits (or net operating surplus) are given by $\Pi = Y - rK - wL$, where r is the rental rate of capital, and w is the wage rate. The marginal profits from an additional employee are $d\Pi/dL = (1-\alpha)\,Y/L - w$, where $dK/dL = 0$ by the envelope theorem if capital is chosen optimally by the firm. Profits per employee are $\Pi/L = Y/L - rK/L - w$. If capital markets are frictionless, then the rental rate equals the marginal product of capital, $r = \alpha Y/K$, so that $\Pi/L = (1-\alpha)\,Y/L - w = d\Pi/dL$.

Hanson (2000), which is available until 2007.

Finally, we need to make assumptions about the unemployment share of the matching function μ and the discount rate r. In our baseline results, we assume $\mu = 0.72$, as in Shimer (2005), and explore the robustness of our results to setting $\mu = 0.5$ as in Şahin, Song, Topa, and Violante (2014), which is at the other end of the plausible range of estimates in Petrongolo and Pissarides (2001). We set the annual discount rate $r = 0.04$, but this assumption matters very little for the results.

5.2 Finding and Separation Rates

We calculate job-finding and separation rates of workers from the unemployment rates in two subsequent months and the number of newly separated workers (short-term unemployed) in the CPS. This way to measure worker flows, suggested by Shimer (2012), has the advantage that it is not subject to time-aggregation bias.[20] We show that our results are robust if we instead calculate job-finding and separation rates from the number of workers transitioning between unemployment and employment from matched CPS data, see Section 6.4.

Workers are attributed to the state where they live and the industry where they work. We attribute unemployed workers, for whom we lack information on industry, to the industry in which they last held a job, following standard practice at the BLS. This assumption is not consistent with our model, which would attribute unemployed workers to the industry in which they are searching for a job. We address this concern with a novel way of constructing segment-specific job finding rates, attributing unemployed workers to the industry in which they eventually find a job, see appendix G. We show in Section 6.4 that our results are robust to this alternative approach.

To calculate worker-finding rates of firms, we would need firm-level data, which are available from the Job Openings and Labor Turnover Survey (JOLTS), but only from the year 2000 onwards. To obtain data on worker-finding rates for a longer sample period, we use equation (19) to construct data for worker-finding rates of firms $\hat{q}_{it}$ from data on job-finding rates of workers $\hat{p}_{it}$.

5.3 Match Surplus

As derived in appendices A.2.1 and A.2.2, the surplus of a match to the worker and the firm is given by a Bellman equation,

$$(1 + r)\, S_{it}^{k} = E_t y_{it+1}^{k} + (1 - \delta_i)\, E_t S_{it+1}^{k} \tag{27}$$

where $k \in \{W, F\}$ and y_{it}^{k} is the flow payoff from the match, which equals $w_{it} - \lambda^u$ for workers and $f(n_{it}; z_{it}) - w_{it} - \lambda^v$ for firms. We observe match payoffs y_{it}^{k} and separation

[20] In February 1994, there was a change in the way unemployment duration is reported in the CPS. To correct for this change, we multiply the official short-term unemployment rate by a factor 1.1579 in months from February 1994 onwards, as suggested by Elsby, Michaels, and Solon (2009).

rates δ_i in our dataset, and use these data and equation (27) to calculate match surplus for the worker and firm, S_{it}^W and S_{it}^F respectively.[21] In order to do this, we need to make assumptions on the evolution of these variables after a match is created.

For our exercise, what matters is the dispersion in surplus across submarkets of the labor markets. Dispersion in surplus is sensitive to the persistence in payoffs and to the segment-specific separation probabilities. The persistence of payoffs matters because match surplus equals the expected net present value of all future payoffs from the match. If payoffs are very persistent, then current payoff differentials will persist into the future, thus generating more dispersion in the expected net present value. Persistence in separation rates matters as well, because it determines to what extent the separation probabilities are segment-specific.

We assume match payoffs follow first-order autoregressive processes that revert to the average across all submarkets. The first-order autocorrelation in wages is 0.94 per year in the state-level data and 0.64 in the industry-level data based on the NAICS classification.[22] This is consistent with Blanchard and Katz (1992), who find an autocorrelation of 0.94 across U.S. states, and Alvarez and Shimer (2011), who find 0.90 for 75 industries at the three-digit level of disaggregation (CES data, 1990-2008). Autocorrelation in profits is 0.96 in the state-level data and 0.72 in the industry-level data. Since wages and profits are close to a random walk in the state-level data, we use this as our baseline.[23] For industries, we assume monthly mean reversion in wages and profits of 0.037 and 0.027, respectively, consistent with the observed autocorrelations. In Section 6.4, we show that our results are robust to these assumptions.

In the model, separation rates are constant over time, and this is our baseline. However, we explore the robustness of our results to higher degrees of mean reversion, because, in the data, separation rates are quite far from a random walk: the first-order autocorrelation is 0.61 per year in the state level data and 0.50 in the industry-level data. Therefore, we allow separation rates to follow an (independent) autoregressive process as well.

Using the stochastic processes for match payoffs y_{it}^k and separation rates δ_{it}, we can solve equation (27) recursively to obtain match surplus. For convenience, we approximate around the separation rate following a random walk so that we can obtain an explicit expression for the solution, see appendix D for the derivation,

$$S_{it}^k \simeq \frac{(r+\delta_{it})(r+\delta_{it}+\rho_\delta)}{(r+\delta_{it})(r+\delta_{it}+\rho_\delta)+\rho_\delta(1+r+\delta_{it})(\bar{\delta}_t-\delta_{it})}\left(\frac{\bar{y}_t^k}{r+\delta_{it}}+\frac{y_{it}^k-\bar{y}_t^k}{r+\delta_{it}+\rho_y^k}\right) \quad (28)$$

[21] We also need values for the parameters λ^u and λ^v. We assume $\lambda^v = 0$ to reflect free entry of vacancies. We also set $\lambda^u = 0$ for symmetry, but explore the robustness of our results to this assumption in Section 6.4.

[22] We report simple first-order autocorrelations in this paragraph. However, the persistence in the data is very similar and, if anything, higher if we use the coefficient on the lagged dependent variable in a dynamic panel regression with fixed-effects.

[23] Strictly speaking, what matters is not the persistence in average wages and profits, but the persistence of wages and profits of a given match. However, as shown by Haefke, Sonntag, and van Rens (2013) and Kudlyak (2014), wages paid out over the duration of a match are more persistent than average wages, so, these estimates, if anything, understate the autocorrelation in wages.

where $\bar{y}_t^k$ is the average of y_{it}^k across segments i. In this expression, ρ_δ and ρ_y^k denote the mean reversion in separation probabilities and match payoffs, so that the autocorrelation coefficient in these variables equals $1-\rho_\delta$ and $1-\rho_y^k$, respectively. The approximation is good if separation rates are persistent, i.e. for ρ_δ close to zero.

If match payoffs follow a random walk, $\rho_y^k = 0$, and turnover is constant, $\rho_\delta = 0$, as in our baseline, then match surplus is the annuity value of the current payoff, $S_{it}^k = y_{it}^k / (r + \delta_{it})$, evaluated at an effective discount rate which includes not only the rate of time preference, but also the separation probability. The higher the wage in a submarket, the higher is the surplus of having a job in that submarket. The more likely it is to lose that job in the future – that is, the higher is δ_{it}– the lower is the surplus.

6 Results

We start the description of our results with our estimates for the total effect of mismatch on the level and the cyclicality of unemployment. Then, we turn to the decomposition of mismatch into its three sources. We explore how well no-mismatch equilibrium conditions (7), (8) and (10) hold in the data in Section 6.2, and we present the results of our mismatch accounting exercise in Section 6.3.

6.1 Mismatch Unemployment

Figure 1 plots the unemployment rate that is due to mismatch across occupations, across states (panel A) and across industries (panel B) over the 1979-2015 period. For comparison, the graphs also show the overall unemployment rate over the same period, although on a different scale. We will use the series in these graphs to address the questions of how large the impact of labor market mismatch is on unemployment, and how it fluctuates over the business cycle.

Unemployment due to mismatch across three-digit occupation-state cells averages almost 1 percentage point. Comparing to an average unemployment rate of around 7%, it is clear that occupational mismatch is responsible for a substantial part (around 13%) of unemployment. Mismatch across states and industries is much smaller at 0.05 to 0.1 percentage points, or 0.7 to 1.5% of unemployment, respectively. Clearly the level of disaggregation matters for the observed amount of mismatch, and there is likely to be substantial mismatch within states and within industries. However, the cyclical pattern of mismatch unemployment looks similar across occupations, states, industries. It is worthwhile, therefore, to further explore mismatch across states and industries, as a proxy for overall labor market mismatch.[24]

Figure 1 clearly shows that the cyclical fluctuations in mismatch unemployment are very similar to those in the overall unemployment rate. Mismatch unemployment

[24] An additional argument why mismatch across industries and states may be a reasonable proxy for mismatch across occupations is decribed in appendix E, where we use a back-of-the-envelope correction for aggregation to argue that the estimates for mismatch across states and industries imply a level of mismatch that is of a similar magnitude as the observed mismatch across occupations.

closely follows the business cycle, rising in the 1982, 1991, 2001 and 2008 recessions, and declining slowly during the recoveries, as does the unemployment rate. The relative amplitude of these fluctuations is very similar to those in the total unemployment rate. There is no evidence that mismatch unemployment is less cyclical or more persistent than the overall unemployment rate. Finally, there is no indication that the fraction of the increase in unemployment in the Great Recession that was due to mismatch was larger than in other recessions.

To obtain a summary statistic for the importance of mismatch to the overall unemployment rate, we regress mismatch unemployment u_t^{MM} on a constant and the overall unemployment rate u_t in deviation from its average $\bar{u}$.

$$u_t^{MM} = \beta_0 \bar{u} + \beta_1 \left(u_t - \bar{u}\right) \tag{29}$$

The intercept β_0 in this regression measures the contribution of mismatch to the average level of unemployment, whereas the slope coefficient β_1 measures the contribution of mismatch to fluctuations in unemployment. We report both statistics in Table 1, see the rows labelled "Mismatch across occupations" and "Baseline." The contribution of mismatch to fluctuations in unemployment is roughly similar to the contribution to the level of unemployment: 20% for mismatch across occupations, and 3.2% and 0.7% for mismatch across states and industries, respectively.

Figure 2 shows an alternative presentation of these results on the contribution of mismatch to unemployment for mismatch across states (panel A) and industries (panel B). Here, we plot $\log \bar{u}_t - \log \bar{u}_t^* \simeq \left(\bar{u}_t - \bar{u}_t^*\right)/\bar{u}_t$, which measures unemployment due to mismatch as a fraction of the overall unemployment rate. The four lines in these graphs represent the exact contribution of mismatch to unemployment, calculated using equations (51) and (53) in appendix B, and the approximation using equation (23), with and without controlling for parameter heterogeneity. It is clear from these graphs that the log-normal approximation used to derive equation (23) is very good. It is also clear that controlling for parameter heterogeneity is important. Without these controls, the contribution of mismatch to unemployment is about two (for states) to three (for industries) times larger. Moreover, the effect of parameter heterogeneity changes over time and with the business cycle. Of course, as explained in Section 4.2, it is possible that by taking out parameter heterogeneity, we are also removing some inefficient dispersion in job-finding rates. Therefore, our estimates for mismatch unemployment should be thought of as a lower bound. There is no obvious cyclical pattern in the graphs of the relative contribution of mismatch to unemployment, confirming our finding that mismatch comoves with the overall unemployment rate.

Our estimates are broadly in line with Şahin, Song, Topa, and Violante (2014), who employ different data and conclude that geographic mismatch is very small, but industry-level mismatch (at the two-digit level) explains around 14% of the increase in unemployment in the Great Recession. The estimates in their Figure 3 imply a similar contribution of mismatch to the level of unemployment (although the authors do not

report this in their text). Consistent with our argument that aggregation importantly biases the estimate of the contribution of mismatch, Şahin, Song, Topa, and Violante (2014) also find that when they disaggregate further, to three-digit occupation level, the contribution of mismatch increases to 29%. However, we emphasize that our estimates of the contribution of mismatch to the level of unemployment are rough, and the estimates in Şahin, Song, Topa, and Violante (2014) are the more credible ones. The reason is that while we use data on worker flows from the CPS, Şahin, Song, Topa, and Violante (2014) also use disaggregated data on vacancies from JOLTS and HWOL, which are available only from December 2000 and May 2005, respectively. The contribution of the current study is in the estimates of the sources of mismatch, to which we now turn.

6.2 Deviations from the No-Mismatch Conditions

We now turn to the most interesting part of our results: the decomposition of mismatch unemployment into the sources of the mismatch. The idea behind our accounting exercise is to compare the relationship between job-finding rates and worker surplus, between job-filling rates and firm surplus, and between worker and firm surpluses to the predictions of the model for these relationships in the absence of mismatch. We will start, therefore, by exploring what these relationships look like in the data.

Figure 3 shows scatterplots of states around the worker-mobility, job-mobility and wage-determination conditions. These graphs are for 2010, but they look similar for other years. Deviations across states from the no-mismatch conditions are large and systematic. Nevertheless, the positive correlation between worker and firm surpluses predicted by wage-setting condition (10), and the negative correlation between firm surplus and job-filling rates predicted by the worker-mobility condition (7) are somewhat visible in the data. These graphs suggest that frictions preventing firms from moving jobs across states play the most important role as a source of mismatch. Figure 4 shows similar results for the equilibrium conditions across industries. The plots look similar to those for states, and again suggest that job-mobility frictions are the most important source of mismatch.

Scatter plots around the no-mismatch equilibrium conditions may not give the full picture if the deviations from these conditions are correlated. However, in practice this is not much of a concern. The correlation between the wedges in the worker-mobility condition $\hat{\gamma}_{it}^{WM}$ and the wedges in the job-mobility condition $\hat{\gamma}_{it}^{JM}$ is on average -0.23 for states, 0.07 for (SIC) industries over the 1979-1997 period, and -0.14 for (NAICS) industries 1998-2015. Given these low correlations, it makes sense to think of barriers to worker and job mobility as separate frictions.

6.3 Sources of Mismatch

Figure 5 shows the results of our mismatch accounting exercise described in Section 4. The figure shows the evolution over time of the three sources of unemployment due to

mismatch across states and industries.

Mismatch across states is mainly generated by job-mobility frictions, with a smaller contribution of worker-mobility frictions and virtually no role for wage-setting frictions. Mismatch across industries looks very similar, with a possibly even smaller role for worker-mobility frictions.

To summarize the contribution of each source of mismatch to the unemployment rate, we regress mismatch unemployment due to each source on the total unemployment rate due to mismatch (in deviation from its mean).

$$u_t^{XX} = \beta_0^{XX} \bar{u}^{MM} + \beta_1^{XX} \left(u_t^{MM} - \bar{u}^{MM} \right) \tag{30}$$

where XX stands for the source of mismatch, i.e., $XX \in \{WM, JM, WD\}$.[25] The intercept in this regression measures the contribution of each of the frictions to the average level of mismatch unemployment, so that $\beta_0^{XX} = \bar{u}^{XX}/\bar{u}^{MM}$, whereas the slope coefficient measures the contribution of mismatch to fluctuations in unemployment. The slope coefficient captures both the degree of correlation of unemployment due to a particular source of mismatch with the total mismatch unemployment rate and the size of fluctuations in mismatch due to that source, i.e., $\beta_1^{XX} = corr\left(u_t^{XX}, u_t^{MM}\right) sd\left(u_t^{XX}\right) / sd\left(u_t^{MM}\right)$. Note that because $u_t^{WM} + u_t^{JM} + u_t^{WD} = u_t^{MM}$, the contributions of the three sources to the total add up to one, i.e. $\beta_0^{WM} + \beta_0^{JM} + \beta_0^{WD} = 1$ and $\beta_1^{WM} + \beta_1^{JM} + \beta_1^{WD} = 1$, so that this is an exact decomposition.

Results of the mismatch accounting exercise are reported in Table 1. Barriers to job mobility contribute 79% to the level of and 80% to the fluctuations in mismatch across states and 78% to the level and 65% to the fluctuations of mismatch across industries. Barriers to worker mobility are responsible for roughly a fourth of that: 20% of the level and 19% of the fluctuations of mismatch across states, and 19% of the level and 27% of the fluctuations of mismatch across industries. The contribution of wage-setting frictions to mismatch is virtually zero, both for the level of mismatch and for its fluctuations, and both across states and across industries.

6.4 Robustness

A number of assumptions were necessary to construct the data needed for our analysis. In this subsection we explore the robustness of our results to these assumptions. We summarize the results in terms of the contribution of mismatch to the level and fluctuations of the overall unemployment rate, as explained in Section 6.1; and in terms of the contribution of barriers to worker mobility, barriers to job mobility and deviations from the efficient wage determination equation to labor market mismatch, as described in Section 6.3. These summary statistics are presented for a number of robustness checks in Table 1.[26] In the top and bottom panels of this table, the first line shows our baseline

[25] $u_t^{MM} = (\log \bar{u}_t - \log \bar{u}_t^*)\, \bar{u}_t$, where $\log \bar{u}_t - \log \bar{u}_t^*$ as in (22) and (23), and u_t^{XX} is calculated similarly.

[26] A few entries in the table are negative. The contribution of a friction to mismatch unemployment may be negative because the correlation between deviations from the different no-mismatch conditions

estimates for state-level and industry-level data, respectively.

For the construction of job-filling rates from job-finding rates, we made the assumption that the *matching technology* is well described by a Cobb-Douglas matching function with an elasticity of unemployment μ of 0.72, see Sections 3.3 and 5.2. In the table, we show the effect of varying this elasticity from 0.5 or 0.8. A higher (lower) elasticity increases (decreases) the concavity of the aggregate job-finding rate in the segment-specific job-finding rates, see Section 4, and therefore increases (decreases) the estimated contribution of mismatch to unemployment. This effect is fairly strong for the estimates for the overall amount of mismatch, but the decomposition into its sources is largely unaffected.

We used short-term unemployment to *measure job-finding and separation rates*, as suggested by Shimer (2012). Our results are very similar if we instead measure worker flows from transitions of workers between unemployment and employment using basic monthly CPS data matched between subsequent months. In what is possibly the most contentious assumption we made in measuring worker flows, we calculated job-finding rates by industry of origin rather than by industry of destination. It is not possible to calculate these rates in the same way by industry of destination, because we do not have information about in which industry unemployed workers are searching for a job. However, we can use matched CPS data, combined with information on unemployment duration, to back out a rough measure of job-finding rates, see appendix G. This measure is much noisier than our baseline measure, because it uses a smaller sample consisting only of unemployed workers who find a job within the sample. Nevertheless, the results are very similar.

For the *construction of match surpluses,* we made a number of choices, among which the assumptions that price deflators are the same across states, see Section 5.1, that the opportunity cost of an additional unemployed worker λ^u equals zero, that match payoffs (wages or profits) follow an autoregressive process, and that match turnover is constant, see Section 5.3. The next set of lines in the table explores the robustness of our results to these assumptions. Since none of these assumptions affect the observed dispersion in job-finding rates, the estimates of the contribution of mismatch to unemployment are not affected, except for the state-specific price deflators, which generate slightly more dispersion and, therefore, a slightly higher estimate of mismatch unemployment.[27] The composition of mismatch into its sources is affected, but the effect is very small. To explore the effect of non-zero opportunity costs of unemployment, we vary the home production of non-participants λ^u from 0 to 20, 50 and 70% of the global average wage. For $\lambda^u \geq 50\%$, this leads to negative worker surplus in some industries in some year. When this happens, we drop the entire industry from the sample, which explains why also the contribution of overall mismatch changes in these cases. Despite the changing sample, however, the results for both the overall level of mismatch and its composition

is not exactly zero.

[27] We use a state-specific deflator provided by Berry, Fording, and Hanson (2000), which is available until 2007.

change very little.

For some assumptions, we cannot directly explore robustness, but we can argue they are unlikely to affect our findings. *Measurement error,* while substantial, clearly does not drive our results. Classical measurement error would generate non-systematic deviations from all equilibrium relationships, whereas we find the wage-setting conditions, and, to a lesser extent, the worker-mobility condition in the data, while deviations from all three conditions look systematic. A similar argument can be made for *on-the-job search.* If workers are searching for a new job while employed, this increases workers' match surplus, but, given observed wages and job-finding rates, this effect is not taken into account in the way we construct match surplus, see Section 5.3. If on-the-job search intensity is the same for all workers and all firms, then this does not affect our results, because we work in deviations from the cross-sectional mean. If on-the-job search intensity varies systematically with the value of a match, then on-the-job search would increase or decrease the slope of the worker-mobility curve, (mis)leading us to conclude that worker-mobility frictions are giving rise to mismatch. For the same reason, our findings cannot be driven by *workers looking for jobs in surrounding regions and occupations* as Marinescu and Rathelot (2016) show they do, because this effect would also make it less likely to find a worker-mobility condition in the data.

A more serious issue is that of *discouraged workers.* It is possible that unemployed workers leave labor market segments with low surplus (wages), not by moving to a different labor market segment, but by dropping out of the labor force. This mechanism would make it seem like the no-arbitrage condition for worker mobility is satisfied, while there is substantial mismatch, leading not to unemployment but to non-employment. Unfortunately, without better data, there is very little we can do to explore this issue.

Finally, we explore the effect of *heterogeneity.* As described in Section 4.2, in our baseline we control for time-invariant heterogeneity by removing the segment-specific time-series averages from $\hat{p}_{it}$, $\hat{S}^W_{it}$, $\hat{q}_{it}$ and $\hat{S}^F_{it}$, similar to controlling for fixed effects in a regression. Next, we explore the robustness of our results if we control for observed worker heterogeneity. If demographic characteristics of the workforce change over time, removing time-series averages does not control for this effect. We address this concern by adjusting worker- and job-finding rates, separation rates and earnings for observable worker characteristics, by regressing earnings as well as the likelihood of becoming unemployed and experiencing short-term unemployment on potential labor market experience (age minus years of schooling minus 6), and dummies for educational attainment, gender, race, marital status.[28] For each year and for each state or industry, we then impute the fitted values for a hypothetical worker with average demographics. When we do this, our results change very little.

[28] For wages we use a log-linear specification, as is common in the literature, see Card (1999). In order to get fitted values for wages, we use the fitted values for log wages and apply the correction factor suggested by Cameron and Trivedi (2010).

7 Conclusions

Mismatch unemployment is unemployment due to inefficient dispersion in labor market conditions across submarkets. We proposed an accounting framework using two arbitrage equations and an efficient wage determination equation that allows us to estimate mismatch unemployment and decompose it into its sources. This framework uses data on the values of unemployment and vacancies, rather than on their quantities, as inputs; thus, available data allowed us to present estimates for the 1979-2009 period, going further back in time than previous studies. More importantly, this paper is the first to report on the causes of mismatch.

We argue that mismatch was quantitatively important in the United States over the last four decades, with mismatch across detailed occupations explaining around 13% of unemployment. The cyclical behavior of mismatch unemployment is very similar to that of the overall unemployment rate. This finding is driven by the fact that dispersion in labor market conditions across states and industries moves closely with the business cycle. The unemployment that derives from this dispersion is as cyclical as the overall unemployment rate, and it is no more persistent. As a corollary, the nature of the increase in unemployment in the Great Recession is no different from previous recessions, although it is of course more severe.

The underlying frictions that causes mismatch to persist are predominantly barriers to job mobility, which explains between 65% and 80% of mismatch across both states and industries. The main reason for these frictions is probably the production technology, which allows only for limited possibilities for substituting one type of worker for another. Barriers to entry into particular industries, or lack of industry-specific know-how or brand recognition may also play a role.

We find a much smaller role for worker-mobility frictions, which account only for about 20% of mismatch. This finding is perhaps surprising in light of the debate on policies aimed at increasing worker mobility, see e.g., Katz (2010). On the other hand, the finding is consistent with the observation that U.S. workers are quite flexible, and are willing, for instance, to move between states in order to find a job (Molloy, Smith, Trezzi, and Wozniak (2016)).

Wage-setting frictions play virtually no role for mismatch. This finding is consistent with the flexibility of the U.S. market, which is characterized by flexible wages, particularly for newly hired workers (Haefke, Sonntag, and van Rens (2013)), and by low levels of unionization since the 1980s (Farber and Western (2002)). We make no claim that our results apply to different countries or different time periods, and it is quite possible that in European countries, for instance, both worker-mobility frictions and wage-setting frictions are much more important due to language barriers and more rigid wage-setting institutions.

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Table 1.A
Robustness Analysis, mismatch across states

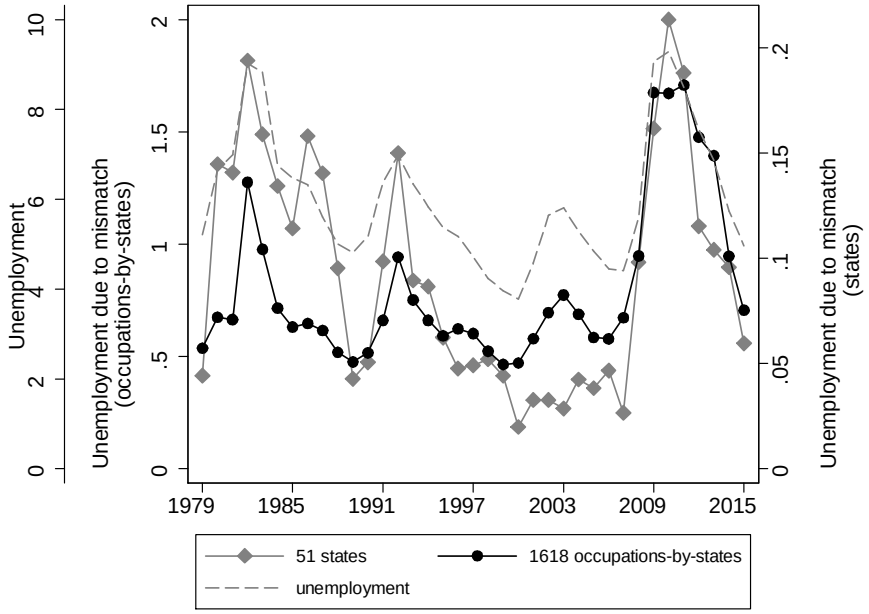
	MMU		Sources of MMU					
	level	cycle	level			cycle		
Mismatch across occupations	13.3	20.0						
Mismatch across states			WM	JM	WD	WM	JM	WD
Baseline	1.5	3.2	20	79	1	19	80	1
Elasticity matching function, $\mu = 0.5$	0.6	1.3	36	62	2	34	64	2
____, $\mu = 0.6$	0.9	1.9	29	70	2	27	71	2
____, $\mu = 0.7$	1.4	2.9	22	77	1	20	78	1
____, $\mu = 0.8$	2.3	4.9	14	85	1	14	86	1
Finding rates using transitions	1.6	2.8	34	64	1	33	65	2
State-specific deflators	1.3	2.8	23	78	−1	26	72	1
Opportunity cost job seeking, $\lambda^u = 0.2\bar{w}$	1.5	3.2	20	79	2	18	80	2
____, $\lambda^u = 0.5\bar{w}$	1.5	3.2	18	79	2	15	80	5
____, $\lambda^u = 0.7\bar{w}$	1.5	3.2	16	79	6	8	80	12
Mean-reversion payoffs, $\delta_y = 0$	1.5	3.2	20	79	1	19	80	1
____, $\delta_y = 0.02$	1.5	3.2	21	78	1	20	79	1
____, $\delta_y = 0.04$	1.5	3.2	21	78	1	21	78	1
____, $\delta_y = 0.06$	1.5	3.2	21	78	0	22	78	1
____, $\delta_y = 0.08$	1.5	3.2	21	78	0	22	78	1
Mean-reversion separation rate, $\delta_\tau = 0$	1.5	3.2	20	79	1	19	80	1
____, $\delta_\tau = 0.02$	1.5	3.2	23	76	1	21	78	1
____, $\delta_\tau = 0.04$	1.5	3.2	24	75	1	22	77	1
____, $\delta_\tau = 0.06$	1.5	3.2	24	74	1	23	76	1
____, $\delta_\tau = 0.08$	1.5	3.2	25	74	1	23	76	1
Control for observed worker heterogeneity	1.4	2.9	25	75	1	24	75	1

Table 1.B
Robustness Analysis, mismatch across industries

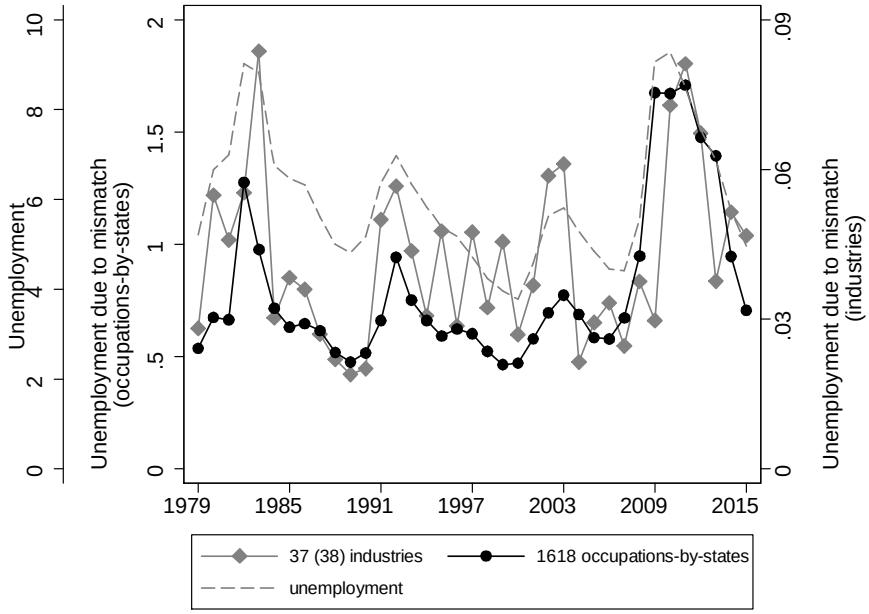
	MMU		Sources of MMU					
	level	cycle	level			cycle		
Mismatch across occupations	13.3	20.0						
Mismatch across industries			WM	JM	WD	WM	JM	WD
Baseline	0.7	0.7	19	78	4	27	65	8
Elasticity matching function, $\mu = 0.5$	0.3	0.3	33	60	7	49	37	14
____, $\mu = 0.6$	0.4	0.4	27	68	5	39	49	11
____, $\mu = 0.7$	0.6	0.6	20	76	4	29	62	9
____, $\mu = 0.8$	1.1	1.1	13	84	3	20	75	6
Finding rates using transitions	0.8	0.5	27	71	1	30	65	5
Finding rates by destination	0.9	1.0	26	75	−1	24	75	1
Opportunity cost job seeking, $\lambda^u = 0.2\bar{w}$	0.7	0.7	18	78	4	27	65	8
____, $\lambda^u = 0.5\bar{w}$	0.8	0.9	17	78	5	28	64	8
____, $\lambda^u = 0.7\bar{w}$	0.9	0.8	17	78	5	24	71	5
Mean-reversion payoffs, $\delta_y = 0.02$	0.7	0.7	18	78	4	27	64	9
____, $\delta_y = 0.04$	0.7	0.7	19	78	3	27	66	7
____, $\delta_y = 0.06$	0.7	0.7	19	78	3	28	67	5
____, $\delta_y = 0.08$	0.7	0.7	19	79	2	28	68	4
Mean-reversion separation rate, $\delta_\tau = 0$	0.7	0.7	19	78	4	27	65	8
____, $\delta_\tau = 0.02$	0.7	0.7	24	72	4	29	63	8
____, $\delta_\tau = 0.04$	0.7	0.7	26	71	4	29	63	8
____, $\delta_\tau = 0.06$	0.7	0.7	26	70	4	28	64	8
____, $\delta_\tau = 0.08$	0.7	0.7	26	70	4	28	64	8
Control for observed worker heterogeneity	0.6	0.8	21	73	6	28	58	15

Figure 1
Mismatch unemployment

A. Across US states



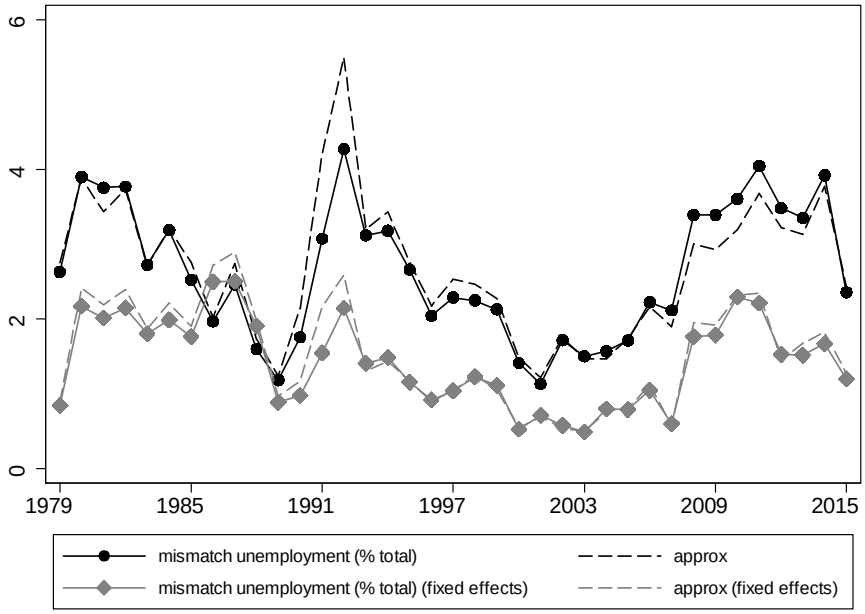
B. Across industries



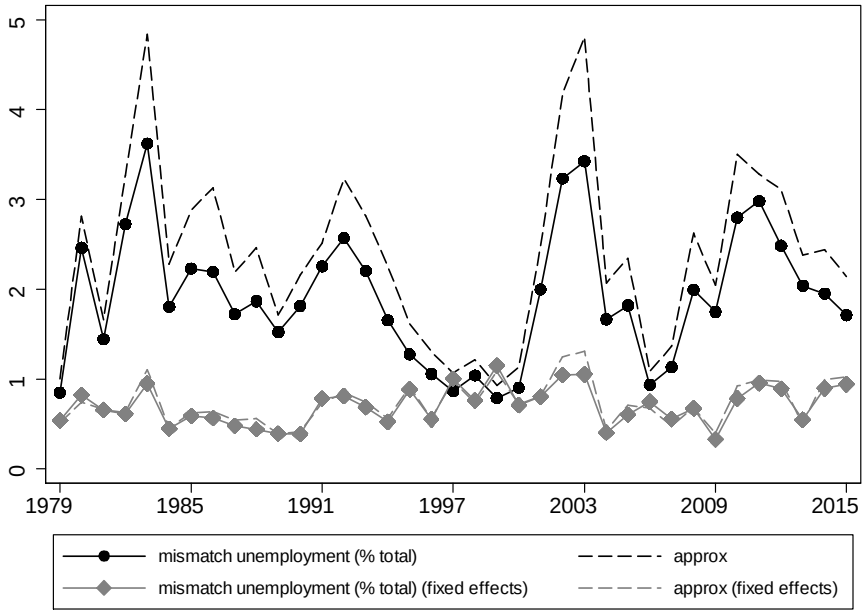
Unemployment due to mismatch across occupations, states and industries, calculated as explained in Section 4.3. The dashed line shows the actual unemployment rate for comparison.

Figure 2
Unemployment due to mismatch as a percentage of total unemployment

A. Across US states



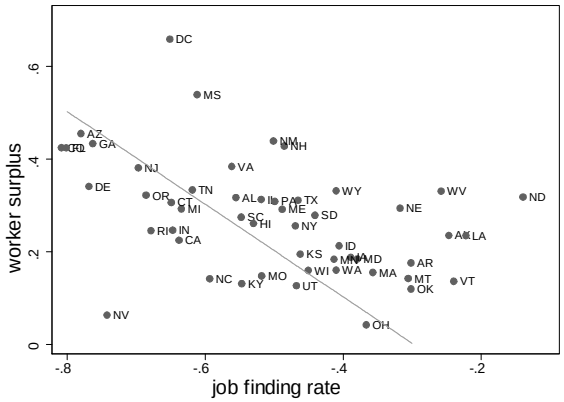
B. Across industries



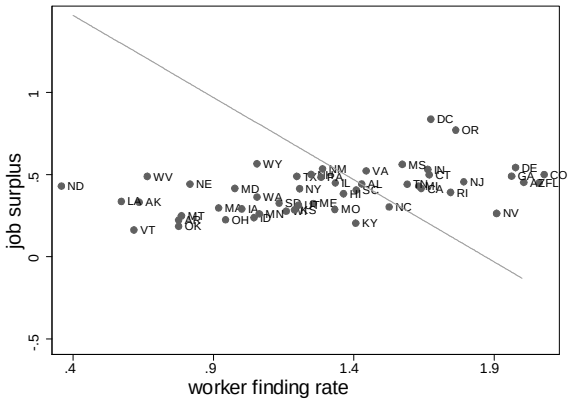
Percentage increase in the unemployment rate due to mismatch, with and without controlling for heterogeneity, and approximation as explained in Section 4.

Figure 3
Worker mobility, job mobility and wage determination curves across US states

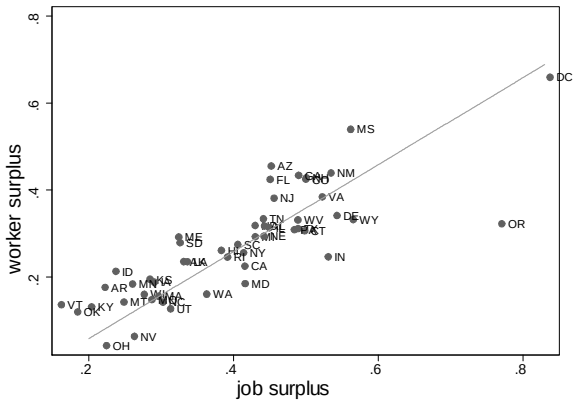
A. Worker mobility condition



B. Job mobility condition



C. Wage setting condition

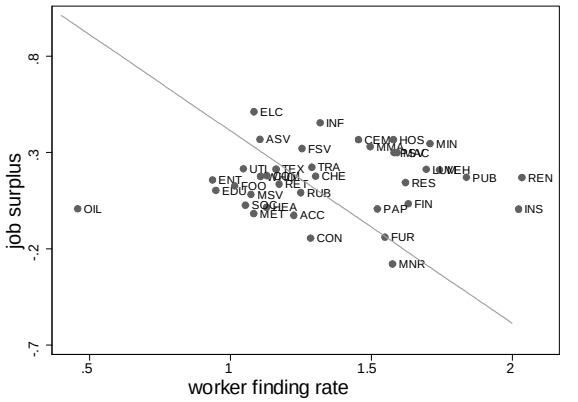


Lines represent the equilibrium relations corresponding to a labor market without any mismatch. Data are for 2010.

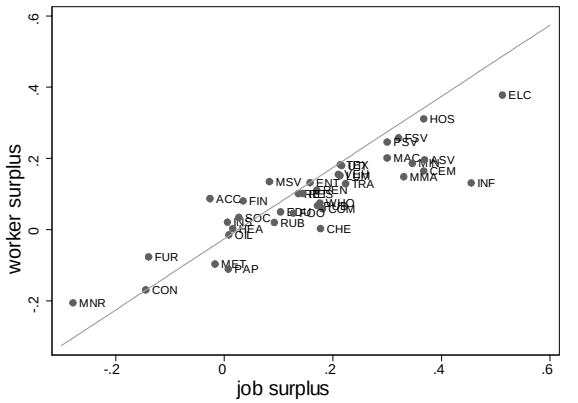
Figure 4
Worker mobility, job mobility and wage determination curves across industries

A. Worker mobility condition

B. Job mobility condition



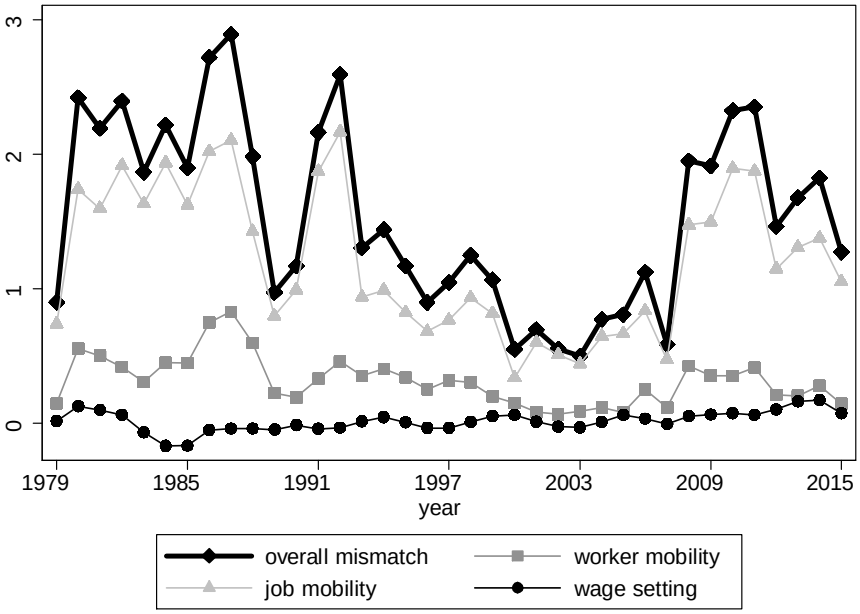
C. Wage setting condition



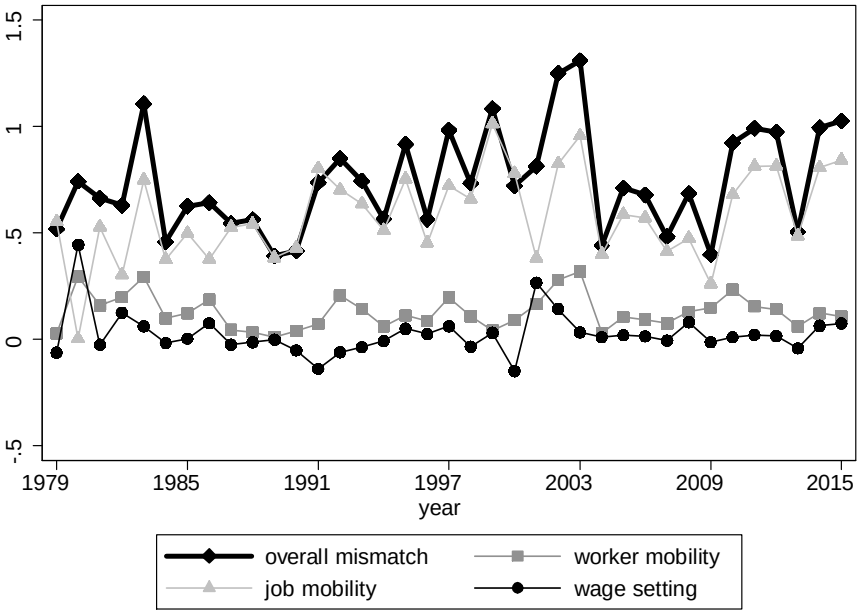
Lines represent the equilibrium relations corresponding to a labor market without any mismatch. Data are for 2010.

Figure 5
Sources of labor market mismatch

A. Across US states



B. Across industries



The thicker line is our baseline estimate for the aggregate effect of mismatch as in Figure 2. The other lines show the contribution of worker mobility costs (WM), job mobility costs (JM) and wage setting frictions (WD) to mismatch, see Section 4.