Accounting for Mismatch Employment

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Accounting for Mismatch Unemployment

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Abstract

We investigate unemployment due to mismatch in the US over the past three decades. We propose an accounting framework that allows us to estimate the overall amount of mismatch unemployment, as well as the contribution of each of the frictions that caused the mismatch. Mismatch is quantitatively important for unemployment and the cyclical behavior of mismatch unemployment is very similar to that of the overall unemployment rate. Geographic mismatch is driven primarily by wage frictions. Mismatch across industries is driven by wage frictions as well as barriers to job mobility. We find virtually no role for worker mobility frictions.

Keywords: mismatch, structural unemployment, worker mobility, job mobility
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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)). There was, however, little empirical work using disaggregated data to either support or reject this hypothesis.

In this paper, we estimate mismatch unemployment on the US labor market, study its evolution over time and explore what frictions caused mismatch to arise. To do so, we use an accounting framework that puts just enough structure on the data to allow us to quantify the sources of mismatch unemployment.

Our accounting framework models the labor market as consisting of multiple submarkets or segments. Mismatch is defined as 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. There are four types of frictions that generate mismatch: worker mobility costs, job mobility costs, wage setting frictions and heterogeneity in matching efficiency. Figure 1 visualizes the framework.

The data required to estimate mismatch unemployment and its sources using our approach, are job and worker finding rates, and worker and job surplus by labor market segments, which we operationalize as states or industries. We construct these variables over the 1979-2009 period using data on worker flows and wages from the Current Population Survey (CPS) and data on profits from the National Income and Product Accounts (NIPA).

Consistent with other recent studies, we argue that mismatch is an important reason for unemployment. A back-of-the-envelope calculation correcting our estimates for aggregation bias suggests that mismatch is responsible for a large part of both the level and the fluctuations in the unemployment rate. 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 two decades ago.[1] 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

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

previous recessions, although it was of course more severe.[2] We find no evidence that mismatch unemployment is 'structural', in the sense that it would not be not responsive to stabilization policy.[3]

Our most interesting and novel set of results concerns the sources of labor market mismatch. We find that most mismatch is caused by dispersion in the share of surplus that goes to workers, i.e. by wage setting 'frictions'. Industries and states with high wages tend to have low profits. This implies that those states and industries that are attractive to workers are unattractive to firms, and vice versa. Little or no mismatch is due to worker mobility frictions. These conclusions are based on the 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). In the data, we find that deviations from this correlation are small and non-systematic. An implication of these results is that policies aimed at increasing worker mobility, as advocated e.g. by Katz (2010), are likely to have small effects and may even be counterproductive.

The detailed empirical analysis we provide, indicates that it is fruitful to think of mismatch as a possible micro-foundation for unemployment. In most modern macro-economic models of the labor market there is unemployment because of search frictions. But the micro-foundations for search frictions and the aggregate matching function are not very well developed. If unemployment is truly due to a time cost of search, it seems there should be a secular downward trend in the unemployment rate as computers and the internet improve the search technology available to firms and workers. Instead, we think of search frictions as "a modeling device that captures the implications of the costly trading process without the need to make the heterogeneity and the other features

[2] This result is not inconsistent with observation that there was an outward shift in the Beveridge curve, the negatively sloped relation 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 are not contradictory with the observation that exogenous shocks to mismatch are not an important as a source of unemployment fluctuations (Furlanetto and Groshenny (2013)).

[3] 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 Groshen and Potter (2003) for versions of this argument. Early critics include Krugman (2010), DeLong (2010), Lazear 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)).

that give rise to it explicit" (Pissarides (2000, p.4)). Mismatch generates heterogeneity and therefore gives rise to unemployment. The results in this paper shed light on the question what are the frictions that give rise to mismatch.[4]

Previous empirical studies on mismatch tend to focus 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)) and there is little recent empirical work using disaggregated data.[5] Two recent contributions, however, are closely related to this paper. Şahin, Song, Topa, and Violante (2014) use disaggregated data on unemployment and vacancies to construct indices of mismatch, using data from the JOLTS and the HWOL for the 2001-2011 and 2005-2011 periods respectively. Barnichon and Figura (2013) use the CPS to explore how much dispersion in labor market conditions contributes to movements in matching efficiency. Our findings are consistent with these papers in terms of the contribution of mismatch across states and industries to the increase in unemployment in the Great Recession.[6] Compared to Şahin, Song, Topa, and Violante (2014), we provide an alternative method to estimate mismatch unemployment, which gives us a much longer time series. The longer series allows us to better explore the cyclical behavior of mismatch unemployment. Compared to Barnichon and Figura (2013), our focus is on unemployment rather than matching efficiency. Our main contribution with respect to both papers is the accounting framework that allows us to decompose mismatch into it sources and to estimate the contribution of each of these sources to unemployment.

This paper is organized as follows. In the next section we present the accounting framework to formalize the sources of dispersion in labor market conditions across submarkets of the labor market. We identify four sources of mismatch, three of which we can estimate: worker mobility costs, job mobility costs and wage setting frictions. Section 3 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. Section 4 presents the empirical results and Section 5 concludes.

[4]Some recent studies discuss this issue from a theoretical perspective. Shimer (2007) formally shows that mismatch between the distributions of workers and jobs over segments of the labor market gives rise to a relation between the job finding probability and labor market tightness that is very similar to the relation 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), and waiting unemployment as in Birchenall (2011) 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 unemployment that can be used to test the theoretical models of mismatch unemployment.

[5]Older studies include work by Padoa Schioppa (1991) and Phelps (1994).

[6]The finding that geographic mismatch cannot explain why the increase in unemployment in the Great Recession is so much larger than in previous recessions is also consistent with work by Kaplan and Schulhofer-Wohl (2011), who show that most of the a drop in interstate migration in the Great Recession is a statistical artifact.

2 Accounting Framework

The theoretical framework presented here allows us to formalize the mechanisms, by which heterogeneity in labor market conditions across submarkets of the labor market leads to mismatch unemployment. In addition, we use the framework to guide the empirical exercise how to estimate mismatch unemployment and how to decompose it into its sources. We try to make as little assumptions as possible. In particular, we do not assume anything about vacancy creation, but model only the distribution of vacancies and unemployed workers over submarkets.

Unemployed workers look for jobs, and firms with vacancies look for unemployed workers on the labor market. But not each unemployed worker can match with each vacancy. We model this idea as a labor market that is segmented into submarkets. A 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. We assume that there is a one-to-one mapping of the set of workers and firms that search for each other, ruling out that workers or firms spread out their search effort over several submarkets.[7] In addition, we assume that in each submarket, there is a technology to match unemployed workers with vacancies.[8]

Under these assumptions, labor market conditions in a submarket can be completely characterized by four variables: the probability that an unemployed workers finds a job, the increase in life-time earnings by a worker who finds a job, the probability that a vacant job finds a worker, and the increase in life-time profits by a firm that fills a vacant job. These four variables are the job finding rate f_i^W, worker surplus S_i^W, the job filling rate or worker finding rate f_i^F and job surplus S_i^F in submarket i, respectively.

Any labor market model with a segmented labor market must describe how labor market conditions are related across submarkets. We show which relations effectively reduce the segmented labor market to a single market, as in the standard search and matching model with homogeneous workers and jobs, in the tradition of Diamond (1982), Mortensen (1982) and Pissarides (1985). We take these relations as a benchmark and explore the effect of deviations from it. Unemployment that results under the benchmark conditions may be due to a variety of frictions, for instance search frictions. We refer to this unemployment as 'frictional'. Unemployment that results from deviations from the benchmark conditions (and is therefore due to dispersion in labor market conditions) is called mismatch unemployment.

[7] This assumption is without loss of generality as long as the total amount of search effort is limited. It is, of course, difficult to operationalize this concept of a submarket empirically. In practice, we use either states or industries in most of our estimates, which is a much higher level of aggregation compared to the ideal. In Sections 2.2 and 4.2.1, we discuss how this affects our estimates.

[8] Our accounting framework is based on worker and job mobility arbitraging away differences in the value of searching in each submarket. In order for arbitrage to be possible, we need the (plausible) assumption that the matching technology has positive and diminishing returns in each of its inputs. In other words, we assume that adding an additional unemployed worker to a submarket, ceteris paribus, makes it harder for workers to find jobs and easier for firms to fill vacancies (and similar for adding an additional vacancy).

2.1 Benchmark Relations

The relation between the job finding rate f_i^W and worker surplus S_i^W across submarkets is determined by assumptions about worker mobility between submarkets, the relation between the worker finding rate f_i^F and job surplus S_i^F by assumptions about job mobility (mobility of vacancies), the relation between worker and job surplus by assumptions about wage determination, and the relation between job and workers finding rates by assumptions about the matching technology. These four relations, which are summarized in Figure 1, fully determine conditions in submarkets of the labor market. We now discuss each of these four relations in turn.

2.1.1 Worker Mobility

An unemployed worker, searching for a job in submarket i, receives an unemployment benefit b_i^W (which, as usual, includes the utility from leisure). With probability f_i^W, this worker finds a job, in which case she receives the worker surplus S_i^W from the match. Thus, the per-period value of searching for a job in submarket i, assuming it is constant over time, is given by $z_i^W = b_i^W + f_i^W S_i^W$.[9]

If workers may freely decide in which submarket to search, i.e. if there are no barriers to worker mobility, it must be that the value of searching is equalized across submarkets, so that $z_i^W = z^W$ for all i. Using a bar over a variable to denote its mean over all submarkets and a hat to denote relative deviations from this mean, e.g. $\hat{f}_i^W = \left(f_i^W - \bar{f}^W\right)/\bar{f}^W$, equalization of the value of searching in all submarkets implies the following relation between f_i^W and S_i^W, which we label the worker mobility curve.[10]

$$\hat{f}_i^W + \hat{S}_i^W = -\frac{\bar{b}^W}{z^W - \bar{b}^W}\hat{b}_i^W \tag{1}$$

Assuming unemployment benefits are the same in all submarkets, we get $\hat{f}_i^W = -\hat{S}_i^W$. The worker mobility curve is a no-arbitrage condition. It states that attractive jobs must be hard, and unattractive jobs easy to find, in order for workers to be indifferent which job they search for.[11] If unemployment benefits differ across submarkets, then submarkets with high unemployment benefits must have low job finding rates or low worker surplus or both.

If there are barriers to worker mobility, for example because it is costly to move

[9] The assumption that z_i^W is in steady state seems reasonable, because average unemployment duration, compared to the length of a typical business cycle, is short in the US.

[10] The condition is exact for log-deviations but only a first-order approximation for relative deviations from the mean. The same caveat applies to conditions (3), (4) and (5) below. The reason we nevertheless prefer relative deviations is because empirically log-deviations are problematic in the (rare) cases that variables are negative.

[11] 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) prosposes differences in job finding rates as an explanation for persistent wage differentials across industries.

from one state to another, or because moving into a different industry requires costly retraining, then there may be differences in the value of searching across submarkets. We denote these differences by α_i^{WM}, so that the worker mobility curve is given by

$$\hat{f}_i^W + \hat{S}_i^W = \alpha_i^{WM} \tag{2}$$

If unemployment benefits are the same across submarkets, the dispersion in α_i^{WM} is a measure of worker mobility costs. If the difference in the value of searching in a particular submarket i becomes to high compared to the average, it becomes worthwhile for workers to pay the mobility cost and move into that submarket. Unemployed workers moving into market i make it harder to find a job in that submarket, reducing f_i^W and therefore α_i^{WM}. If unemployment benefits vary across submarkets, then differences in the value of searching may also reflect differences in unemployment benefits, $\alpha_i^{WM} = -\frac{\bar{b}^W}{z^W - \bar{b}^W}\hat{b}_i^W$.

2.1.2 Job Mobility

Having a vacancy looking for a worker in submarket i yields the firm b_i^F, which may be a negative number, i.e. vacancy posting costs. With probability f_i^F, this vacancy gets filled, in which case the firm gets surplus S_i^F from the match. Thus, the (steady state) per-period value of searching for a worker in submarket i is given by $z_i^F = b_i^F + f_i^F S_i^F$.

If firms can freely relocate vacancies across submarkets, no-arbitrage requires that the value of searching for a worker must be equal across submarkets. Analogous to the worker mobility curve, we get a job mobility curve, which states that jobs that are attractive to firms must be hard to fill. If there are barriers to job mobility, these give rise to differences in the value of a vacancy across submarkets.

$$\hat{f}_i^F + \hat{S}_i^F = \alpha_i^{JM} \tag{3}$$

Dispersion in α_i^{JM} may reflect job mobility costs and/or dispersion in vacancy posting costs, $\alpha_i^{JM} = -\frac{\bar{b}^F}{\bar{z}^F - \bar{b}^F}\hat{b}_i^F$.

2.1.3 Wage Determination

The relation between worker and firm surplus is determined by assumptions on how worker and firm divide the total surplus from their match. The instrument that is used to divide the surplus is the wage. In our benchmark relation, which is the only relation that does not give rise to any mismatch, firm and worker share the surplus in fixed proportions across segments. This relation would be true in standard labor market models, which commonly assume that wages are set by generalized Nash bargaining. Here, however, we are not making any specific assumptions on the wage determination process, but merely stating a benchmark relation for surplus sharing that does not give rise to mismatch.

If the share of match surplus that goes to the worker ϕ_i, often referred to as the worker's bargaining power, is constant across submarkets, then worker and job surplus are proportional across submarkets, $\hat{S}_i^W = \hat{S}_i^J$. In general, wages may deviate from this benchmark relation, for example because bargaining power varies across segments or because wages are not rebargained in each period. This is captured by deviations from the wage determination curve.

$$\hat{S}_i^W = \hat{S}_i^F + \alpha_i^{WD} \tag{4}$$

Dispersion in α_i^{WD} may reflect wage bargaining costs or heterogeneity in workers bargaining power, $\alpha_i^{WD} = \widehat{\frac{\phi_i}{1-\phi_i}}$, but may also reflect that wages are determined by a completely different mechanism than bargaining. In the interest of brevity, we refer to deviations from the benchmark wage determination curve as evidence for wage setting 'frictions'.

2.1.4 Matching Technology

The final relation needed to close the model, between worker and job finding rates, is determined by assumptions on the matching technology. In our benchmark relation, the probability that workers find jobs and the probability that firms find workers are inversely log-proportional. This is true, for instance, if matches are formed from unemployed workers and vacancies through a constant returns to scale Cobb-Douglas matching function. Under this assumption, the worker and job finding rates are both iso-elastic functions of the vacancy-unemployment ratio θ_i, often referred to as labor market tightness, $f_i^F = B_i \theta_i^{-\mu}$ and $f_i^W = B_i \theta_i^{1-\mu}$, where μ is the elasticity of unemployment in the matching function and B_i is matching efficiency. This gives rise to the following curve, describing the matching process.

$$\hat{f}_i^F = -\frac{\mu}{1-\mu}\hat{f}_i^W + \alpha_i^{MT} \tag{5}$$

Dispersion in α_i^{MT} reflects dispersion in matching efficiency across submarkets, $\alpha_i^{MT} = \frac{\hat{B}_i}{1-\mu}$. If the elasticity of the matching function is not constant across submarkets, then the above relation still holds in first order approximation, and α_i^{MT} reflects all differences in the matching function across submarkets, $\alpha_i^{MT} = \frac{\hat{B}_i}{1-\mu} - \frac{\mu}{1-\mu}\left(\bar{f}^W - \bar{f}^F\right)\hat{\mu}_i$.

Our data do not allow us to test the benchmark relation on the matching technology. Therefore, in the empirical work we will assume that $\alpha_i^{MT} = 0$ for all i. There is some evidence from other data sources that this assumption may not be too far from the truth (Şahin, Song, Topa, and Violante (2014)), see Section 3.2 for a short discussion. In the description of the framework in this section, we will allow for α_i^{MT} to be non-zero for completeness.

2.2 Mismatch Unemployment

Combine equations (2), (3), (4) and (5) to solve for the distribution of job finding rates across segments.

$$\hat{f}_i^W = (1-\mu)\left(\alpha_i^{WM} - \alpha_i^{JM} - \alpha_i^{WD} + \alpha_i^{MT}\right) \tag{6}$$

Note that the benchmark relations were defined so that only deviations from these equations give rise to dispersion in labor market conditions. If there is perfect worker mobility, perfect job mobility, wages are set to share match surplus in constant proportions, and there is a matching function with constant matching efficiency, then labor market conditions are identical in all submarkets: setting $\alpha_i^{WM} = \alpha_i^{JM} = \alpha_i^{WD} = \alpha_i^{MF} = 0$ in equation (6) gives $\hat{f}_i^W = 0$ or $f_i^W = \bar{f}^W$ for all i. Substituting back into the various equations, it is straightforward to show that the worker finding rate, and worker and firm surplus are equalized as well. In this case, the model reduces to a standard labor market model, in which we can effectively think of the labor market as a single, unsegmented market. Unemployment in this case is entirely due to frictions within submarkets, e.g. search frictions.

Dispersion in labor market conditions generates unemployment because the job finding rate is concave in labor market tightness. Therefore, the distribution of vacancies and unemployed workers that results in the highest aggregate job finding rate, keeping fixed the total number of vacancies and unemployed, is to equalize labor market tightness over submarkets. To formalize this, consider a mean-preserving change in the distribution of labor market tightness from θ_i to θ_i'. The counterfactual unemployment rate u^{CF} that prevails under the new distribution is given by,

$$\frac{u^{CF}}{u} \simeq \frac{\bar{f}^W}{\bar{f}^{W,CF}} = \left(\frac{E\left[\left(1+\hat{f}_i^{W,CF}\right)^{\frac{1}{1-\mu}}\right]}{E\left[\left(1+\hat{f}_i^{W}\right)^{\frac{1}{1-\mu}}\right]}\right)^{1-\mu} \propto \frac{V\left[\theta_i^{CF}/\bar{\theta}^{CF}\right]}{V\left[\theta_i/\bar{\theta}\right]} \tag{7}$$

where $0 < \mu < 1$ is the elasticity of unemployment in the matching function. See appendix A for the derivation of equation (7). The aggregate job finding rate is higher and therefore the unemployment rate lower, $\bar{u}^{CF} < \bar{u}$, if and only if the dispersion in $f_i^{W,CF}$ is smaller than the dispersion in f_i^W, in the sense that θ_i is a mean-preserving spread of θ_i^{CF} (i.e. the distribution of θ_i^{CF} second-order stochastically dominates the distribution of θ_i).[12]

To calculate the contribution of mismatch to unemployment, we use the actual job finding rates for $\hat{f}_i^W$ and set the counterfactual finding rates $\hat{f}_i^{W,CF} = 0$ to represent the full equalization of labor market conditions that would prevail in the absence of mismatch. Then, $\left(u - u^{CF}\right)/u$ is the fraction of unemployment that is due to mismatch. The importance of mismatch estimated in this manner will depend on the time period as

[12] The first approximation is just for ease of interpretation. In the empirical work, we calculate the counterfactual job finding rate using (7) and then calculate the counterfactual steady state unemployment rate as $u = \lambda/\left(\lambda + f\right)$.

well as on the level of disaggregation. Benchmark conditions (2), (3) and (4) assume the labor market is in steady state. Given the speed of transition dynamics in unemployment and the fact that we use annual data, we do not expect the results to be affected very much by this assumption. However, to the extent that some of the adjustment may not yet have been realized, our estimates provide an upper bound for the amount of mismatch due to each source. The effect of the level of disaggregation is more important. 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 the overall amount of mismatch in Section 4.2.1.

2.3 Mismatch Accounting

Deviations from any of the four benchmark relations generate dispersion in labor market tightness and job finding rates. There are four sources of dispersion across submarkets of the labor market: α_i^{WM} represents heterogeneity in unemployment benefits and barriers to worker mobility, α_i^{JM} heterogeneity in vacancy posting costs and barriers to job mobility, α_i^{WD} heterogeneity in wage bargaining power or other wage setting frictions, and α_i^{MT} heterogeneity in matching efficiency. All four sources lead to unemployed workers and vacancies being in different submarkets and thus cause mismatch unemployment. For example, if $\alpha_i^{WM} > 0$, too few unemployed workers are searching for jobs in submarket i, either because unemployment benefits are relatively low there or because mobility costs prevent more unemployed workers from moving into that submarket. If $\alpha_i^{WD} > 0$, too many unemployed workers and too few vacancies are in submarket i, because wages are higher (and profits lower) than in comparable jobs in other submarkets so that workers reap a disproportionately large share of match surplus in this submarket.

Equations (6) and (7) allow us to decompose mismatch unemployment into its four sources. The idea is that if we remove, for example, the worker mobility frictions, setting $\alpha_i^{WM} = 0$, but leave the job mobility frictions, wage setting frictions, and heterogeneity in matching efficiency in place, then α_i^{JM}, α_i^{WD} and α_i^{MT} would stay the same. Notice that this is probably not a good assumption for the short run, because worker or job mobility or wage renegotiations affect equations (2), (3) and (4) simultaneously. In the long run, however, after many shocks have hit the labor market, we would expect deviations because of job mobility, wage setting frictions, or heterogeneity in matching efficiency to be similar to what they were. Thus, the question we can answer is what unemployment rate would prevail in the long run, if we removed one or more deviations from the benchmark model.

The procedure to decompose mismatch unemployment into its sources is implemented in three steps. First, we estimate the α's using equations (2), (3), (4) and (5) and data on the surpluses and finding rates (section 3 below describes how we obtain these data). Second, given estimates for α_i^{WM}, α_i^{JM}, α_i^{WD} and α_i^{MT}, we use equation (6) to calculate what the job finding rates in each submarket would be if we set one or more of the α's equal to zero. Finally, using equation (7), we calculate the unemployment rate that would prevail under these scenarios. We refer to this exercise as mismatch accounting.

The last step of the decomposition is always relative to a baseline level of unemployment, see equation (7). This means we can always estimate the contribution of each source in two different ways, introducing the friction with respect to a baseline, in which the friction was absent, or removing the friction with respect to a baseline, in which it was present. In general, the two approaches will give different answers because the alpha's may be correlated.[13] More importantly, the contribution of each friction will depend on the order in which we introduce or remove the various frictions. In appendix B, we show that 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 way, we make sure that our decomposition adds up to the total amount of mismatch unemployment.

2.4 Discussion

Before turning to the data, we briefly discuss a few conceptual issues with the mismatch accounting procedure and compare our approach to the other studies in the (small) recent literature on labor market mismatch. First and foremost, we want to emphasize that we are not taking a stance ex-ante on whether or not we expect the benchmark conditions on worker mobility (2), job mobility (3), and wage determination (4) to be satisfied in the data. These conditions are just benchmark conditions: conditions, under which labor market conditions are fully equalized across segments. Deviations from the benchmark conditions represent sources of labor market mismatch.

The benchmark conditions on wage determination (4) and matching technology (5) are of a different nature than the conditions for worker mobility (2) and job mobility (3). The latter are no-arbitrage conditions, and deviations from these conditions have a straightforward interpretation as evidence for barriers to worker or job mobility across segments. The interpretation of deviations from the wage determination and matching technology conditions is less straightforward. Consequently, one could have a semantic debate whether dispersion in labor market conditions originating from deviations from these conditions should even be labeled as 'mismatch'. Our pragmatic solution to this

[13] Note that this also means that removing one or more of these sources of mismatch does not necessarily decrease unemployment as the different frictions may reinforce or counteract each other. This result is intuitive. Imagine two otherwise identical submarkets of the labor market, 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 removed the mobility costs but left 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 structural unemployment. In the empirical analysis in section 4, we will show that this is in fact a realistic mechanism.

issue is to define mismatch as dispersion in labor market conditions for any reason. Clearly, this choice affects how we interpret our results and we try to be careful about this issue throughout the paper.

The benchmark 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 little assumptions. However, we could also think of these conditions as equilibrium conditions in the context of a directed search model. Yet a different interpretation of the benchmark conditions is as efficiency conditions. This last interpretation is the one preferred by Şahin, Song, Topa, and Violante (2014), who derive a benchmark condition for a labor market without mismatch, similar to condition (6), as the first-order condition of a social planner who is free to move workers across labor market segments. In this interpretation, we can derive conditions similar to (2) and (3) if we assume the planner can also move vacancies across segments, and unemployment benefits, vacancy posting costs and matching functions are identical across labor market segments, but match productivities and job destruction rates are not. Note that in this case the conditions would of course be in terms of total match surplus, because the planner could redistribute that surplus between workers and firms. However, under the Hosios condition, which implies our benchmark wage determination condition (4), these efficiency conditions and our worker and job mobility conditions (2) and (3) are identical.

To complete the comparison between the benchmark conditions in this paper and those in Şahin, Song, Topa, and Violante (2014), we could ask ourselves what happens in our framework if we assume the distribution of vacancies over labor market segments is exogenous as in Şahin, Song, Topa, and Violante (2014). In that case, there is no reason for job mobility condition (3) to hold. Substituting equal surplus sharing (4) into the job mobility condition (2), setting the alphas to zero, we obtain a benchmark condition for a labor market without mismatch similar to the allocation chosen by the planner in Şahin, Song, Topa, and Violante (2014) with heterogeneous productivities and job destruction rates, equation (2) in their paper. This condition is weaker than condition (6), with all alphas set to zero, because job mobility, in combination with homogeneous matching technologies (5), additionally implies that total match surplus is equalized across labor market segments. This makes sense. If workers are free to move, but vacancies are stuck in the segment they are in, the value of being unemployed in each segment will be equalized, but not necessarily the total value of a match. In this case, there may be dispersion in job finding rates in the benchmark case, so that this dispersion is not attributed to mismatch. However, if firms are free to move vacancies across segments, then the value of a vacancy must be equalized as well. If it is further the case that match surplus accruing to workers and firms is positively related, as condition (4) holds, then it must be that job finding and job filling rates are (weakly) positively related as well: if segments that have relatively high worker surplus also have relatively high firm surplus, both job finding and job filling rates must be relatively low in these segments. Since the matching technology implies a (weakly) negative rather than a positive correlation between job finding and job filling rates, see condition (5), it must be that both job finding and job filling rates, and therefore also match surplus, are fully equalized across labor market segments. Therefore, any dispersion in labor market conditions in our framework will be attributed to mismatch. To summarize: mismatch as defined by Şahin, Song, Topa, and Violante (2014) will be attributed to worker mobility or wage setting frictions in our framework (although Şahin, Song, Topa, and Violante (2014) do not separate the two sources of mismatch), whereas mismatch due to job mobility frictions will not be picked up by the Şahin, Song, Topa, and Violante (2014) mismatch index.

Few assumptions were needed to derive benchmark conditions (2), (3) and (4) 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). Here, we highlight two assumptions in particular that do not affect the benchmark conditions. First, we assumed workers and firms can only search in one labor market segment at the same moment in time. The benchmark 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 (2014). We return to this issue when we discuss the robustness of our results in Section 4.4.

A second concern we often encounter is how the benchmark conditions would change in the presence of on-the-job search. On-the-job search does not affect the conditions in any way, although it will affect the way we operationalize the concept of match surplus, see Section 3.3 below. The reason is that the benchmark conditions describe the behavior of unemployed workers, not that of the employed. On a side note: there may be mismatch of employed workers as well, i.e. mismatch between the skill set of workers and the skill requirements of the jobs they are employed in, a topic also known as underemployment or overqualification. This paper does not address this interesting line of research at all, and we only consider mismatch between unemployed workers and vacancies.

Finally, a brief comment on the welfare implications of our results. There are none. The type of mismatch that we consider may be inefficient, e.g. because workers cannot relocate to segments where there are more vacancies, or efficient, e.g. because workers do not want to relocate to a different labor market segment because the flow value of being unemployed b_i^W is high in the segment that they are in. Since our approach cannot distinguish efficient from inefficient mismatch, our results are informative only about unemployment, not about welfare.

3 Data and Measurement

To test the relations we derived in the previous section, we need empirical measures of the job-finding rate f_i^W, the worker-finding rate f_i^F, worker surplus S_i^W, which is closely related to wages, and job surplus S_i^F, closely related to profits, for submarkets of the labor market. In this section, we describe how we obtain these measures. In section 3.1, we describe the micro-data we use to extract disaggregated measures for finding rates, wages and profits. Then, in sections 3.2 and 3.3, 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 and these sections anticipate a number of robustness checks, which we will revisit after discussing our results in section 4.4.

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 that 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 50 US states to explore geographic mismatch and around 33 industries to explore skill mismatch.[14] This choice is driven by data limitations and follows other empirical contributions in this literature (Şahin, Song, Topa, and Violante (2014), Barnichon and Figura (2013)). Unfortunately, it is not possible to use very small submarkets, because we would have too little data about each submarket.[15] It is also not possible to use occupations, as Şahin, Song, Topa, and Violante (2014) do, even though occupations arguably better describe categories of jobs that require similar skills than industries, because data on profits by occupation are not available.

3.1 Data Sources

Our primary data sources are the January 1979 to December 2009 basic monthly files of the Current Population Survey (CPS) administered by the Bureau of Labor Statistics (BLS). We limit the sample to wage and salary workers between 16 and 65 years of age, with non-missing data for state and industry classification. From the matched basic monthly files we construct job finding and separation rates, using the variable labor

[14] For the state-level data, we exclude Alaska, which has extreme wages and profits, and include DC. For the industry-level data, we have 33 industries based on the SIC classification for the 1983-1997 period and 32 industries based on the NAICS classification for the 2003-2009 period.

[15] 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.

force status, which indicates which workers are unemployed and which are employed. 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 $23,000$ and $500,000$ observations per year, respectively. 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 $150,000$ 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 rate and the average wage for the state-year and industry-year cells. The average cell size for job finding rates is 569 per year for the state-level data and 679 per year for the industry-level data and the smallest cells have 158 and 102 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 and is the measure of business income from the NIPA that is closest to economic profits. Since data on net operating surplus are not available at the state and industry level, 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.[16] We drop the industries "Mining", "Utilities", "Real estate and rental and leasing" and "Petroleum and coal products manufacturing" because reported profits are extremely large in these industries.

In 1998, the industry classification system changes 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 $\hat{f}_i^W$, $\hat{f}_i^F$, $\hat{S}_i^W$ and $\hat{S}_i^F$ over the full sample period. The only problem with this approach is that the change in classification may introduce jumps in the variances in 1998 because of sampling error (although the industries are subsamples of the data with on average the same size before and after 1998, they are different draws). We solve this problem by imposing that the variances may change smoothly over time but may not jump in 1998. We implement this by regressing the squares of the four variables on a polynomial time trend and a post-1998 dummy. Because all variables are in deviations from their mean, the average of the square equals the variance and the polynomial trend captures smooth

[16] 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 $\Pi/L = (1-\alpha)\,Y/L - w = d\Pi/dL$.

changes in this variance. We then correct the post-1998 data for the estimated jump in the variance.

We use nominal data on wages and profits and do not use a price deflator in our baseline estimates. The reason is that if we were to use an aggregate series for the deflator, this would not affect our results, which use only the cross-sectional variation in the data. As a robustness check, we also show results for unemployment due to geographic mismatch using a state-specific deflator provided by Berry, Fording, and Hanson (2000), which is available until 2007.

Finally, we need to make assumptions on unemployment benefits (including the utility from leisure) b_{it}^W, vacancy posting costs $-b_{it}^F$, the discount rate r and the elasticity of the matching function μ. In our baseline results, we assume the replacement ratio b_{it}^W/w_{it} equals 0.73, which is the value preferred by Hall (2009) and Nagypál and Mortensen (2007). We explore the robustness of our results to setting the replacement ratio to 0.4 (as in Shimer (2005)) or 0.95 (as in Hagedorn and Manovskii (2008)), as well as to allowing for the replacement ratio to vary across states according to the weekly benefit amounts published by the U.S. Department of Labor (2010). We assume $\mu = 0.6$ in our baseline results, again following Nagypál and Mortensen (2007), and explore robustness to setting $\mu = 0.5$ or $\mu = 0.7$, the lower and upper bound of the plausible range of estimates in Petrongolo and Pissarides (2001). We set the annual discount rate $r = 0.04$ and vacancy posting costs $-b_{it}^F/\pi_{it} = 0.03$, but these assumptions matter very little for the results.

3.2 Finding Rates

We calculate job finding rates of workers from Current Populations Survey as the number of workers whose status changes from unemployed to employed as a fraction of the total number of unemployed workers in a submarket.[17] Workers are attributed to the state where they live and the industry where they work. Unemployed workers, who do not work and therefore have no information about industry, are attributed to the industry where they last held a job, following standard practice at the BLS.

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 give up on testing equation (5) and impose this equation holds with $\alpha_i^{MT} = 0$ for all i. Then, we use this relation to construct data for worker finding rates of firms f_i^F from data on job finding rates of workers f_i^W. Although second-best, we prefer this solution over limiting the time period, mostly because a longer time series is important for studying mismatch over the business cycle, but also because heterogeneity in matching efficiency is arguably the least interesting of the four sources of labor market mismatch. Our

[17] This is a common way to measure worker flows, see Shimer (2012). There are several reasons why the level of worker flows constructed in this way is biased, like measurement error (Abowd and Zellner (1985)) and time aggregation bias. Since we use only worker flows in deviations from the average across submarkets, these biases should not affect our results.

choice is further supported by the evidence from the JOLTS reported in Şahin, Song, Topa, and Violante (2014). Şahin, Song, Topa, and Violante (2014) estimate submarket-specific matching efficiency by regressing matches on unemployment and vacancies. They find that while there is substantial variation in matching efficiency, this seems to not affect the amount of mismatch. If there is mismatch coming from heterogeneity in the matching technology, then this will not alter our estimates of the level and cyclical behavior of mismatch unemployment, but it will affect the decomposition of mismatch into its sources.[18]

3.3 Match Surplus

We assumed that matches in submarket i are formed by combining an unemployed worker and a vacant job, both of which were searching in submarket i. If we further assume that when matches are destroyed, both worker and vacancy remain in submarket i, at least initially, then the surplus of match in submarket i must satisfy the following Bellman equation,

$$(1+r)\, S_{it} = y_{it} + E_t\left[(1-\tau_{it+1})\, S_{it+1}\right] \tag{8}$$

where S_{it} may be worker or firm surplus, y_{it} is the flow payoff from the match (to worker or firm) and τ_{it} is turnover in submarket i.

We observe match payoffs y_{it} and turnover τ_{it} in our dataset. For the worker, payoffs y_{it}^W equal wages minus unemployment benefits and the disutility from working, and turnover equals the separation rate λ_{it} plus the job finding rate, $\tau_{it}^W = \lambda_{it} + f_{it}^W$. For the firm, payoffs from a filled job y_{it}^F equal profits gross of vacancy posting costs, and turnover equals the separation rate plus the worker finding rate, $\tau_{it}^F = \lambda_{it} + f_{it}^F$. We use these data and equation (8) to calculate match surplus for the worker and firm, S_{it}^W and S_{it}^F respectively. In the context of the standard search and matching model, it is straightforward to derive equation (8) from the Bellman equations for workers and firms, see appendix C.1.

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 turnover. 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 turnover matters because it determines to what extent turnover is segment-specific. Segment-specific turnover introduces a negative correlation between surplus and turnover across segments, pushing towards the correlation expected in the WM and JM curves.

[18] The direction of the bias is not clear. If, for example, states with high job finding rates tend to have higher matching efficiency, $\alpha_i^{MT} > 0$, we would tend to underestimate the worker finding rate in those states, see equation (5). This would then bias our estimates of the job mobility frictions, see equation (3). Whether we would over- or underestimate the contribution of these frictions would depend on whether states with high job finding rates tend to have higher or lower than average profits.

We assume payoffs and turnover follow autoregressive process that reverts to the average across all submarkets.

$$y_{it+1} = (1 - \delta_y)\, y_{it} + \delta_y \bar{y}_t + \varepsilon_{y,it+1} \Rightarrow E_t y_{it+s} = \bar{y}_t + (1 - \delta_y)^s (y_{it} - \bar{y}_t) \quad (9)$$

$$\tau_{it+1} = (1 - \delta_\tau)\, \tau_{it} + \delta_\tau \bar{\tau}_t + \varepsilon_{\tau,it+1} \Rightarrow E_t \tau_{it+s} = \bar{\tau}_t + (1 - \delta_\tau)^s (\tau_{it} - \bar{\tau}_t) \quad (10)$$

By varying the parameters δ_y and δ_τ, we explore the robustness of our results to the amount of persistence in match payoffs and turnover. In the baseline results, we assume the processes for payoffs y_{it} and turnover τ_{it} are independent.

The first-order autocorrelation in wages is 0.99 per year in the state-level data and 0.94 in the industry-level data based on the NAICS classification.[19] This is consistent with Blanchard and Katz (1992), who find an autocorrelation of 0.94 across US states, and Alvarez and Shimer (2011), who find 0.90 for 75 industries at the 3-digit level of disaggregation (CES data, 1990-2008), and conclude that wages are nearly a random walk. Autocorrelation in profits is lower, but still 0.99 in the state-level data and 0.65 in the industry-level data. In our baseline results, we assume wages and profits are a random walk, $\delta_y = 0$, but our results are robust to a higher degree of mean-reversion.[20] The first-order autocorrelation in turnover is 0.61 per year in the state level data and 0.50 in the industry-level data. Although turnover seems to be further from a random walk than payoffs, we still use the random walk assumption as our baseline. However, in section 4.4 we explore the robustness of our results to higher degrees of mean-reversion.

Using stochastic processes (9) and (10), we can solve equation (8) recursively to obtain match surplus. For convenience, we approximate around turnover being a random walk so that we can obtain an explicit expression for the solution, see appendix C.2 for the derivation. The approximation will be good for relatively small deviations of δ_τ from our baseline value of zero.

$$S_{it} \simeq \frac{(r + \tau_{it})(r + \tau_{it} + \delta_\tau)}{(r + \tau_{it})(r + \tau_{it} + \delta_\tau) + \delta_\tau (1 + r + \tau_{it})(\bar{\tau}_t - \tau_{it})} \left(\frac{\bar{y}_t}{r + \tau_{it}} + \frac{y_{it} - \bar{y}_t}{r + \tau_{it} + \delta_y} \right) \quad (11)$$

If match payoffs follow a random walk, $\delta_y = 0$, and turnover is constant, $\delta_\tau = 0$, as in our baseline, then match surplus is the annuity value of the current payoff, $S_{it} = \frac{y_{it}}{r+\tau_{it}}$, evaluated at an effective discount rate which includes not only the rate of time preference, but also the turnover rate. 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 λ_{it} and therefore τ_{it} – the lower is the surplus. Also, the easier it is for an unemployed person in this market to find a job – the higher f_{it}^W and therefore

[19] 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.

[20] 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 (2011), wages paid out over the duration of a match are more persistent than average wages, so if anything these estimates understate the autocorrelation in wages.

τ_{it} – the smaller is the advantage of already having a job.

Some assumptions were needed to derive expression (11) for match surplus in addition to the ones discussed above. Implicit in Bellman equation (8) are the assumptions that workers cannot vary their search effort and that they cannot search while holding a job. Endogenous search effort and on-the-job search would change the expression for surplus, but cannot explain our results, see the discussion in section 4.5. Implicit in the stochastic processes for match payoffs (9) and turnover (10) is the assumption that these processes are independent. In particular, we may be concerned that turnover depends on payoffs because of endogenous match destruction. We will explore the robustness of our results if this is the case, see section 4.4. Finally, in the calculation of match payoffs themselves, we assume the replacement ratio is constant across segments, implicitly assuming that unemployment benefits and/or the value of leisure depend positively on wages. We will explore the robustness of our results to this assumption as well.

3.4 Heterogeneity

We estimate mismatch unemployment from the dispersion in wages, profits and finding rates. Heterogeneity is a concern, because it may generate dispersion that is unrelated to mismatch. Our benchmark conditions were derived assuming all workers and jobs are the same. In reality , wages, profits and even job finding rates may vary across workers not only because of deviations from these conditions, but also because workers have different education, experience or other characteristics. If we do not control for these differences, we may spuriously attribute the dispersion they generate as mismatch.

In our baseline results, we do not control for heterogeneity. There are three reasons for this. First, we will find that the data show remarkably small deviations from our benchmark worker and job mobility curves. Since worker and firm heterogeneity would tend to generate deviations from these conditions, we interpret this as evidence that heterogeneity seems to largely 'average out' between states and industries. Second, there is a price to pay for controlling for heterogeneity: we can no longer estimate the overall level of mismatch unemployment. However, we do check the robustness of our results about the cyclicality and the sources of mismatch. If anything, these results become stronger when we control for worker and job heterogeneity, which is the third reason why we feel comfortable ignoring heterogeneity in the baseline. Results controlling for heterogeneous workers and firms are reported in section 4.4 along with a number of other robustness checks. However, because of the importance of this particular robustness check, we describe it here, before turning to the results.

Differences across workers are to large degree observable. Our approach to deal with this type of heterogeneity is to calculate surplus and finding rates for homogeneous groups of workers and then to average the values we get for $\hat{S}_i^W$, $\hat{S}_i^F$, $\hat{f}_i^W$ and $\hat{f}_i^F$ over all groups of workers. We use 40 groups of homogeneous workers based on all observable worker characteristics in our dataset: education, experience, gender, race and marital status, see appendix D.1 for details. Our results change very little if we do this. However, as one may still be concerned about unobservable differences across workers and – more importantly – across firms, we pursue a second approach of controlling for heterogeneity as well.

There are other differences between jobs than just the wage. In particular, residual wage differentials have been interpreted as compensating differentials: non-monetary job amenities like flexible hours or safe working conditions, in return for which workers are willing to accept lower wages, see Rosen (1979) and Roback (1982).[21] These differences are completely unobservable in our dataset. Therefore, as our second approach to deal with heterogeneity, we assume compensating differences are constant over time and remove the time-series average of the values for $\hat{S}_i^W$, $\hat{S}_i^F$, $\hat{f}_i^W$ and $\hat{f}_i^F$ in each year. Details on this procedure, which is similar in spirit to a fixed-effects regression, are in appendix D.2. The advantage of this approach is that it controls for all time-invariant heterogeneity, observable as well as unobservable and across workers as well as across firms. The disadvantage is that we can no longer estimate the size of the deviations from our benchmark conditions, but only their relative size compared to the time-series averages. As a result, equation (7) no longer gives the correct level of the unemployment rate that is due to mismatch. We do show, however, that our results regarding the cyclicality and decomposition of mismatch are not only robust to controlling for heterogeneity, but in fact look even stronger than the baseline results.

4 Results

We start the description of our results by exploring how well our benchmark conditions (2), (3) and (4) hold in the data. Then, we present our estimates for mismatch unemployment resulting from deviations of these conditions in section 4.2.1, and explore its behavior over the business cycle in section 4.2.2. Finally, in section 4.3, we present the results of our mismatch accounting exercise decomposing mismatch unemployment into the contribution of each of its three sources.

4.1 Benchmark Relations

Figure 2 shows scatterplots for states around the worker mobility, job mobility and wage determination curves. These graphs are for 2000, but look similar for other years. Deviations across states from worker mobility condition (2) and job mobility condition (3) are small and non-systematic. On the other hand, there are large and systematic deviations from the benchmark wage determination curve (4).

These graphs suggest that mobility of workers and jobs across states seems to be sufficient to arbitrage away most differences in the values of being unemployed and having a vacancy across states, a finding that we will confirm in the accounting exercise in Section 4.3. Mismatch is primarily due to variation across states in the share of match

[21] 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 unobservable differences between jobs.

surplus that is attributed to workers versus firms. If workers and firms were to share surplus in fixed proportions, as in benchmark wage determination condition (4), then states that are attractive to firms are attractive to workers as well. If total match surplus varies across states, for example because labor productivity is different in different states, this maps out the benchmark wage determination condition. In reality, it seems that differences in wages across states are much larger than differences in labor productivity. Since states with high wages generate high surplus for workers but low surplus for firms, this generates mismatch as firms with vacancies and unemployed workers move away from each other.

Figure 3 shows similar results for the benchmark conditions across industries. The worker mobility plot looks qualitatively similar to that for states. This is in line with high rates of worker mobility across industries found in PSID data, see Kambourov and Manovskii (2008). Barriers to job mobility seem to play a role in mismatch across industries, but deviations from the benchmark wage determination curve are large and systematic as well. In Section 4.3 we will show that the importance of barriers to job mobility depends on the time period, but throughout the sample variation in the surplus share of workers is an important source of mismatch across industries as well, although less important than for mismatch across states.

The patterns in the data that we reveal are surprising to many, possibly because most of the debate about labour market mismatch has focused on worker mobility frictions, see e.g. Kocherlakota (2010), Frey (2009), Katz (2010), Kaplan and Schulhofer-Wohl (2011) and Şahin, Song, Topa, and Violante (2014). Moreover, the evidence that restrictions to worker mobility seem to not contribute at all to mismatch is very striking and the correlation in the scatter plots looks almost 'too good to be true'. One might think, therefore, that there is something in our treatment of the data that spuriously generates these patterns or that we make convenient assumptions that make the results look stronger than they really are. We will try to convince the reader that this is not the case with an extensive robustness analysis, discussed in section 4.4, and we will discuss the question what may explain our results in section 4.5. First, however, we complete the description of the results by exploring how important mismatch is as a source of unemployment, and by formalizing the finding that mismatch is primarily driven by deviations of wage determination from the benchmark condition, both in terms of the average level of mismatch and for fluctuations in mismatch over time.

4.2 Mismatch Unemployment

Figure 4 plots the unemployment rate that is due to mismatch across states over the 1979-2009 period. Figure 5 shows a similar graph for mismatch across industries. These counterfactual unemployment rates were constructed using the observed dispersion in job finding rates as explained in section 2.2. For comparison, the graphs also show the actual unemployment rate over the same period, although on a different scale on the right-hand side axis of the graphs.[22]

We will use the series in these graphs to address the questions how large is the impact of labor market mismatch on unemployment and how does it fluctuate over the business cycle. Estimating the impact of mismatch on unemployment is complicated by the fact that the level of disaggregation matters. We discuss this issue in section 4.2.1 below. However, it is worth noting that the similarity in the fluctuations in mismatch and overall unemployment are striking. We return to this in section 4.2.2 where we discuss the cyclicality of mismatch.

4.2.1 Level of Mismatch Unemployment

Our measure of the contribution of labor market mismatch to unemployment is simply the ratio of the average mismatch unemployment over the average actual unemployment rate over our full sample period. In Figure 4, unemployment due to mismatch across states averages around 0.1%-points compared to an average unemployment rate of around 5%. Mismatch across states contributes 2.3% to the overall unemployment rates according to these estimates. The estimates in Figure 5 show that mismatch across across industries contributes around 2.1% to unemployment. Taken at face value, the contribution of mismatch to unemployment seems very small. However, clearly the level of disaggregation matters for the observed amount of mismatch. Since there is likely to be substantial mismatch within states and within industries, we underestimate the contribution of mismatch to unemployment.

We try to address the aggregation issue in two ways. First, we disaggregate further. For the purposes of this subsection only, we use data that are disaggregated by both state and industry. Instead of 50 states or 33 industries, this gives us $50*33 = 1650$ labor market segments. Although 1650 submarkets is probably a more realistic segmentation of the US labor market, it is in all likelihood still to coarse. Therefore, the second part of our solution is to find a correction factor that relates the observed amount of mismatch in our data to the amount of mismatch we would observe if we were to disaggregate to the right level.

An ideal labor market segment would consist of very similar jobs within a geographic area that allows workers to commute to these jobs without moving house. Using UK data, Barnichon and Figura (2013) estimate the correct level of disaggregation would be to use 232 so-called travel-to-work areas and 353 detailed occupational groups. They then aggregate these data to a level that is comparable to US states and major occupational categories and find that the observed amount of mismatch decreases by a factor 6. Thus, we will correct the observed amount of mismatch unemployment in the data that are disaggregated by both states and industries by multiplying our estimates with 6. Appendix E describes the justification for this correction.

[22] In this graph, as well as in all other graphs in the paper, the 'overall' or 'total' unemployment rate is the steady state unemployment rate corresponding to the average finding and separation rates across states or industries. This steady state unemployment rate, which is comparable to our estimates for structural unemployment, is very close to the actual unemployment rate.

Disaggregation by both states and industries, while alleviating the aggregation problem, gives rise to a different bias because of sampling error. Barnichon and Figura (2013) use a very large dataset consisting of the universe of job seekers in the UK. The US data, however, are survey-based and in our dataset we have only about $23,000$ unemployed workers per year, which means that the 1650 labor market segments on average contain only 14 observations and because not all states and industries are equally large, some cells are even much smaller than that. As a result, our estimates for the job finding rate in each segment will be very imprecise. This sampling error will translate into dispersion across segments and bias our estimate for the amount of mismatch unemployment. We address this issue by estimating the variance of the sampling error in each segment and correcting the estimated variance of the job finding rates by subtracting the average variance of the sampling error, see appendix E for more details.[23]

Mismatch across state*industry segments contributes 15% to unemployment, substantially more than mismatch across states or industries only. The bias because of sampling error is fairly small, bringing the contribution of mismatch down to 14%, indicating the dispersion in job finding rates across segments is large compared to the sampling error. After correcting for aggregation, these estimates suggest that mismatch is responsible for 84% of unemployment.[24] It is important to note that a good amount of guesswork was needed for the aggregation correction and the estimate is therefore rather imprecise. Nevertheless, these estimates indicate that it is at least a possibility that mismatch is an important contributor to unemployment and that potentially even the majority of unemployment may be due to mismatch.

Our estimates are, roughly, in line with Şahin, Song, Topa, and Violante (2014), who –using very different data– find 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. Although they do not report this in the text, the estimates in their Figure 3 imply a similar contribution of mismatch to the level of unemployment. 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 very rough and the estimates in Şahin, Song, Topa, and Violante (2014) are the more credible ones. The contribution of the current study is in the estimates of the cyclicality of mismatch and its sources, to which we now turn.

[23] Workers in each segment find a job with probability f_i^W. The variance of the realization of this Bernoulli process equals $f_i^W\left(1-f_i^W\right)$, so that the variance of the observed mean probability is equal to $f_i^W\left(1-f_i^W\right)/N_i$, where N_i is the number of observations in segment i. The variance of the signal in f_i^W across segments, by the ANOVA formula, is then given by the observed variance $var\left(f_i^W\right)$ minus the average variance of the sampling error $E\left[f_i^W\left(1-f_i^W\right)/N_i\right]$. We do not use segments with less than 5 observations because these would contribute more noise than signal.

[24] These estimates are summarized in Table 3 in appendix F.

4.2.2 Cyclicality of Mismatch Unemployment

Figures 4 and 5 clearly show that the cyclical fluctuations in mismatch unemployment are very similar to those of the overall unemployment rate. Mismatch unemployment closely follows the business cycles in the overall unemployment rate. Mismatch rises in the 1982, 1991, 2001 and 2008 recessions, declining slowly during the recovery 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 increase in unemployment in the Great Recession was more than in other recessions due to mismatch.

The volatility of the two series is not directly comparable, unless we correct for aggregation bias discussed above in section 4.2.1. To obtain a summary statistic for the importance of mismatch to the overall unemployment rate, we regress mismatch unemployment on a constant and the overall unemployment rate in deviation from its average.

$$u_t^{MM} = \beta_0 \bar{u} + \beta_1 \left(u_t - \bar{u}\right) \tag{12}$$

The intercept in this regression –after correcting for aggregation bias– measures the contribution of mismatch to the average level of unemployment, which we reported in section 4.2.1, whereas the slope coefficient measures the contribution of mismatch to fluctuations in unemployment.[25]

Our estimates for the contribution of mismatch to fluctuations in unemployment are somewhat similar to our estimates for the contribution to the level of unemployment: 3.4% for mismatch across states (cf. 2.3% of the level) and 1.2% for mismatch across industries (cf. 2.1% of the level). After a rough correction for aggregation bias, as explained in Section 4.2.1 above, these estimates imply that mismatch may be responsible for a large part to all of fluctuations in unemployment (precisely, the estimates range from 48 to 136%, but as mentioned before should be expected to be very imprecise).

These results suggest that unemployment may to a large extent be due to labor market mismatch. It is important to note that there is nothing in our estimation procedure that would introduce a comovement of mismatch unemployment with the overall unemployment rate by construction. In fact, all our estimates are relative to the cross-sectional mean in each year, so we explicitly remove any aggregate fluctuations from our data. The fact that we find such strong comovement therefore seems to suggest that we may think of mismatch as a micro-foundation for 'search frictions' in the tradition of Diamond (1982), Mortensen (1982) and Pissarides (1985).[26]

[25] The contribution to fluctuations $\beta_1 = corr\left(u_t^{MM}, u_t\right) sd\left(u_t^{MM}\right) / sd\left(u_t\right)$ depends not only on the correlation, but also on the relative standard deviation of the two series, which is why the same correction for aggregation bias is appropriate.

[26] Pissarides (2000) describes search frictions as "a modeling device that captures the implications of the costly trading process without the need to make the heterogeneity and the other features that give rise to it explicit" (p.4). Our mismatch accounting framework makes the underlying heterogeneity explicit and allows us to explore the causes of this heterogeneity.

4.3 Sources of Mismatch

We now turn to the part of our results that is arguably the most interesting: the decomposition of mismatch unemployment into the sources of the mismatch. From section 4.1 we know that benchmark conditions for worker mobility and job mobility approximately hold in the data, whereas there are large and systematic deviations from the benchmark condition for wage determination. This suggests that most mismatch is driven by wage setting. Here, we formalize that conclusion.

Figures 6 and 7 show the results of our mismatch accounting exercise described in section 2.3. The figures show the evolution over time of mismatch unemployment as well as its three sources, for mismatch across states and industries respectively.

Mismatch unemployment due to wage setting 'frictions' alone closely tracks total unemployment due to mismatch across states, see Figure 6, reflecting the fact that variation in the share of match surplus that is captured by wage earners is the most important impediment to equalization of job finding rates across states. The contribution of deviations from free mobility of workers and jobs is very small and largely acyclical. Removing any frictions to geographic worker or job mobility, while leaving existing wage determination mechanisms in place, would reduce unemployment very little and might even increase it.[27] For mismatch across industries the picture is slightly more complicated, see Figure 7. The contribution of worker mobility frictions is again very small, but the contribution of barriers to job mobility seems to increase over the sample. Wage determination is the most important source of mismatch in the first half of the sample, but its importance declines since the 1990s and becomes particularly small or even negative in the Great Recession.

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

$$u_t^{XX} = \beta_0^{XX} \bar{u}^{MM} + \beta_1^{XX} \left(u_t^{MM} - \bar{u}^{MM} \right) \tag{13}$$

where XX stands for the source of mismatch, i.e. $XX \in \{WM, JM, WD\}$. 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 coeffi-

[27] How can the contribution of barriers to worker mobility to unemployment be negative? The answer is related to the correlations between the deviations from the worker mobility curve (2), the job mobility curve (3) and the wage determination curve (4). States with high worker surplus and low job surplus because of relatively high worker bargaining power, i.e. states with high α_i^{WD}, tend to attract unemployed workers and loose jobs, resulting in a lower than average job finding rate and higher than average worker finding rate in that state, everything else equal. However, the same states tend to have low α_i^{WM} and α_i^{JM}, meaning frictions to worker and job mobility costs tend to keep more unemployed workers and vacancies in the state than we would expect based on worker and job surplus there. The barriers to worker mobility reduce job finding rates, reinforcing the effect of the high wage, but the barriers to job mobility costs reduce worker finding rates as well, partially offsetting the effect. These conclusions are interesting in terms of their policy implication. The effects on the unemployment rate of a policy that reduces worker mobility costs, for example relocation or retraining subsidies to unemployed workers, are likely to be small and may even be negative.

cient 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 a true decomposition.

Frictions to worker mobility contribute 6% to the level of and 15% to the fluctuations in mismatch across states and -10% to the level and -2% to the fluctuations of mismatch across industries. Barriers to job mobility account for none of the mismatch across states (0% of the level and 1% of the fluctuations), but for a substantial part of the level of mismatch across industries (48%) and all of the fluctuations (113%), although –as already pointed out– the summary statistics hide a clear change over time in the importance of this type of frictions to mismatch unemployment. As a result, variation in the share of match surplus that is paid out to workers in the form of wages accounts for almost all of the level and fluctuations in mismatch across states (93% and 83%, respectively), a good share of the level of mismatch across industries (64%), but none of the fluctuations in industry-level mismatch (-11%).

4.4 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 Sections 4.2.1 and 4.2.2, and the contribution of barriers to worker mobility, barriers to job mobility and deviations from the benchmark wage determination equation to labor market mismatch, as described in Section 4.3. These summary statistics are presented for a number of robustness checks in Table 1. The first line in the top and bottom panels of this table shows our baseline 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 0.6, see Sections 2.1.4 and 3.2. The second and third line in the table shows the effect of assuming an elasticity of 0.5 or 0.7. A higher (lower) elasticity increases (decreases) the concavity of the aggregate job finding rate in the segment-specific job finding rates, see equation (7), and therefore increases (decreases) the estimated contribution of mismatch to unemployment. This effect is fairly strong, but for the (commonly accepted) range of values for μ considered, the result that mismatch is an important contributor to unemployment does not change qualitatively. A higher elasticity also increases the dispersion in job filling rates given the same job finding rates and therefore attributes more of a role to wage determination and less to job mobility frictions as a source of mismatch. This effect is small, however.

For the construction of match surpluses, we made a number of choices, see Section 3.3, among which the assumption that the replacement ratio equals 0.73, price deflators are the same across states, and the assumption that match payoffs (wages or profits) follow a random walk and match turnover is constant. Lines 4 through 10 explore 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 at all, except for the state-specific price deflators, which generate slightly more dispersion and therefore a slightly higher estimate of mismatch unemployment. The composition of mismatch into its sources is affected, but the effects are small. The only exception is mean-reversion in match turnover, which generates a larger role for worker and job mobility frictions. We cannot rule out, therefore, that these frictions are more important than our baseline estimates suggest. Even with mean reversion of 50% per year, however, deviations from the benchmark wage determination curve are a very important source of mismatch across states, whereas the finding that job mobility frictions are the most important source of mismatch across industries is actually strengthened with respect to the baseline estimates.

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 benchmark relations, whereas we clearly find the worker and job mobility curves in the data, and deviations from the wage determination benchmark condition are 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 3.3. 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. Since we find very little evidence for the importance of worker mobility frictions, it seems unlikely that the results would change much if we allowed for on-the-job search. For the same reason, our findings cannot be driven by workers looking for jobs in surrounding regions and occupations as Marinescu and Rathelot (2014) show they do, because this effect would also push against finding 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. Without better data, there is unfortunately very little we can do to explore this issue, so we just mention it here as a caveat.

Finally, we explore the effect of heterogeneity, as described in detail in Section 3.4. Controlling for observed worker heterogeneity affects the results remarkably little. If anything, controlling for this type of heterogeneity makes mismatch across industries look more important. When we control for unobserved heterogeneity by removing the time series mean from all our data series, akin to controlling for fixed effects in a regression, the importance of mismatch for unemployment seems to fall. This, however, is by construction and should not be misinterpreted: by removing the average dispersion across states and industries we are removing part of the mismatch from the data. The results of the mismatch accounting exercise are largely (and surprisingly) robust to removing all time-invariant unobserved heterogeneity from the data. The only thing that changes when we control for observed worker heterogeneity or for all time-invariant heterogeneity, is that we find a larger role for deviations from the benchmark wage determination curve for mismatch across industries, lending further relevance to our earlier caveat that the overriding importance of barriers to job mobility for this type of mismatch is hiding the fact that wage determination is important as well, especially in the first part of the sample.

4.5 Discussion

What may explain our findings? We want to emphasize that we feel we have relatively little to say about an explanation, because the approach we take in this paper is primarily a (structured) exploration of the data. However, the question is interesting enough to discuss at least briefly. The finding that wage determination is an important source of mismatch is driven by a negative correlation between wages and profits observed both across states and across industries. This pattern in the data often comes as a surprise to macroeconomists studying business cycles, because the time series correlation between (aggregate) wages and profits is of course positive. However, upon reflection, the negative cross-sectional correlation is less surprising that it may seem at first. Productivity does not vary much across states and industries. This may the natural outcome of labor mobility, in combination with diminishing returns to labor in the production function. Given constant productivity, any increase in the wage constitutes a decrease in profits, and vice versa, because surplus sharing is a zero-sum game.

What drives the observed variation in wages across states and industries if not productivity differentials? A natural candidate is differences in bargaining power or outside options across states and industries, e.g. caused by differences in unionization rates. If such differences are roughly constant over time, then the data do not support this explanation: when we control for time-invariant differences, the systematic deviations from the wage determination benchmark condition survive, and if anything get stronger, see Table 1. But perhaps differences in bargaining power or outside options trend slowly over time.[28] To explore this explanation, Figures 8 and 9 plots the evolution of worker surplus

[28] There may be good reasons to think this is the case. Non-wage employee compensation, for instance,

and job finding rates over time for five states and industries respectively. These states and industries were chosen to be somewhat representative, while making the graphs easy to read. States travel back and forth over the entire worker mobility curve, indicating that this curve largely mapped out by relatively high-frequency variation in job finding rates and wages within states over time. For industries the pictures is not quite as clear. Over time, the within-industry variation maps out a section of the worker mobility curve, but these movements are relatively small compared to the variation across industries, suggesting that persistent difference across industries also contribute to the dispersion in job finding rates. This explains why controlling for unobserved heterogeneity ('fixed effects') affects the estimates for industry-level mismatch more than it affects the estimates for mismatch across states. However, both movements over time and differences across industries seem to respect the worker mobility benchmark condition, making it unlikely our results are primarily driving by low-frequency movements in institutions affecting wage determination. Finally, productivity or demand shocks to neighboring segments may give rise to high-frequency state- and industry-specific variation in workers' outside options. Such a channel would operate, for instance in the structural model of Carrillo-Tudela and Visschers (2013). However, this type of shocks would affect firms' outside options as well and is therefore unlikely to explain our findings.

One explanation that is consistent with our result, is that of differential wage rigidity across states and industries, in combination with aggregate shocks. Suppose that, in response to a negative aggregate shock, wages in some occupations and therefore in some states and industries stay roughly constant, whereas wages in other occupations wages fall. As a result, the rigid-wage jobs are attractive to workers in a recession, and unemployment increases as (too) many unemployed workers direct their search towards these jobs. If we further assume that the rigid-wage jobs pay on average relatively low wages, then we get that workers moving from high to low-wage jobs in recessions and from low to high-wage jobs in booms, make the aggregate wage and the average wage of newly hired workers flexible, as we have found elsewhere, see Haefke, Sonntag, and van Rens (2013). In the process, dispersion in labor market conditions moves almost mechanically with aggregate fluctuations, as we find in this paper. We leave it for future research to further explore this view of the effect of aggregate fluctuations on the labor market.

5 Conclusions

Mismatch unemployment is unemployment due to dispersion in job finding rates across submarkets of the labor market, which results in mismatch in the distribution of vacancies and unemployed workers over submarkets. We proposed an accounting framework using two arbitrage equations and a benchmark wage determination equation that allows

is not only state-specific, but changes substantially over our sample period. Similarly, school quality and retirement benefits vary both in the cross-section and over time.

us to estimate mismatch unemployment and decompose it into its sources. Since this framework takes data on the values of unemployment and vacancies rather than their quantities as inputs, available data allowed us to present estimates for the 1979-2009 period, much further back in time that previous studies, in particular Şahin, Song, Topa, and Violante (2014). This paper is also the first to report on the causes of mismatch.

We find that mismatch is an important reason for unemployment, in line with earlier studies. 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 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 cause mismatch to exist and persist are barriers to job mobility (across industries) and deviations from surplus sharing in equal proportions across industries and particularly across states. States with high wages tend to have low profits. This implies that states and industries that are attractive to workers are unattractive to firms and vice versa, generating dispersion in vacancy-unemployment ratios and mismatch unemployment. Little to no mismatch derives from worker mobility frictions. This finding is perhaps surprising in light of the debate on policies aimed at increasing worker mobility.

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Table 1
Robustness Analysis

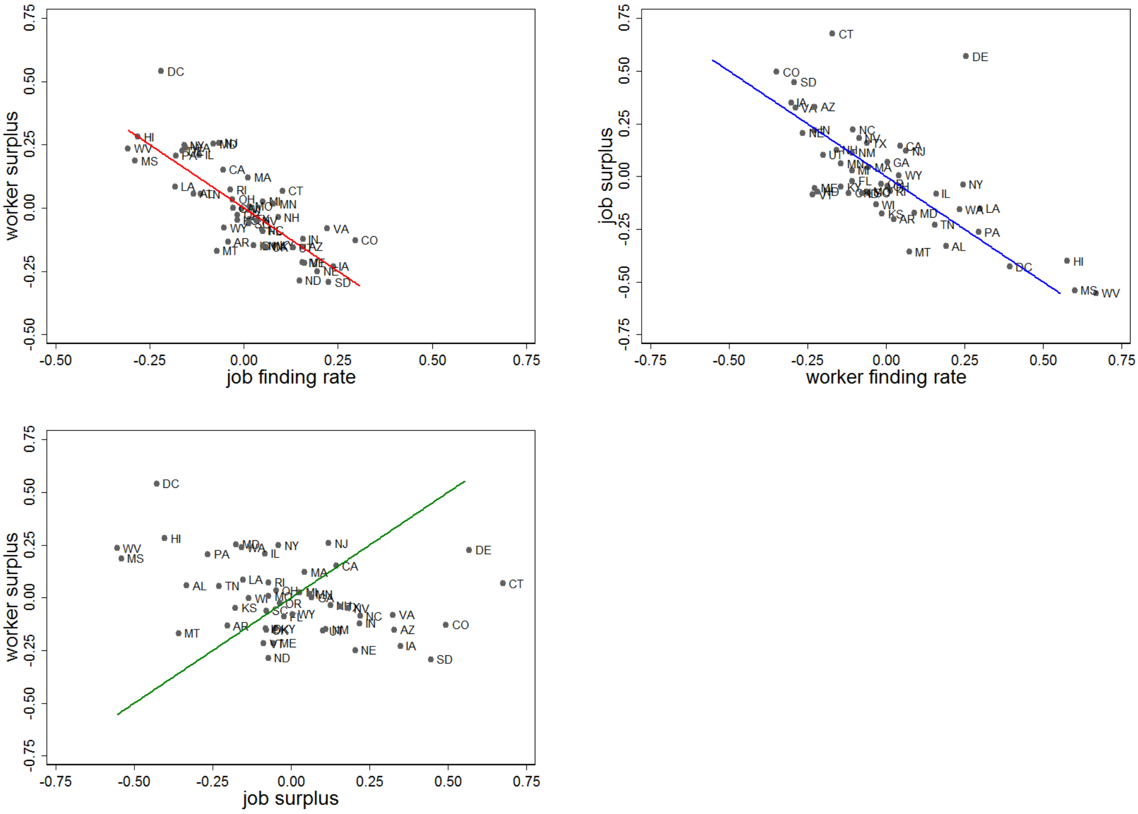
	MMU level	MMU cycle	Sources of MMU: level WM	level JM	level WD	cycle WM	cycle JM	cycle WD
Mismatch across states			WM	JM	WD	WM	JM	WD
Baseline	2.3	3.4	6	0	93	15	1	83
Elasticity matching function, $\mu = 0.5$	1.6	2.4	8	5	88	20	10	70
____, $\mu = 0.7$	3.4	5.1	5	−9	104	11	−13	102
Flow payoff unemployment, $b = 0.4$	2.3	3.4	6	0	93	15	1	83
____, $b = 0.9$	2.3	3.4	6	0	93	15	1	83
State-specific deflators	2.6	3.7	12	−2	89	17	1	82
Mean-reversion payoffs, $\delta_y = 0.3$	2.3	3.4	7	2	90	16	5	79
____, $\delta_y = 0.5$	2.3	3.4	8	3	89	16	6	77
Mean-reversion turnover, $\delta_\tau = 0.3$	2.3	3.4	23	39	47	27	26	47
____, $\delta_\tau = 0.5$	2.3	3.4	29	38	33	31	33	36
Control for observed worker heterogeneity	2.0	3.1	10	1	89	16	5	79
Control for unobserved heterogeneity	1.4	2.0	12	7	81	20	18	62
Mismatch across industries			WM	JM	WD	WM	JM	WD
Baseline	2.1	1.2	−10	46	64	−2	113	−11
Elasticity matching function, $\mu = 0.5$	1.5	1.0	−13	57	56	1	103	−3
____, $\mu = 0.7$	3.0	1.6	−6	21	86	0	88	12
Flow payoff unemployment, $b = 0.4$	2.1	1.2	−10	46	64	−2	113	−11
____, $b = 0.9$	2.1	1.2	−10	46	64	−2	113	−11
Mean-reversion payoffs, $\delta_y = 0.3$	2.1	1.2	−2	36	67	6	89	5
____, $\delta_y = 0.5$	2.1	1.2	0	34	66	7	76	17
Mean-reversion turnover, $\delta_\tau = 0.3$	2.1	1.2	11	61	28	18	114	−32
____, $\delta_\tau = 0.5$	2.1	1.2	16	70	14	21	117	−38
Control for observed worker heterogeneity	3.6	3.2	−6	39	67	0	43	57
Control for unobserved heterogeneity	1.1	0.3	8	14	79	30	31	39

The contributions of mismatch to the level and cyclicality of unemployment is estimated using the following regression, $u_t^{MM} = \beta_0 \bar{u} + \beta_1 (u_t - \bar{u})$, where $\beta_0 = \bar{u}^{MM}/\bar{u}$ measures the contribution to the level and $\beta_1 \left(= \Delta u^{MM}/\Delta u\right)$ the contribution to fluctuations in unemployment. Similarly, the contributions of the various sources to mismatch are estimated using $u_t^{XX} = \beta_0^{XX} \bar{u}^{MM} + \beta_1^{XX} \left(u_t^{MM} - \bar{u}^{MM}\right)$, where XX stands for the source, i.e. $XX \in \{WM, JM, WD\}$.

Figure 1
Sources of labor market mismatch

$$\begin{tikzcd}[column sep=huge, row sep=huge]
\text{worker surplus } (\widehat{S_i^W}) \arrow[r, leftrightarrow, "\text{wage determination (WD)}"] \arrow[d, leftrightarrow, "\text{worker mobility (WM)}"'] & \text{firm surplus } (\widehat{S_i^F}) \arrow[d, leftrightarrow, "\text{job mobility (JM)}"] \\
\text{job finding rate } (\widehat{f_i^W}) \arrow[r, leftrightarrow, "\text{matching technology (MT)}"'] & \text{worker finding rate } (\widehat{f_i^F})
\end{tikzcd}$$

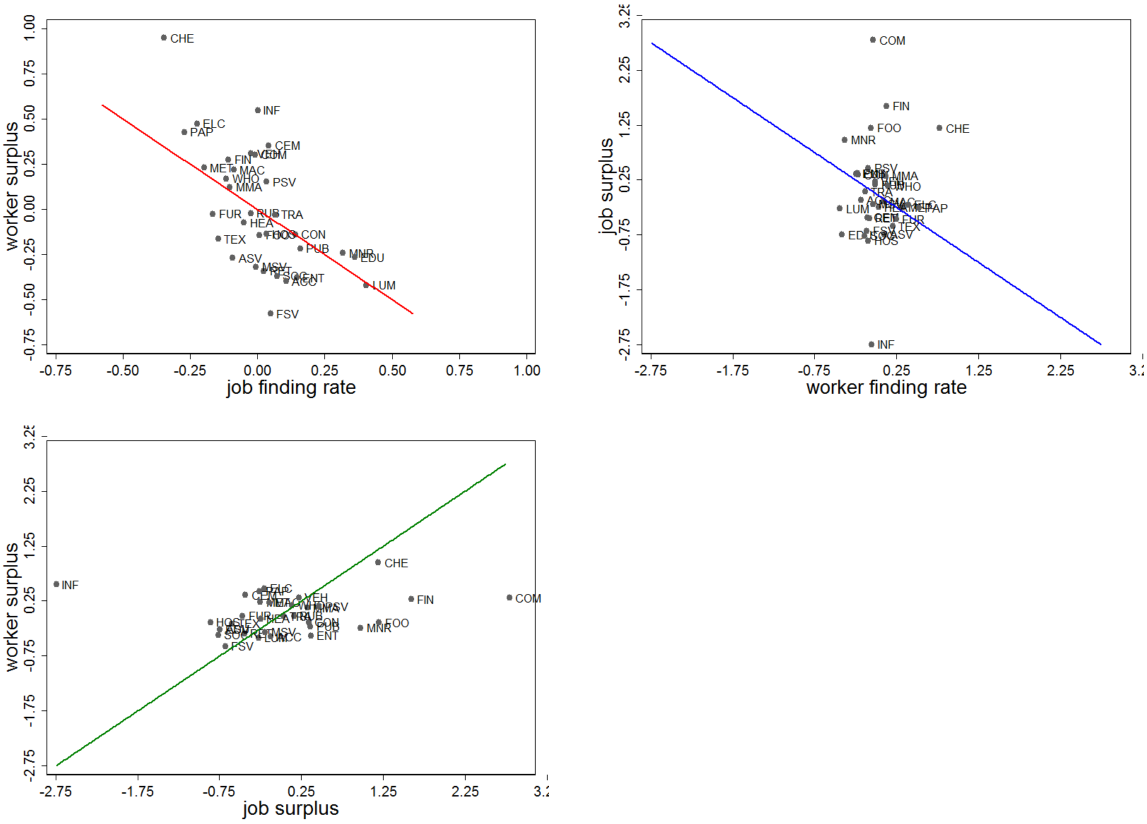
Figure 2
Worker mobility, job mobility and wage determination curves across US states



Lines represent the benchmark relations corresponding to a labor market without any mismatch. Data are for 2000.

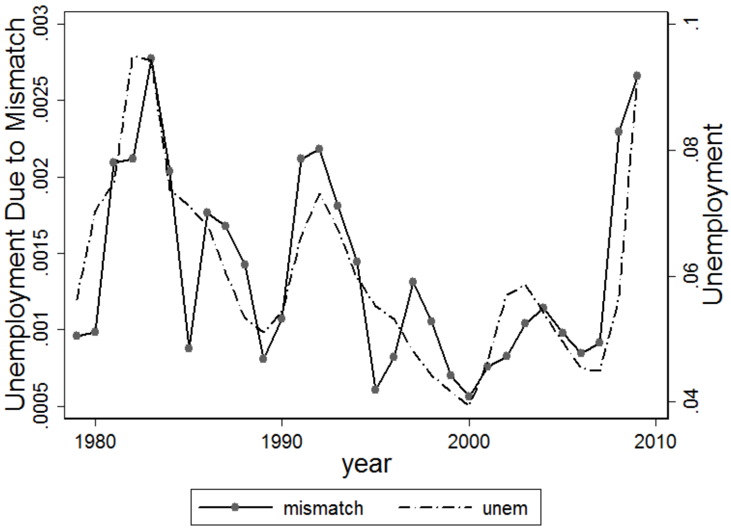
Figure 3

Worker mobility, job mobility and wage determination curves across industries



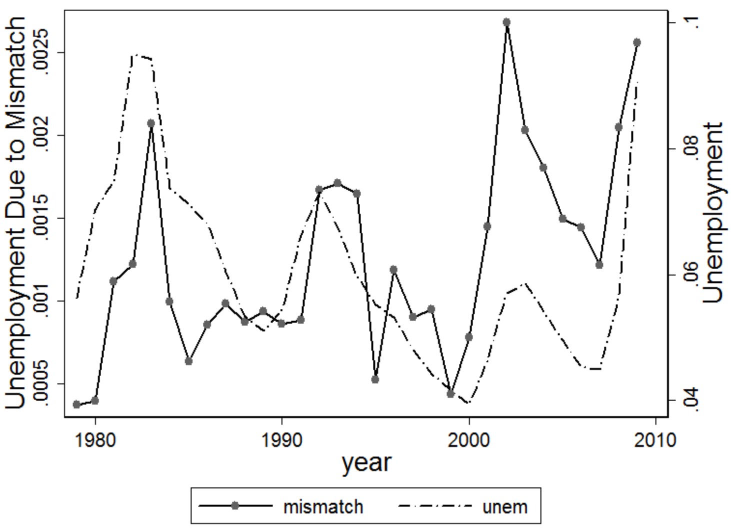
Lines represent the benchmark relations corresponding to a labor market without any mismatch. Data are for 2000.

Figure 4
Cyclicality of mismatch unemployment across US states



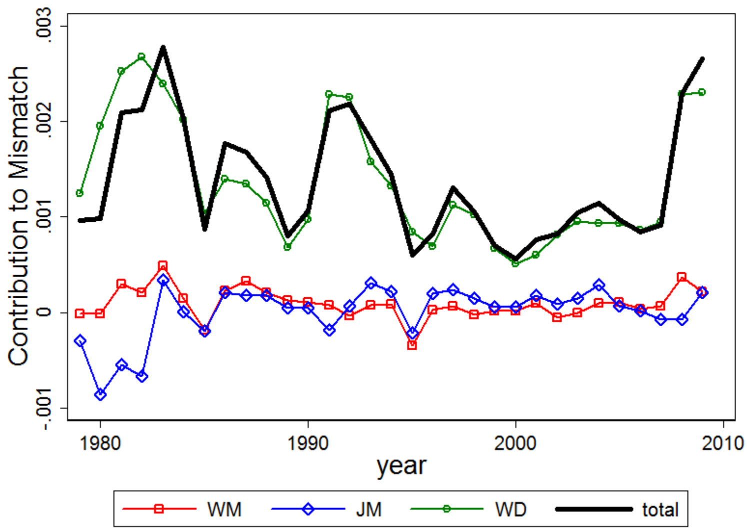
Unemployment due to mismatch across US states, calculated as explained in 2.2. The dashed line shows the actual unemployment rate for comparison (right-hand side axis).

Figure 5
Cyclicality of mismatch unemployment across industries



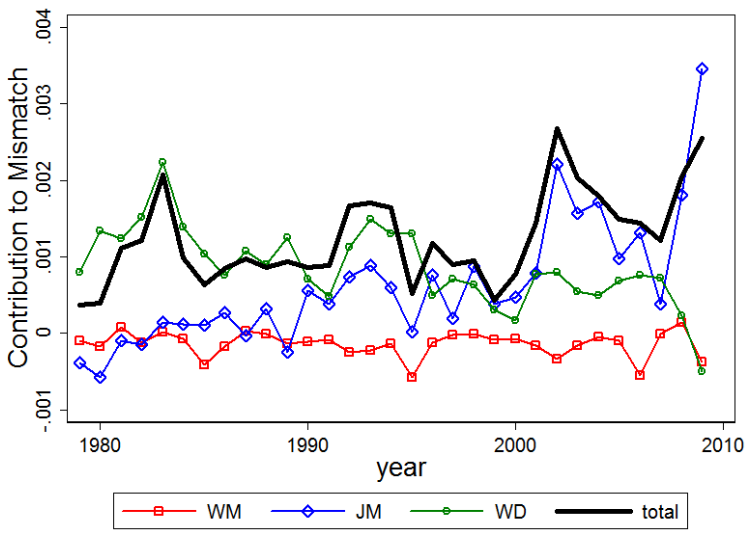
Unemployment due to mismatch across industries, calculated as explained in 2.2. The dashed line shows the actual unemployment rate for comparison (right-hand side axis).

Figure 6
Sources of labor market mismatch across US states



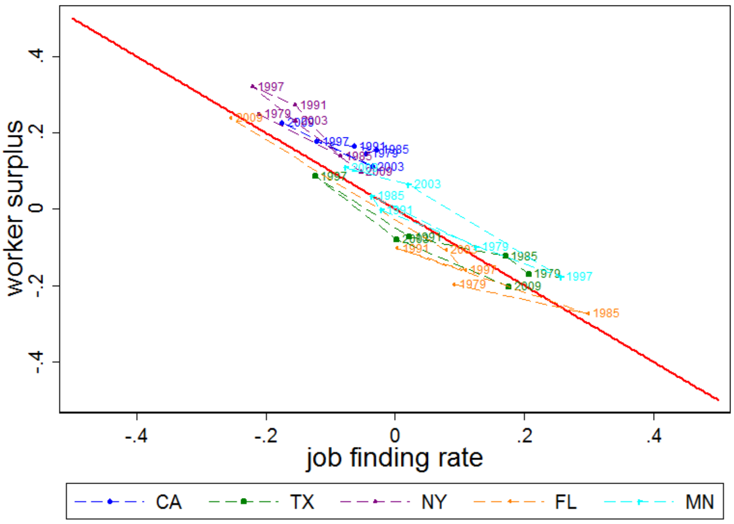
The solid line is our baseline estimate for mismatch unemployment, calculated as explained in 2.2. The other lines show the contribution of worker mobility costs (WM), job mobility costs (JM) and wage setting frictions (WD) to mismatch, see 2.3.

Figure 7
Sources of labor market mismatch across industries



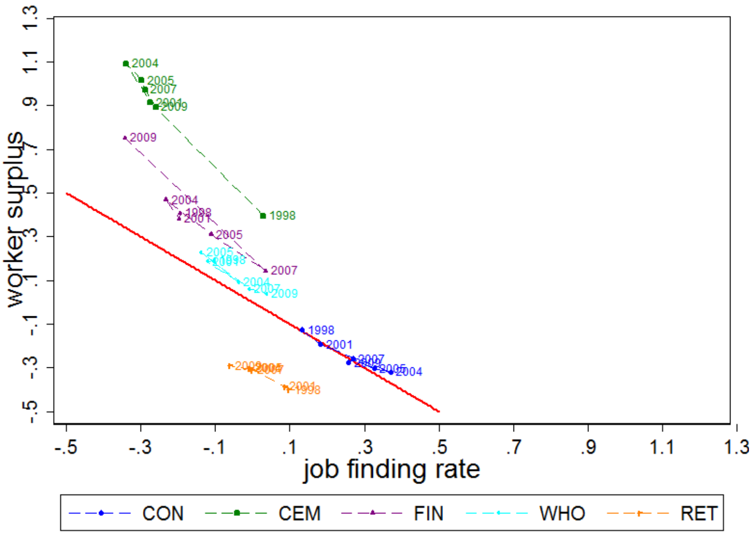
The solid line is our baseline estimate for mismatch unemployment, calculated as explained in 2.2. The other lines show the contribution of worker mobility costs (WM), job mobility costs (JM) and wage setting frictions (WD) to mismatch, see 2.3.

Figure 8
Mapping out the worker mobility curve across states



The graph shows the evolution of the job finding rate f_i^W and worker surplus S_i^W over time in five states: California, Texas, New York, Florida and Minnesota. Since this graph is meant to be illustrative, these states were chosen partly based on size, but also partly based on making the graph easier to read. However, the evolution of these variables looks similar in other states.

Figure 9
Mapping out the worker mobility curve across industries



The graph shows the evolution of the job finding rate f_i^W and worker surplus S_i^W over time in five industries: construction, computer and electronics manufacturing, finance, wholesale trade and retail trade. Since this graph is meant to be illustrative, these industries were chosen because they are of particular interest for our story or particularly large (wholesale and retail trade). However, the evolution of these variables looks similar in other industries.