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Benedikt Herz
Thijs van Rens

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Benedikt Herz
Universitat Pompeu Fabra

Thijs van Rens*
CREI and Universitat Pompeu Fabra

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Abstract

Structural unemployment is due to mismatch between available jobs and workers. We formalize this concept in a simple model of a segmented labor market with search frictions within segments. Worker mobility, job mobility and wage bargaining costs across segments generate structural unemployment. We estimate the contribution of these costs to fluctuations in US unemployment, operationalizing segments as states or industries. Most structural unemployment is due to wage bargaining costs, which are large but nevertheless contribute little to unemployment fluctuations. Structural unemployment is as cyclical as overall unemployment and no more persistent, both in the current and in previous recessions.

Keywords: structural unemployment, mismatch, dispersion labor market conditions, worker mobility, job mobility, wage rigidities
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†Preliminary. For the latest version, please see http://www.crei.cat/~vanrens/SU/.

1 Introduction

Is unemployment in the Great Recession different from previous recessions? Narayana Kocherlakota (2010), president of the Federal Reserve Bank of Minneapolis, argues it is. In particular, according to Kocherlakota, the dramatic increase in unemployment in 2008 and 2009 was not due to weak aggregate labor market conditions, but to 'structural' problems, which generate mismatch between available jobs and workers:

> "Firms have jobs, but can't find appropriate workers. The workers want to work, but can't find appropriate jobs. There are many possible sources of mismatch - geography, skills, demography- and they are probably all at work."

Other authors agree, pointing specifically to declining geographic mobility as a source of mismatch (Frey (2009), Katz (2010)).

If the increase in unemployment is structural, then policies like job search assistance or sectoral employment programs (Katz (2010)) may be more effective than stabilization policy in bringing down the unemployment rate.

> "Whatever the source, though, 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." (Kocherlakota (2010))

In addition, we might expect the increased unemployment rate to prove more persistent than in previous recessions.

> "Given the structural problems in the labor market, I do not expect unemployment to decline rapidly." (Kocherlakota (2010))

Shortly after the 2001 recession, Groshen and Potter (2003) made a similar argument that misallocation of workers over industries might explain the so called jobless recoveries.

Although aggregate data on unemployment and vacancies seem to indicate a decline in matching efficiency (Elsby, Hobijn, and Sahin (2010), Barnichon and Figura (2010)), there is little direct evidence for mismatch on the US labor market using disaggregated data. As a result, Kocherlakota's claim that unemployment in the Great Recession is structural rather than cyclical, and in particular its implication that stabilization policy is unlikely to be effective, has been heavily criticized (Krugman (2010), DeLong (2010)).

In this paper, we formalize how mismatch generates unemployment in a simple model. Then, we estimate structural unemployment on the US labor market. In our model, the labor market consists of multiple submarkets or segments. Within each segment, search frictions prevent the instantaneous matching of unemployed workers to vacant jobs, resulting in frictional unemployment in the tradition of Diamond (1982), Mortensen (1982) and Pissarides (1985). In addition, various adjustment costs lead to dispersion in job finding rates across submarkets, generating additional unemployment, which we call structural.

The level of disaggregation of submarkets is crucial for our exercise. In the limiting case, if submarkets are sufficiently small such that each unemployed worker and each vacancy is in a separate submarket, all unemployment is 'structural' and due to mismatch. In fact, one way to think about mismatch in the sense of Shimer (2007a), is as a possible micro-foundation for search frictions. Here, we think of search frictions and mismatch as alternative sources of unemployment and explore their differences. Driven by data limitations, we define submarkets of the US labor market either as states or as industries, similar to other papers in the empirical literature on mismatch (Sahin, Song, Topa, and Violante (2010), Barnichon and Figura (2011)). Since the amount of structural unemployment is very sensitive to the level of disaggregation, we focus on its cyclical behavior.

There are four sources of structural unemployment in the model. Each segment of the labor market is characterized by four variables: the job finding rate, which measures how hard it is for workers to find a job; the worker finding rate, which measures how hard it is for firms to find a worker; workers' surplus from having a job over being unemployed; and firms' surplus of having a filled position over a vacancy. In the absence of adjustment costs, worker mobility, job mobility and wage adjustment lead to equalization of labor market conditions across segments. Figure 1 summarizes these relations. Worker and job mobility costs, wage bargaining costs and heterogeneity in matching efficiency generate dispersion in labor market conditions and therefore structural unemployment.

In order to estimate structural unemployment and its sources, we need data on job and worker finding rates and worker and job surplus by states and industries. We construct these variables using data from the Current Population Survey (CPS) and the National Income and Product Accounts (NIPA). One major issue is that in our model all workers are assumed to be identical. Because this is obviously not the case in the real world, we need to control for worker and job heterogeneity when constructing our estimates. We control for observable worker characteristics and for unobservable but time-invariant worker and job characteristics (compensating differentials) by allowing for state and industry-specific fixed effects.

We find four main results: (1) adjustment costs between states and industries are large; (2) nevertheless, the contribution of mismatch across industries to unemployment fluctuations is modest, and the contribution of mismatch across states is very small, and there are no striking differences between the Great Recession and previous recessions; (3) the cyclical behavior and persistence of structural unemployment are similar to that of the overall unemployment rate; and (4) the most important source of structural unemployment is not worker or job mobility costs, but wage bargaining costs. Result 3 casts doubt on the claim that stabilization policy is not effective in curing structural unemployment, as argued by Kocherlakota (2010). Results 2 and 4 suggest that policies aimed at increasing worker mobility, as advocated by Katz (2010), are likely to have small effects. We now discuss each of these results in more detail.

Adjustment costs between states and industries are large. We find that workers are not willing to move between states unless the value of a job in the new state is at least 15% higher than in her current state. Similarly, firms are not willing to move jobs from one state to another unless that move increases profits by at least 18%. Wages are adjusted to better reflect labor market conditions in the state only if wages deviate as much as 33% from those in other states. Retraining a worker to work in a different industry and adjusting industry-level wages is even more costly, and requires an increase in wages of at least 31% and 61% respectively. Therefore, large dispersion in labor market conditions can exist without being arbitraged away.

Nevertheless, the contribution of these adjustment costs to fluctuations in unemployment is small. Mismatch across states contributes at most about 0.1%-points to the 5%-point increase in unemployment in the Great Recession, a contribution of no more than 2%. Mismatch across industries is even less important, with a contribution of 0.03%-points or 0.6%.[1] More importantly, these numbers are very similar for the 1982 and 1991 recessions, suggesting the Great Recession is no different from previous recessions (instead, the 2001 recession, when geographic mismatch did not increase, looks like the exception). Results 1 and 2 are not in contradiction with each other, because the concavity of the job finding rate in labor market tightness is such that even large dispersion in job finding rates translates into modest reductions in the aggregate job finding rates, and because the various adjustment costs partially offset each other. To see this last point, imagine two states with a large difference in wages, which is not being arbitraged away due to wage bargaining costs. If we reduce worker and job mobility costs, leaving the wage bargaining costs in place, workers will move into and job out of the high wage state, increasing mismatch and structural unemployment.

Fluctuations in structural unemployment look very similar to fluctuations in the overall unemployment rate. Dispersion in labor market conditions across states and industries, and therefore structural unemployment, increases in recessions and falls in booms.[2] There is no evidence that structural unemployment is more persistent than the overall unemployment rate. This finding suggests that there may not be any conceptual difference between 'structural' unemployment and frictional unemployment in

[1] However, our estimate for the contribution of mismatch across industries is less robust and may be as high as 0.2%-points or 4% if we do not control for compensating differentials.

[2] This finding is similar to that of Abraham and Katz (1986). 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 show that aggregate shocks can give rise to countercyclical fluctuations in dispersion of employment growth across sectors.

the tradition of Diamond (1982), Mortensen (1982) and Pissarides (1985), and perhaps a better way to link the two concepts is to think of the aggregate matching function as reflecting underlying heterogeneity and mismatch (Pissarides (2000), Shimer (2007a)). In particular, since structural unemployment is as cyclical as the overall unemployment rate, there seems no reason to believe that stabilization policy would be any less effective in curing it.

The main source of structural unemployment is not mobility barriers for either workers or jobs, but wage bargaining costs. This result is driven by our finding that states and industries with high worker suplus (wages) tend to have low job surplus (profits). This observation is inconsistent with Nash bargaining over wages and differences across states and industries being driven by differences in total match surplus (labor productivity). It seems that wages are not only rigid in response to changes in labor productivity, but there are changes in wages that are unrelated to changes in productivity. An exogenous increase in wages increases worker surplus but decreases job surplus, consistent with the data. Wage bargaining costs prevent these wage differentials across states and industries to be arbitraged away. This generates unemployment as unemployed workers move into, and vacancies out of high wage states. Policies aimed at reducing worker and job mobility costs are unlikely to cure this type of structural unemployment, and may even make it worse.

Empirical studies on structural unemployment 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 on mismatch using disaggregated data.[3] Two recent contributions are closely related to this paper. Sahin, Song, Topa, and Violante (2010) use disaggregated data on unemployment and vacancies to construct indices of structural unemployment, using data from the JOLTS for the 2001-2010 period. Barnichon and Figura (2011) 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. The extremely small contribution of mismatch across states is also consistent with work by Kaplan and SchulhoferWohl (2010), who show that most of the a drop in interstate migration in the Great Recession is a statistical artifact. Compared to Sahin et al., we provide an alternative method to estimate structural unemployment, which gives us a much longer time series. Compared to Barnichon and Figura, our focus is on unemployment rather than matching efficiency. We contribute to the results in both papers by providing a theory for the sources of dispersion in labor market conditions, and by estimating the contribution of each of these sources to structural unemployment.

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

This paper is organized as follows. In the next section we present a theoretical framework to formalize how mismatch across submarkets of the labor market can lead to structural unemployment. We identify four sources of structural unemployment, three of which we can estimate: worker mobility costs, job mobility costs and wage bargaining costs. Section 3 describes the data used in the estmation, 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.

2 Theoretical 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 structural unemployment. In addition, we use the model to guide the empirical exercise how to estimate structural unemployment and how to decompose it into its sources. We try to make as little assumptions as possible. In particular, we will not assume anything about vacancy creation, but only model the distribution of vacancies and unemployed workers over submarkets.

2.1 Segmented Labor Market

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 by thinking of the labor market as being 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.[4] In addition, we assume that in each submarket, there is a matching technology with increasing and diminishing returns to each of its inputs: unemployed workers and vacancies.

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 p_i, worker surplus S_i^W, the worker finding rate q_i and job surplus S_i^J in submarket i respectively.

[4] Of course, there is a huge empirical problem how to operationalize this concept of a submarket. Following the literature, we use either states or industries, but a better definition is probably skill-based occupations. Therefore, the real assumption we are making is that workers and firms can only search in one state or industry.

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 starting point and explore the effect of deviations from these relations. Unemployment that results under the benchmark model is frictional unemployment, whereas unemployment that results from deviations from this model is called structural.

The relation between the job finding rate p_i and worker surplus S_i^W across submarkets is determined by assumptions about worker mobility between submarkets, the relation between the worker finding rate q_i and job surplus S_i^J by assumptions about job mobility (mobility of vacancies), the relation between worker and job surplus by assumptions about wage bargaining, and the relation between job and workers finding rates by assumptions about the matching process. 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 (which, as usual, includes the utility from leisure). With probability p_i, 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 is given by $z_i^W = b_i + p_i S_i^W$.

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 $z_i^W = \bar{z}^W$ for all i. Using a bar over a variable to denote its average over all submarkets and a hat to denote relative deviations from this average, e.g. $\hat{p}_i = \frac{p_i - \bar{p}}{\bar{p}}$, equalization of the value of searching in all submarkets implies the following relation between $\hat{p}_i$ and $\hat{S}_i^W$, which we label the worker mobility curve.

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

Assuming unemployment benefits are the same in all submarkets, we get $\hat{p}_i = -\hat{S}_i^W$. This relation 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. 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 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

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

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 worth for workers to pay the mobility cost and move into that submarket. Unemployed workers moving into market i makes it harder to find a job in that submarket, reducing $\hat{p}_i$ 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, $\alpha_i^{WM} = -\frac{\bar{b}}{\bar{z}^W - \bar{b}}\hat{b}_i$.

2.1.2 Job Mobility

Having a vacancy looking for a worker in submarket i costs the firm k_i in terms of vacancy posting costs. With probability q_i, this vacancy gets filled, in which case the firm gets surplus S_i^J from the match. Thus, the per-period value of searching for a worker in submarket i is given by $z_i^J = -k_i + q_i S_i^J$.

If firms can freely relocate vacancies across submarkets, it must be that the value of searching for a worker is equalized 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.

$$\hat{q}_i + \hat{S}_i^J = \alpha_i^{JM} \tag{3}$$

Dispersion in α_i^{JM} may reflect job mobility costs or dispersion in vacancy posting costs, $\alpha_i^{JM} = \frac{\bar{k}}{\bar{z}^J + \bar{k}}\hat{k}_i$.

2.1.3 Wage Bargaining

The relation between worker and job 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 standard labor market models, a common assumption is that wages are set by generalized Nash bargaining, which divides total match surplus in fixed proportions between worker and firm.

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, Nash bargaining over the wage implies that worker and job surplus are proportional across submarkets, $\hat{S}_i^W = \hat{S}_i^J$. In general, wages may deviate from the Nash bargaining solution, for example because wages are not rebargained in each period. This is captured in the wage bargaining curve.

$$\hat{S}_i^W = \hat{S}_i^J + \alpha_i^{WB} \tag{4}$$

Dispersion in α_i^{WB} may reflect wage bargaining costs, preventing the wage to be rebargained to the Nash bargaining solution, or other deviations from Nash bargaining, for example heterogeneity in workers bargaining power, $\alpha_i^{WB} = \frac{\phi_i}{1-\phi_i}$.

2.1.4 Matching

The final relation needed to close the model, between worker and job finding rates, is determined by assumptions on the matching technology. In the standard models, 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, $q_i = B_i \theta_i^{-\mu}$ and $p_i = B_i \theta_i^{1-\mu}$, 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.

$$\hat{q}_i = -\frac{\mu}{1-\mu}\hat{p}_i + \alpha_i^{MF} \tag{5}$$

Dispersion in α_i^{MF} reflects dispersion in matching efficiency across submarkets, $\alpha_i^{MF} = \frac{\hat{B}_i}{1-\mu}$. 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^{MF} reflects all differences in the matching function across submarkets, $\alpha_i^{MF} = \frac{\hat{B}_i}{1-\mu} - \frac{\mu}{1-\mu}\left(\bar{p} - \bar{q}\right)\hat{\mu}_i$.

2.2 Sources of Structural Unemployment

If there is perfect worker mobility, perfect job mobility, Nash bargaining with constant bargaining power and a matching function with constant matching efficiency, then labor market conditions are identical in all submarkets. To see this, combine equations (2), (3), (4) and (5) to solve for the job finding rate.

$$\hat{p}_i = (1-\mu)\left(\alpha_i^{WM} - \alpha_i^{JM} - \alpha_i^{WB} + \alpha_i^{MF}\right) \tag{6}$$

Setting $\alpha_i^{WM} = \alpha_i^{JM} = \alpha_i^{WB} = \alpha_i^{MF} = 0$ gives $\hat{p}_i = 0$ or $p_i = \bar{p}$ 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 search frictions.

Deviations from any of these four relations generate dispersion in labor market tightness and job finding rates. There are four sources of dispersion across submarkets of the labor market segments: 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^{WB} heterogeneity in wage bargaining power and wage rigidities, and α_i^{MF} heterogeneity in matching efficiency. All four sources lead to unemployed workers and vacancies being in different submarkets and thus cause structural 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 $\alpha_i^{WB} > 0$, too many unemployed workers and too few vacancies are in submarket i, because wages are higher than in comparable jobs in other submarkets so that workers reap a disproportionally large share of match surplus in this submarket.

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 fixed, 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 aggregate job finding rate $\bar{p}'$ that prevails under the new distribution is given by,

$$\frac{\bar{p}'}{\bar{p}} = \left(\frac{E\left[(1+\hat{p}_i)^{\frac{1}{1-\mu}} \right]}{E\left[(1+\hat{p}_i')^{\frac{1}{1-\mu}} \right]} \right)^{1-\mu} \tag{7}$$

where $0 < \mu < 1$ is the elasticity of unemployment in the matching function and $\bar{\lambda}$ is the aggregate separation rate. The unemployment rate follows from the aggregate job finding rate by assuming steady state, so that $\bar{u} = \frac{\bar{\lambda}}{\bar{\lambda}+\bar{p}}$. See appendix A.1 for the derivation of equation (7). The aggregate job finding rate is higher, $\bar{p}' > \bar{p}$, and therefore the unemployment rate lower, $\bar{u}' < \bar{u}$, if and only if the dispersion in $\hat{p}_i'$ is smaller than the dispersion in $\hat{p}_i$, in the sense that θ_i is a mean-preserving spread of θ_i' (i.e. the distribution of θ_i' second-order stochastically dominates the distribution of θ_i).

Equations (6) and (7) allow us to decompose structural unemployment into its four sources. The idea is that if we remove, for example, the worker mobility costs, setting $\alpha_i^{WM} = 0$, but leave the job mobility costs, wage bargaining costs and heterogeneity in matching efficiency in place, then α_i^{JM}, α_i^{WB} and α_i^{MF} would stay the same. Notice that this is probably not a good assumption for the short run, because worker or job mobility or wage rebargaining affects 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 and wage bargaining costs 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. Given estimates for α_i^{WM}, α_i^{JM}, α_i^{WB} and α_i^{MF}, we can 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. Then, using equation (7), we can also calculate the aggregate job finding and unemployment rates under these scenarios. To estimate the α's, we use equations (2), (3), (4) and (5) and data on the surpluses and finding rates. The next section describes how we obtain these data.

In the presence of worker or job mobility costs, wage bargaining costs and/or heterogeneity in matching efficiency, unemployment must be higher than if there is no dispersion in labor market conditions. However, this does not imply that removing one or more of these costs necessarily decreases unemployment. The reason is that the various costs may reinforce or counteract each other, so that removing some but not all of these costs may increase unemployment.[5] 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 bargaining costs, 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 bargaining costs 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.

3 Data and Measurement

To test the relations we derived in the previous section, we need empirical measures of worker surplus S_i^W, job surplus S_i^J, the job-finding rate p_i, and the worker-finding rate q_i for submarkets of the labor market. In this section, we describe how we operationalize these concepts empirically and describe the data sources we use to construct them. As we need to make a good number of auxilliary assumptions in order to be able to do this, we also describe how we explore the robustness of our results to these assumptions.

3.1 Defining Submarkets

The first problem is how to empirically define a submarket. A submarket of the labor market is defined as a subset of unemployed workers or vacant jobs that are similar to

[5] Removing some costs may even decrease welfare in a second-best world. Our framework, however, has little to say about welfare, and we restrict ourselves to statements about unemployment. For some thoughts about welfare in a, much simpler, model with heterogeneous workers, see Merkl and van Rens (2011).

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 35 industries to explore skill mismatch.[6] This choice is driven by data limitations and follows other empirical contributions in this literature (Sahin, Song, Topa, and Violante (2010), Barnichon and Figura (2011)). Unfortunately, it is not possible to use very small submarkets, because we would have too little data about each submarket. Shimer (2007a), 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.

It is also not possible to use occupations, correctly defined by the skills required to perform the tasks involved, because not all data we need for our analysis are available by occupation and/or skill. Moreover, such skill-defined occupational groups would likely to be overlapping across different workers. For example, an micro-theorist might look for jobs in economics departments and business schools, whereas a financial economist would look for jobs in private banks and business schools. We are working on an alternative way to estimate mismatch and structural unemployment that would allow to use these overlapping, skill-defined occupational groups, see Herz (2011b). This method would not allow estimating structural unemployment due to barriers to job mobility or wage bargaining costs, but may provide a more credible estimate for structural unemployment due to worker mobility costs.

The choice of the submarkets, in particular the level of aggregation, will affect the level of structural unemployment. The fact that we find very little structural unemployment due to barriers to geographic mobility, for instance, might change if we had data on more detailed geographic locations. And the fact we find little mismatch across industries does not imply there is no skill mismatch across skill-defined occupational groups.

[6] Precisely, we have 37 industries based on the SIC classification for the 1983-1997 period and 35 industries based on the NAICS classification for the 2003-2009 period. For the 1998-2002 period, we do not observe all necessary data by industry, because in these years the wage data from the CPS were still based on the SIC, whereas the profit data from the NIPA were already based on the NAICS.

3.2 Measuring 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,

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

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, $\tau_{it}^{W} = \lambda_{it} + p_{it}$. For the firm, payoffs from a filled job y_{it}^{J} equal profits gross of vacancy posting costs, and turnover equals the separation rate plus the worker finding rate, $\tau_{it}^{J} = \lambda_{it} + q_{it}$. We use these data and equation (8) to calculate match surplus for the worker and firm, S_{it}^{W} and S_{it}^{J} 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 A.2.

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 the *level* of 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. The level of turnover matters because it determines by how much future payoffs are discounted. Notice that persistence in turnover is less relevant. If turnover is currently high and converges back to a lower level, then the expected net present value of payoffs from the match will be in between its values if turnover stays constant at its current high level or at its future lower level. Therefore, we assume turnover is constant over the duration of the match, $\tau_{it+s} = \tilde{\tau}_{it}$ for all $s \geq 0$. In our baseline results, we assume that turnover stays constant at its current level in the submarket, $\tilde{\tau}_{it} = \tau_{it}$, but we explore the robustness of our results if turnover equals average turnover in all submarkets, $\tilde{\tau}_{it} = \bar{\tau}_t$. These two assumptions capture the extreme cases for turnover that maximize and minimize dispersion in surplus.

For payoffs from matches in each submarket, we assume an autoregressive process that reverts to the average payoff across all submarkets.

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

By varying the parameter δ, we explore the robustness of our results to the amount of persistence in match payoffs. The first-order autocorrelation in wages is 0.92 per year in the state-level data and 0.84 in the industry-level data. 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: 0.58 in the state-level data and 0.54 in the industry-level data. In our baseline results, we assume wages and profits are a random walk, $\delta = 0$, but our results are robust more mean-reversion.[7]

The assumptions that turnover is constant over the duration and payoffs follow stochastic process (9) allow us to calculate match surplus by solving forward equation (8).

$$S_{it} = \frac{\bar{y}_t}{r + \tilde{\tau}_{it}} + \frac{y_{it} - \bar{y}_t}{1 + r - (1 - \tilde{\tau}_{it})(1 - \delta)} \simeq \frac{\bar{y}_t}{r + \tilde{\tau}_{it}} + \frac{y_{it} - \bar{y}_t}{r + \tilde{\tau}_{it} + \delta} \tag{10}$$

If match payoffs follow a random walk, $\delta = 0$, 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 p_{it} and therefore τ_{it} – the smaller is the advantage of already having a job.

3.3 Measuring Job and Worker Finding Rates

In order to test whether the matching technology is the same across submarkets, using equation (5), we need data on job and worker finding rates by states and industries. Data on job finding rates are readily available from the Current Populations Survey, see section 3.4. However, to calculate worker finding rates, 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 $\alpha_i^{MF} = 0$ for all i. Then, we use this relation to construct data for worker finding rates q_i from data on job finding rates p_i. In future work, we plan to explore the validity of this assumption, using (confidential) disaggregated JOLTS data for the recent years.

Because we cannot test the homogeneity of the matching technology, we can estimate

[7] 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 (2008) and Kudlyak (2010), 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. The reason that the persistence of payoffs does not affect the results very much, is that mean-reversion enters additively with turnover, see equation (10), which is close to 1 at annual frequency.

only three of the four potential sources of structural unemployment in equation (6). If there is heterogeneity in the matching technology across submarkets, this will not affect our estimates of the level and cyclical behavior of structural unemployment. It will, however, affects our estimates of the sources of structural unemployment. It is not clear what the direction of this bias would be. If, for example, states with high job finding rates tend to have higher matching efficiency, $\alpha_i^{MF} > 0$, 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 costs, see equation (3). Whether we would over- or underestimate these costs would depend on whether states with high job finding rates tend to have higher or lower than average profits.

3.4 Data Sources

Our analysis requires data on wages w_{it} net of unemployment benefits and the disutility from working b_{it}, profits π_{it} gross of vacancy posting costs k_{it}, separation rates λ_{it} and job finding rates p_{it} by states and industries. From these data, we can calculate worker and job surplus and worker finding rates as explained above.

Our primary data source is the Current Population Survey (CPS) administered by the Bureau of Labor Statistics (BLS). From the basic montly files we construct job finding and separation rates. The variable labor force status indicates which workers are unemployed and which are employed. The number of workers whose status changes from unemployed to employed as a fraction of the total number of unemployed workers in a submarket is the job finding rate. The number of workers whose status changes from employed to unemployed as a fraction of the total number of employed workers in a submarket is the separation rate.[8] To calculate job finding rates by industry, we assign unemployed workers to the industry where they last held a job, following the BLS. As a robustness check, we also calculate finding rates, assuming unemployed workers are searching in the industry where they ultimately find a job, following Herz (2011a).

From the outgoing rotation groups, we get wages, calculated as usual weekly earnings divided by usual weekly hours. 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. These data are available at monthly frequency, which we aggregate to annual time series in order to increase the number of observations, ending up with a sample of about $150,000$ workers per year. We currently use data for the 1983-2009 period, although data are in principle available from 1979 (we plan to update the results to include the earlier years of data).

Data on profits by state and industry come from the National Income and Product

[8] This is a common way to measure worker flows, see Shimer (2007b). 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 worker across submarkets, these biases should not affect our results.

Account (NIPA) data collected by the Bureau of Economic Analysis (BEA). We use gross operating surplus per employee as our measure of profits. In addition, compensation of employees provides an alternative measure of wages. Gross operating surplus and compensation of employees add up to value added, net of taxes and subsidies. Thus, our measure of profits includes the return to investments in capital. 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.

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 structural 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}, vacancy posting costs k_{it}, the discount rate r and the elasticity of the matching function μ. In our baseline results, we assume the replacement ratio b_{it}/w_{it} equals 0.73, which is the value preferred by Hall (2009) and Nagypal 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 Department of Labor (2010). We assume $\mu = 0.6$ in our baseline results, again following Nagypal 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 $k_{it}/\pi_{it} = 0.03$, but these assumptions do not matter for the results.

3.5 Controlling for Worker Heterogeneity

We estimate structural unemployment from the dispersion in wages, profits and finding rates. It is crucial, therefore, that we control for heterogeneity. In the model, all workers and jobs are the same, and all dispersion reflects worker or job mobility or wage bargaining costs. In the real world, wages, profits and even job finding rates vary across workers not only because of these adjustment costs, but also because workers have different education, experience or other characteristics. For example, wages in Maine may be higher than in Arkansas because the average education level is higher there.

Our approach to deal with worker heterogeneity in the data, is to calculate worker and job surplus, and job finding rates for homogeneous groups of workers, and then to average $\hat{S}_i^W$, $\hat{S}_i^J$ and $\hat{p}_i$, in relative deviations from the mean across submarkets, over all groups of workers. We define groups of homogeneous workers based on all observable worker characteristics in our dataset: education, experience, gender, race and marital status.

We implement this approach in two steps. First, we regress the variable of interest on observable worker characteristics using a flexible specification. The variable of interest is either the wage, or an dummy variable indicating whether a worker lost or found a job. Second, we calculate fitted values for 40 worker cells, defined based on 2 gender, 5 education groups (less than high school, high school graduate, some college, college graduate, or more than college), and 4 categories for potential labor market experience (0-10 years, 11-20 years, 21-30 years, 31-40 years after completion of schooling), and calculate worker and job surplus and job finding rates for the average worker in each of these 40 cells.

The reasons for the first step are threefold. First, it allows us to control for observable characteristics, race and marital status, which are not used to define worker cells because doing so would result in too few observations per cell. When we calculate fitted values, we set these variables equal to a reference category, effectively calculating hypothetical wages and worker flows as if all workers were white, non-hispanic and married. Second, the regression allows us to control for differences in education and experience within cells. Third, using fitted values makes sure that there are no missing values: if there are no workers in a given cell, we generate a virtual worker with gender, education and experience equal to the cell average. The specification we use must be flexible enough to not change the features of the data, but restrictive enough so that we can identify fitted values for all cells. We includes fourth order polynomials in all controls, plus interactions of the first order effects of all controls with each other as well as with state or industry dummies, see appendix A.3 for the exact specification.

The second step controls for differences in gender, education and experience across cells in a fully non-parametric manner. Because we first take relative deviations from the average across submarkets, and only then average over worker groups, any differences in dispersion because of differences in the composition of the work force over the 40 cells are controlled for.

Controlling for worker heterogeneity in profits is more difficult, because we do not observe profits at the worker level. We attempt to still control for heterogeneity, by assuming that worker heterogeneity affects profits in the same way it affects wages. Then, we can control for heterogeneity by multiplying profits by the ratio of wages controlled for worker heterogeneity w^*_{it} over raw wages w_{it}, $\log \pi^*_{it} = \log \pi^{\text{NIPA}}_{it} - \log w^{\text{CPS}}_{it} + \log w^{*\text{CPS}}_{it}$ or $\log \pi^*_{it} = \log \pi^{\text{NIPA}}_{it} - \log w^{\text{NIPA}}_{it} + \log w^{*\text{CPS}}_{it}$. We explore the robustness of our results if we do not control profits and wages for worker heterogeneity.

3.6 Controlling for Compensating Differentials

There are other differences between jobs than just the wage (and separation rate). 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). Since we want to interpret wage differentials as evidence for worker or job mobility costs or wage bargaining frictions, we need to control for compensating differentials.

Unfortunately, we do not observe the characteristics of jobs, unlike those of workers. Therefore, we assume job amenities are constant over time, so the the true worker surplus is given by $\hat{S}_{it}^{W} + c_i^W$ and the true job surplus equals $\hat{S}_{it}^{J} + c_i^J$. Then, we can control for compensating differentials by using $\hat{S}_{it}^{W}$, $\hat{S}_{it}^{J}$, $\hat{p}_{it}$ and $\hat{q}_{it}$ in deviations from their time series averages. To see how this works, note that equations (2), (3) and (4) hold in each year, so that,

$$\hat{p}_{it} + \hat{S}_{it}^{W} + c_i^W = \alpha_{it}^{WM} \Rightarrow \widehat{\hat{p}}_{it} + \widehat{\hat{S}}_{it}^{W} = \hat{\alpha}_{it}^{WM} \tag{11}$$

$$\hat{q}_{it} + \hat{S}_{it}^{J} + c_i^J = \alpha_{it}^{JM} \Rightarrow \widehat{\hat{q}}_{it} + \widehat{\hat{S}}_{it}^{J} = \hat{\alpha}_{it}^{JM} \tag{12}$$

$$\hat{S}_{it}^{W} + c_i^W - \hat{S}_{it}^{J} - c_i^J = \alpha_{it}^{WB} \Rightarrow \widehat{\hat{S}}_{it}^{W} - \widehat{\hat{S}}_{it}^{J} = \hat{\alpha}_{it}^{WB} \tag{13}$$

where $\widehat{\hat{x}}_{it}$ denotes a variable in deviation from its time series average, where the variable itself is in deviation from its average across submarkets, $\widehat{\hat{x}}_{it} = \hat{x}_{it} - \bar{\hat{x}}_i$ and $\hat{x}_{it} = x_{it} - \bar{x}_t$ and $\hat{\alpha}_{it} = \alpha_{it} - \bar{\alpha}_i$ denotes the adjustment costs in deviations from their time series average. Taking deviations from the time series averages is like including state or industry-specific fixed effects and controls for time-invariant compensating differentials.

By controlling for fixed effects, we can no longer estimate the level of the adjustment costs α_{it}^{WM}, α_{it}^{JM} and α_{it}^{WB}, but only the deviations from their time series averages. As a result, equations (6) and (7) no longer give the correct level of the aggregate job finding rate and unemployment due to structural factors. However, this is not a problem. First of all, the level of structural unemployment strongly depends on the level of disaggregation of submarkets, so that we would not want to interpret the level in any case. Second, the change in the level of structural unemployment due to controlling for fixed effects is small in practice, at least for mismatch across states. The reason is that worker mobility, job mobility and wage bargaining costs are likely to be small in the long run. Therefore, $\bar{\alpha}_i^{WM} = \bar{\alpha}_i^{JM} = \bar{\alpha}_i^{WB} = 0$, which implies $\bar{\hat{p}}_i = 0$, so that $\widehat{\hat{p}}_{it}$ is close to $\hat{p}_{it}$.

4 Results

We start the description of our results by exploring how well equations (2), (3) and (4) hold in the data, and presenting estimates of the adjustment costs that lead to deviations from these equations. In section 4.2, we present our estimates for structural unemployment and explore its cyclical behavior. Finally, in section 4.3, we use equations (6) and (7) to decompose structural unemployment into the contribution each of the adjustment costs across labor market segments.

4.1 Mobility and Wage Bargaining Costs

Figure 2 shows scatterplots for states around the worker mobility, job mobility and wage bargaining curves. These graphs use data for the year 2005, but look very similar for other years. The relation between job finding rates and worker surpluses and the relation between worker finding rates and job surpluses across states are roughly consistent with the worker mobility curve (2) and the job mobility curve (3) in our model, which have a slope of minus one. The dotted regression line shows that the slope of these relations is around minus one in the data. The relation between worker and job surplus, on the other hand, is very different from what the wage bargaining curve (4) in our model would predict.

There is no reason to expect the data to be consistent with the correlations implied by the worker mobility, job mobility and wage bargaining curves. These curves represent partial equilibrium relationships, and the only allocation that is consistent with all three curves, is full equalization of surpluses and finding rates across states. It seems that the relation between job finding rates and worker surpluses and the relation between worker finding rates and job surpluses are largely governed by arbitraging through mobility of workers and jobs respectively. However, wage bargaining power seems to vary substantially across states.

Nash bargaining over wages, as in equation (4), prescribes that workers and firms share the surplus from a match in fixed proportions, so that matches that are relatively attractive to firms are relatively 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 wage bargaining curve. In reality, it seems that differences in wages across states are much larger than differences in labor productivity. Since matches with high wages generate high surplus for workers, but low surplus for firms, these differences generate downward rather than upward sloping relation between worker and job surplus. As a result, we observe deviations from the wage bargaining curve that are much larger than deviations from the worker mobility and job mobility curves, suggesting that wage bargaining costs are more important as a source of structural unemployment than worker or job mobility costs.

Figure 3 and shows similar results for mismatch across industries. These plots for industries look very similar to those for states, although the dispersion around the curves is roughly twice as large. As for states, we find that the job and mobility curves are roughly as in the model, whereas there is substantial heterogeneity in wage bargaining across industries.

If our interpretation of deviations from the curves as adjustment costs is correct, then we would expect states or industries that are 'close' to each would on average be more similar in terms of deviations from the worker mobility, job mobility and wage bargaining curves, since the cost of arbitraging away differences would be smaller between these states. Table 1 reports the 5 pairs of states with the largest and 5 pairs with the smallest distance in terms of their deviation from the worker mobility curve, $\left|\alpha_i^{WM} - \alpha_j^{WM}\right|$, and their physical distance. It is clear from the table, that the distance between states that are more similar to each other in terms of the value of searching for a job is on average much shorter. Notice that the relation is not monotonic, but we also did not expect it to be, because even if costs of arbitrage are very high, states may have similar labor market conditions because they were subject to similar shocks. Table 2 reports similar results for industries. These results are harder to interpret because it is not clear what measure to use for distance between industries. We are working on a distance measure based on the skill requirements of different occupations, see Herz (2011b).

Dispersion of states and industries around the worker mobility, job mobility and wage bargaining curves is a measure of the size of the costs of arbitrage in each of these relations. As a summary statistic for dispersion, we use the standard deviation, represented by the dashed lines in Figures 2 and 3. The units of this measure of adjustment costs are intuitive. Since worker and firm surplus are measured in relative deviations from their cross-sectional average, their standard deviation represents the typical deviation relative to the cross-sectional average. For example, a standard deviation of 0.2 means that a typical state or industry has a surplus that is up to 20% higher or lower than the average across states/industries.

Table 3 summarizes our estimates of the worker and job mobility costs and wage bargaining costs. This table uses pooled data for all years over the 1983-2009 sample period in order to get more precise estimates of the standard deviations. All of the adjustment costs are high, ranging from 15% for moving workers across states to 61% for adjusting wages across industries. Mobility costs for workers and jobs are roughly similar, whereas wage bargaining costs are about twice as high. Adjustment costs across industries are roughly twice as high as across states. Of course these estimates are sensitive to the level of disaggregation. According to our estimates, retraining a worker who is currently employed in the telecommunications industry to work in machine manufacturing is about twice as costly as moving that worker from Wyoming to Massachussets or New York.

If we do not control for compensating differentials, see Section 3.6, we find estimates for the adjustment costs across states that are roughly double and for costs across industries that are roughly triple our baseline estimates. The relative importance of the three adjustment costs, however, does not change very much whether or not we remove state and industry-specific fixed effects. The estimates are robust to reasonable variations in the elasticity of the matching function μ. If we assume a higher replacement ratio, b_{it}/w_{it}, worker mobility costs become more, and wage bargaining costs less important. However, even for an implausibly high replacement ratio of 0.95, wage bargaining costs are still as high as worker mobility costs and twice as high as job mobility costs. Assuming a lower replacement ratio affects the estimates very little. The assumption we make on turnover rates seems to be somewhat important for the results. If we assume turnover is constant across states and industries, then adjustment costs across industries decrease to the same level as adjustment costs across states, and both across states and across industries wage bargaining costs become less important than job mobility costs.

4.2 Cyclicality of Structural Unemployment

Worker and job mobility costs and particularly wage bargaining costs are high. These adjustment costs generate dispersion in job finding rates across states and industries, which leads to structural unemployment. We now turn to the question how much of unemployment is due to these structural factors, and whether the cyclical behavior (volatility, persistence) of structural unemployment is different from that of unemployment caused by search frictions or other factors.

Figure 4 plots the overall steady state unemployment rate in the US over the 1983-2009 period, as well as the counterfactual steady state unemployment rates if there were no mismatch across states or industries.[9] The counterfactuals are constructed using equations (6) and (7) to calculate the counterfactual job finding rate that would prevail if there were no deviations from the worker and job mobility and wage bargaining curves, $\alpha_i^{WM} = \alpha_i^{JM} = \alpha_i^{WB} = 0$ for all i. In order to correct for compensating differentials, we calculated dispersion in job finding rates after subtracting the time series average of the job finding rate in each state and industry. Therefore, we should refrain from interpreting the average distance of the counterfactuals from the actual unemployment rate. However, we can analyze the change in the distance between the two between recessions and booms. The contribution of mismatch, both across states and across industries, to fluctuations unemployment is tiny. If we do not control for compensating differentials, the contribution of mismatch across industries is slightly larger, but still very small as a fraction of movements in the total unemployment rate.

[9] 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.

Figure 5 shows the difference between the actual unemployment rate and the counterfactual unemployment rate if there were no dispersion in job finding rates across states. This difference can be interpreted as structural unemployment due to geographic mismatch. The dotted line in the figure shows the actual unemployment rate, plotted on a different scale on the right-hand axis, in order to compare the fluctuations in the two series. This graph allows us to answer the question whether structural unemployment due to mismatch across states is less cyclical and more persistent than unemployment due to other factors, as suggested by Kocherlakota (2010). It also allows us to compare the Great Recession to previous recession episodes.

Structural unemployment closely follows the business cycles in total unemployment. At the beginning of the sample, structural unemployment is high but declining coming out of the 1982 recession. Structural unemployment increases again in the 1991 recession and more so in the Great Recession, starting at the end of 2007. The relative amplitude of these fluctuations is similar to those in the total unemployment rate, with the exception of the 2001 recession, when the overall unemployment rate moderately increased, but structural unemployment almost did not change at all. There is no evidence that structural unemployment due to geographic mismatch is more persistent than the overall unemployment rate. Nor is there any indication that the increase in unemployment in the Great Recession was more than in other recessions due to structural factors. Although the level is different, the cyclical pattern in structural unemployment due to geographic mismatch is very similar whether or not we control for compensating differentials.[10]

Figure 6 shows similar results for structural unemployment due to mismatch across industries. Again fluctuations in structural unemployment look very similar to fluctuations in the overall unemployment rate. If anything, the similarity is even more striking that for structural unemployment due to mismatch across states, because structural unemployment due to mismatch across industries is higher in all recessions in our sample period, including the 2001 recession.

Concluding, we find that fluctuations in structural unemployment, due to geographic mismatch as well as mismatch across industries, are small compared to fluctuations in the overall unemployment rate, and exhibit very similar patterns. The finding that structural unemployment is a small part of total unemployment depends heavily of the level of disaggregation of the submarkets and should not be over-interpreted. However, the finding that the cyclical behavior of structural unemployment is very similar to that of the overall unemployment rate casts serious doubts on Kocherlakota's claim that stabilization policy is not effective against structural unemployment.

How can the finding that the contribution of structural unemployment to total unemployment is small be reconciled with the finding in section 4.1 that adjustment costs

[10] Several other choices, which we mentioned as robustness checks in Table 3, affect the decomposition of structural unemployment but not its overall level, and are therefore not relevant for this graph.

are very large, particularly for wages. There are two reasons. First, large dispersion in job finding rates translates into an only modestly lower average job finding rate because the concavity of job finding rates in labor market tightness is not very strong. To illustrate this, we consider equation (7) for the aggregate job finding rate and make distributional assumptions that allow us to evaluate the expectation operator in that equation, see appendix A.4. Table 4 shows the results for this exercise. Given our estimates for σ of around 0.3 for worker and job mobility costs across industries, see Table 3, and assuming $\mu = 0.6$, we would expect mismatch to contribute at most 6 to 12% to the overall unemployment rate. The second reason why high adjustment costs do not translate into a lot of unemployment, and the reason that the actual contribution is even smaller than what we would expect based on our estimates of the adjustment costs, is that the various costs partially offset each other. The next subsection looks at this effect.

4.3 Sources of Structural Unemployment

Our approach, in particular equations (6) and (7), allows us not only to estimate the total contribution of structural factors to unemployment, but also to decompose structural unemployment into its sources. In particular, we can assess the contribution of barriers to worker mobility, barriers to job mobility and wage bargaining costs. From the results in section 4.1, we know that wage bargaining costs are large compared to worker and job mobility costs. It seem reasonable to expect, therefore, that these costs also contribute most to structural unemployment.

Figure 7 shows the evolution of structural unemployment due to mismatch across states, and its three sources. As expected, structural unemployment due to wage bargaining costs alone closely tracks total structural unemployment, reflecting the fact that wage bargaining costs seem to be the most important impediment to equalization of job finding rates across states. The contribution of worker and job mobility costs is small and largely acyclical, with the exception of the Great Recession, when the contribution of worker mobility costs to structural unemployment is about as large as that of wage bargaining costs. Removing mobility costs, while leaving wage bargaining costs in place, would reduce unemployment very little, and in the period 1986-1988 would even have increased the unemployment rate.

How can the unemployment rate increase when we remove one of the adjustment costs across submarkets? The answer is related to the correlations between the deviations from the worker mobility curve (2), the job mobility curve (3) and the wage bargaining curve (4), which are given in Figure 8. States with high worker surplus and low job surplus because of relatively high worker bargaining power, i.e. states with high α_i^{WB}, 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 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 worker mobility costs reduce job finding rates, reinforcing the effect of the wage bargaining costs, but the job mobility costs reduce worker finding rates as well, partially offsetting the effect of the wage bargaining costs.

Figures 9 and 10 show similar results for the decomposition of structural unemployment due to mismatch across industries. The decomposition of structural unemployment due to mismatch across industries in Figure 9 is noisier than its equivalent for states. Nevertheless it is clear that wage bargaining costs explain most of the increase in mismatch across industries in the 1991 and 2007 recessions. Across industries, the correlations between the various adjustment costs are more pronounced than across states, see Figure 10. Moreover, across industries, both worker and job mobility costs counteract the effect of wage bargaining costs. This explain why, although adjustment costs are substantially higher across industries than across states, the contribution of mismatch across industries to structural unemployment is smaller than the contribution of mismatch across states.

Two clear conclusions emerge regarding the sources of structural unemployment. First, wage bargaining costs are not only larger than worker and job mobility costs, but they also contribute more to structural unemployment. Second, the various sources of structural unemployment may reinforce as well as offset each other, particularly across industries. 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 or even negative.

5 Conclusions

Structural 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 a simple model of a segmented labor market that allows us to think about the sources of structural unemployment: worker and job mobility costs, frictions in the wage bargaining process and heterogeneity in the matching technology across submarkets. Using data on wages and finding rates from the CPS and on profits from the NIPA, we constructed measures of the first three of these sources of mismatch across US states and industries

We find that adjustment costs are high across states and even higher across industries. Wage bargaining costs are larger than worker and job mobility costs and are responsible for most of structural unemployment. However, because of limited concavity in the job finding rate and because worker and job mobility costs partly offset the effect of wage bargaining costs, fluctuations in structural unemployment are small compared to the overall unemployment rate. This is true for structural unemployment due to mismatch across states, and even more so for mismatch across industries. Moreover, structural unemployment is equally cyclical and no more persistent than overall unemployment, suggesting there may be no conceptual difference between structural and frictional unemployment. Reducing some but not all of the sources of structural unemployment is likely to have little effect, and may even increase the unemployment rate.

A number of caveats are in order. First, the level of disaggregation is crucial for our results. If we were to use more disaggregated submarkets, either by considering smaller geographic areas and more detailed industry classifications, or by interacting geographic areas with industries, the part of unemployment fluctuations that is due to structural factors would increase by construction. Second, rather than industries, one would probably want to define submarkets based on skill-defined occupational groups. We are trying to do this in a different paper, see Herz (2011b). Third, the finding that fluctuations in structural unemployment are small does not mean the welfare effects are small, and even though reducing adjustment costs reduces unemployment by little, it may improve welfare substantially. In related work, we are trying to evaluate the welfare costs of unemployment in a model with heterogeneous workers, see Merkl and van Rens (2011).

A Appendices

A.1 Derivation of equation (7) for the aggregate job finding rate

Since we are considering a mean-preserving change in the distribution of labor market tightness, we know that $\bar{\theta} = \bar{\theta}'$. Then, with $p_i = B\theta_i^{1-\mu} \Leftrightarrow \theta_i = (p_i/B)^{\frac{1}{1-\mu}}$, we get

$$\bar{\theta} = E\left[\left(\frac{p_i}{B}\right)^{\frac{1}{1-\mu}}\right] = E\left[\left(\frac{p_i'}{B}\right)^{\frac{1}{1-\mu}}\right] = \bar{\theta}' \tag{14}$$

Substituting $\hat{p}_i = (p_i - \bar{p})/\bar{p} \Leftrightarrow p_i = \bar{p}(1+\hat{p}_i)$ and re-arranging gives equation (7) in the main text.

A.2 Worker and Firm surplus

The value of an employed worker in submarket i, W_{it}, and the value of an unemployed worker in that submarket, U_{it}^W, satisfy the following set of Bellman equations,

$$(1+r)W_{it} = w_{it} + \lambda_{it}E_t U_{it+1}^W + (1-\lambda_{it})E_t W_{it+1} \tag{15}$$

$$(1+r)\,U^W_{it} = b_{it} + p_{it}E_t W_{it+1} + (1-p_{it})\,E_t U^W_{it+1} \tag{16}$$

where λ_{it} is the separation rate, p_{it} is the job finding rate, w_{it} is the wage and b_{it} is the flow value of being unemployed, which consists of unemployment benefits and the value of leisure. Worker surplus equals the difference between the payoff from having a job in submarket i minus the payoff of looking for a job in that submarket, $S^W_{it} = W_{it} - U^W_{it}$, so that

$$(1+r)\,S^W_{it} = w_{it} - b_{it} + (1-\lambda_{it} - p_{it})\,E_t S^W_{it+1} \tag{17}$$

where $w_{it} - b_{it}$ is the worker's flow payoff from having a job net of the payoff from being unemployed, and $\lambda_{it} + p_{it}$ is worker turnover.

The value of a filled job in submarket i, J_{it}, and the value of a vacancy in that submarket, U^J_{it}, satisfy the following set of Bellman equations,

$$(1+r)\,J_{it} = \pi_{it} + \lambda_{it}E_t U^J_{it+1} + (1-\lambda_{it})\,E_t J_{it+1} \tag{18}$$

$$(1+r)\,U^J_{it} = -k_{it} + q_{it}E_t J_{it+1} + (1-q_{it})\,E_t U^J_{it+1} \tag{19}$$

where q_{it} is the worker finding rate, π_{it} are flow profits and k_{it} are vacancy posting costs. Job surplus equals the difference between the payoff from having a filled job in submarket i minus the payoff of having a vacancy in that submarket, $S^J_{it} = J_{it} - U^J_{it}$, so that

$$(1+r)\,S^J_{it} = \pi_{it} + k_{it} + (1-\lambda_{it} - q_{it})\,E_t S^J_{it+1} \tag{20}$$

where $\pi_{it} + k_{it}$ is the firm's flow payoff from having a filled job gross of vacancy posting costs, and $\lambda_{it} + q_{it}$ is job turnover.

A.3 Worker Heterogeneity

The specification to control for observable worker heterogeneity must be flexible enough to not change the features of the data across 40 cells based on gender (2 categories), education (5 categories) and potential labor market experience (4 categories), but restrictive enough so that we can identify fitted values for all cells. We use the following specification for worker w in state or industry i,

$$\begin{aligned} y_{wi} = {} & D_i'\beta_0 + \beta_1 f_{wi} + \beta_2 b_{wi} + \beta_3 m_{wi} + \beta_4 s_{wi} + \beta_5 x_{wi} \\ & + \beta_6 s^2_{wi} + \beta_7 s^3_{wi} + \beta_8 s^4_{wi} + \beta_9 x^2_{wi} + \beta_{10} x^3_{wi} + \beta_{11} x^4_{wi} \\ & + \beta_{12} f_{wi} * s_{wi} + \beta_{13} f_{wi} * s^2_{wi} + \beta_{14} f_{wi} * x_{wi} + \beta_{15} f_{wi} * x^2_{wi} \\ & + s_{wi} * D_i'\beta_{16} + x_{wi} * D_i'\beta_{17} + x_{wi} * S'_{wi}\beta_{18} + x^2_{wi} * S'_{wi}\beta_{19} + \varepsilon_{wi} \end{aligned} \tag{21}$$

where D_i is a vector of dummies for states or industries, f_{wi} is a dummy variable for female workers, b_{wi} a dummy for African American workers, m_{wi} a dummy for married workers, s_{wi} is schooling in years, x_{wi} is potential labor market experience (age minus schooling minus 6) and S_{wi} is a vector of dummies for the five education categories.

The dependent variable y_{wit} is either the logarithm of the wage or a dummy variable indicating whether that worker lost or found a job. If y_{wit} is a dummy variable, we use a probit model to guarantee that the fitted values lie between 0 and 1. For wages we use a log-linear specification, as is common in the literature, see Card (1999). In order to get fitted values for wages, we use the fitted values for log wages and apply the correction factor suggested by Cameron and Trivedi (2010, p.108). For the regressions of the probability to find or loose a job we use the sample weights from the basic monthly files. For regressions of wages we use the earnings weights, because wages are only available in the outgoing rotation groups.

A.4 Effect dispersion on unemployment

If we consider the counterfactual with no dispersion in job finding rates, then equation (7) simplifies to

$$\frac{\bar{p}'}{\bar{p}} = \left(E\left[(1+\hat{p}_i)^{\frac{1}{1-\mu}}\right]\right)^{1-\mu} \tag{22}$$

Additional assumptions are needed to evaluate the expectation operator.

Assuming $\hat{p}_i$ is uniformly distributed with mean zero and variance σ^2, $U\left[-\sigma\sqrt{3}, \sigma\sqrt{3}\right]$, we get

$$\frac{\bar{p}'}{\bar{p}} = \left(\frac{1}{2\sigma\sqrt{3}}\frac{1-\mu}{2-\mu}\left[\left(1+\sigma\sqrt{3}\right)^{\frac{2-\mu}{1-\mu}} - \left(1-\sigma\sqrt{3}\right)^{\frac{2-\mu}{1-\mu}}\right]\right)^{1-\mu} \tag{23}$$

Alternatively, taking a second order approximation around the cross-sectional mean $\hat{p}_i = 0$ for the expression inside the expectation operator,

$$\frac{\bar{p}'}{\bar{p}} = \left(1 + \frac{\mu}{(1-\mu)^2}\sigma^2\right)^{1-\mu} \tag{24}$$

where in both expressions σ is the standard deviation of $\hat{p}_i$. Notice a few (fairly obvious) special cases: $\mu = 0$ implies the finding rate is linear in θ_i so that dispersion does not matter and $\bar{p}' = \bar{p}$ for all σ. If $\sigma = 0$ there is no dispersion in finding rates and $\bar{p}' = \bar{p}$ for all μ.

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Table 1

Differences in labor market conditions between US states

States with largest difference		$\lvert\alpha_i^{WM} - \alpha_j^{WM}\rvert$	distance (miles)
Wyoming	Alaska	0.86	2297
Wyoming	Massachusetts	0.61	1798
Wyoming	New York	0.61	1565
Alaska	Florida	0.59	3840
Wyoming	Kansas	0.57	552
Average distance			2010

States with smallest difference		$\lvert\alpha_i^{WM} - \alpha_j^{WM}\rvert$	distance (miles)
South Dakota	DC	0.0001	1239
North Dakota	Ohio	0.0005	994
Louisiana	Kentucky	0.0005	589
New Mexico	Indiana	0.0011	1138
North Dakota	Utah	0.0011	797
Average distance			952

State pairs with the largest and smallest differences in the value of looking for work and their distance in kilometers. Data for year 2005.

Table 2

Differences in labor market conditions between industries

Industries with largest difference		$\left\lvert \alpha_i^{WM} - \alpha_j^{WM} \right\rvert$
Broadcasting and telecom	Machinery manufacturing	1.07
Broadcasting and telecom	Chemical manufacturing	1.03
Broadcasting and telecom	Publishing (except internet)	0.99
Broadcasting and telecom	Furniture and fixtures manufacturing	0.97
Broadcasting and telecom	Textile, apparel, and leather manuf.	0.90

Industries with smallest difference		$\left\lvert \alpha_i^{WM} - \alpha_j^{WM} \right\rvert$
Transportation and warehousing	Motion picture and sound recording	0.00017
Wholesale trade	Nonmetallic mineral product manuf.	0.0008
Accommodation	Computer and electronic product manuf.	0.00116
Retail trade	Food services and drinking places	0.00133
Miscellaneous manufacturing	Arts, entertainment, and recreation	0.00138

Industry pairs with the largest and smallest differences in the value of looking for work.
Data for year 2005.

Table 3

Worker mobility, job mobility and wage bargaining costs

	across states			across industries		
	WM costs	JM costs	WB costs	WM costs	JM costs	WB costs
baseline	0.15	0.18	0.33	0.31	0.29	0.61
no comp diff	0.35	0.29	0.53	0.98	0.92	1.41
$\mu = 0.5$	0.15	0.16	0.26	0.30	0.26	0.55
$\mu = 0.7$	0.17	0.21	0.46	0.33	0.36	0.70
$b_{it}/w_{it} = 0.4$	0.10	0.18	0.34	0.21	0.29	0.55
$b_{it}/w_{it} = 0.95$	0.69	0.18	0.60	1.83	0.29	1.85
$\tilde{\tau}_{it} = \bar{\tau}_t$	0.21	0.28	0.14	0.17	0.30	0.27

Pooled data for the 1983-2009 sample, by US states and industries. The measure of adjustment costs is the median absolute deviation from the worker mobility, job mobility and wage bargaining curves as in equations (2), (3) and (4).

Table 4

Effect dispersion in labor market conditions on unemployment

Uniform approximation

		σ					
		0.01	0.1	0.2	0.3	0.4	0.5
	0	1.00	1.00	1.00	1.00	1.00	1.00
	0.5	1.00	1.00	1.02	1.04	1.08	1.12
μ	0.6	1.00	1.01	1.03	1.06	1.11	1.16
	0.7	1.00	1.01	1.04	1.09	1.16	1.23
	0.9	1.00	1.04	1.13	1.24	1.36	1.48

Second-order approximation

		σ					
		0	0.1	0.2	0.3	0.4	0.5
	0	1.00	1.00	1.00	1.00	1.00	1.00
	0.5	1.00	1.01	1.04	1.09	1.15	1.22
μ	0.6	1.00	1.01	1.06	1.12	1.21	1.30
	0.7	1.00	1.02	1.08	1.17	1.27	1.38
	0.9	1.00	1.07	1.16	1.25	1.31	1.37

Ratio of counterfactual job finding rate without structural unemployment to actual job finding rate, $\bar{p}'/\bar{p}$, as in equation (7). For calculations see appendix A.4

Figure 1

Four sources of structural unemployment

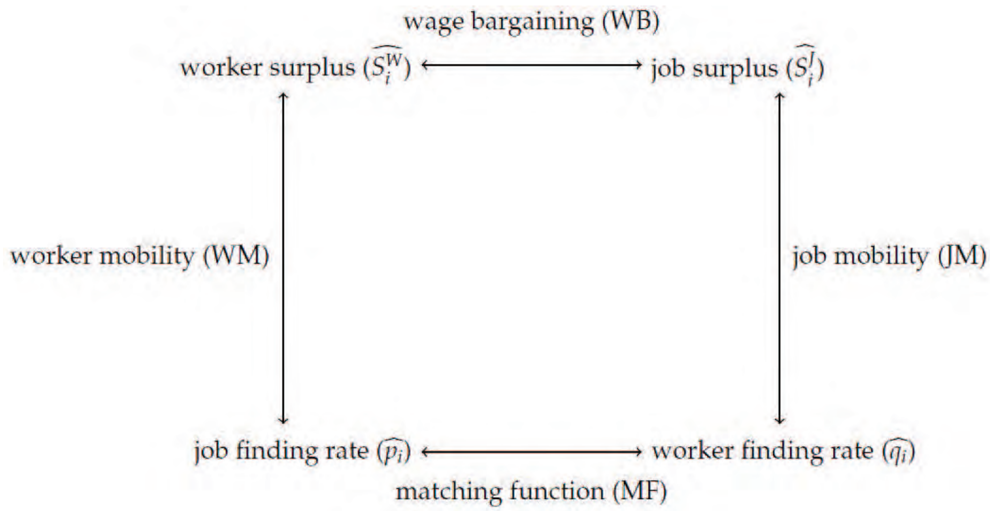
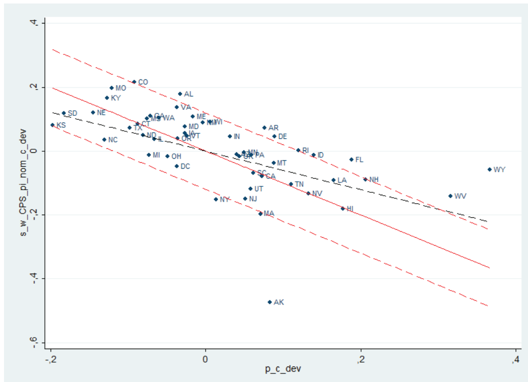
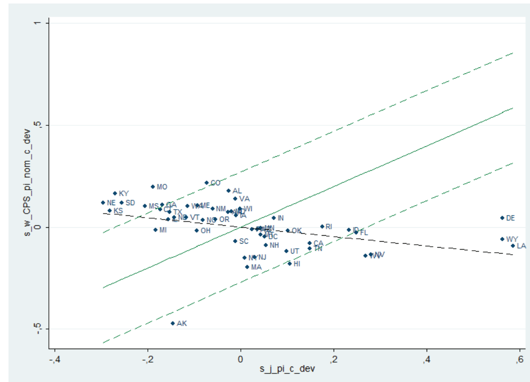


Figure 2

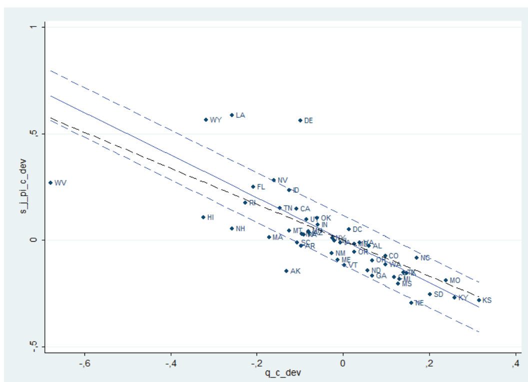
Worker mobility, job mobility and wage bargaining curves across US states



Worker mobility curve



Wage bargaining curve

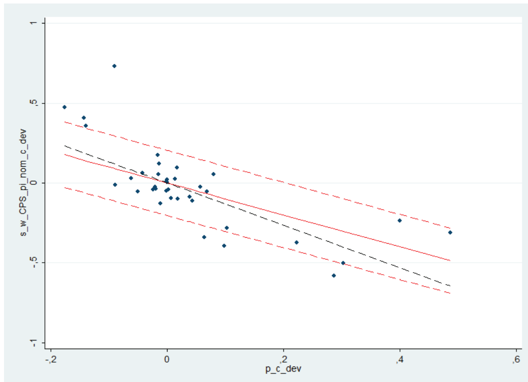


Job mobility curve

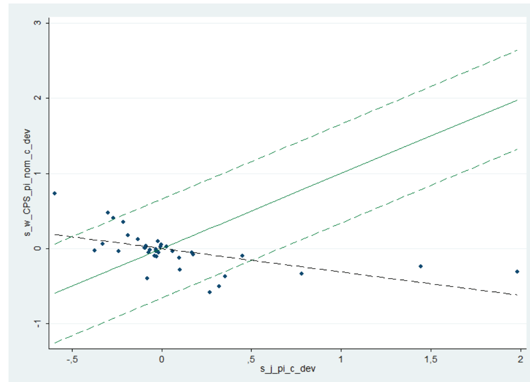
Dashed lines are one standard deviation away from the curve. Dotted lines represent regression lines. Data for year 2005.

Figure 3

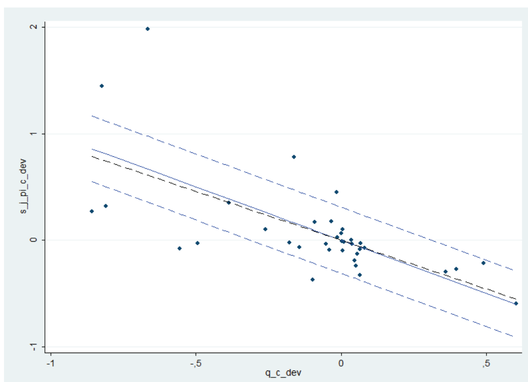
Worker mobility, job mobility and wage bargaining curves across industries



Worker mobility curve



Wage bargaining curve

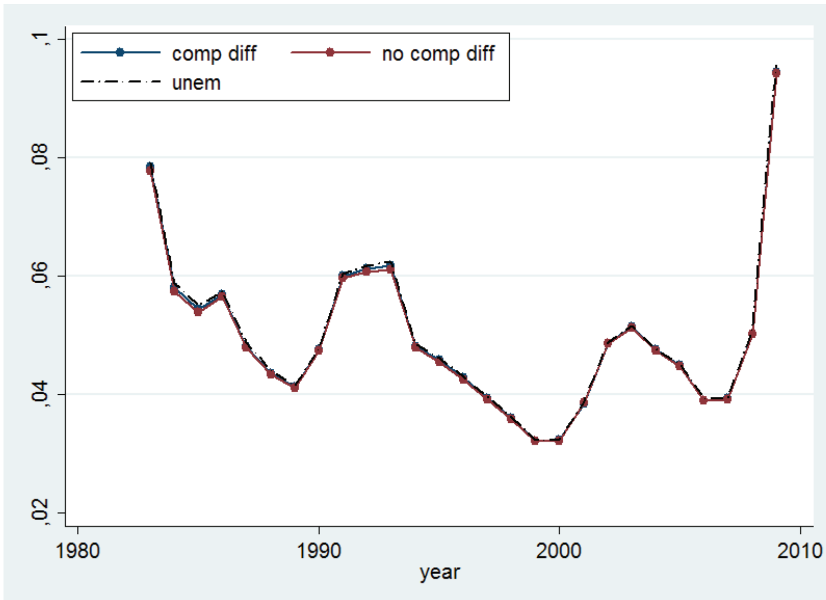


Job mobility curve

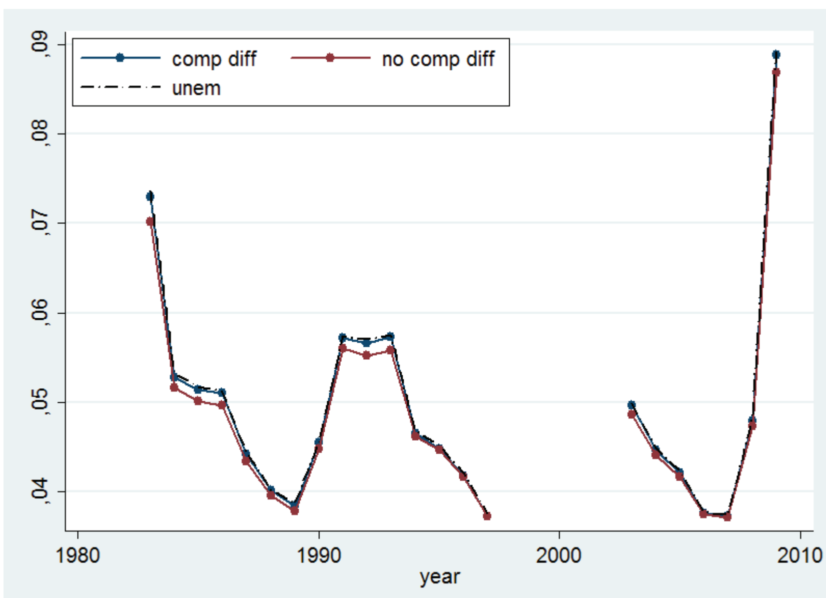
Dashed lines are one standard deviation away from the curve. Dotted lines represent regression lines. Data for year 2005.

Figure 4

Structural unemployment due to mismatch across US states and industries



Contribution mismatch across US states to unemployment

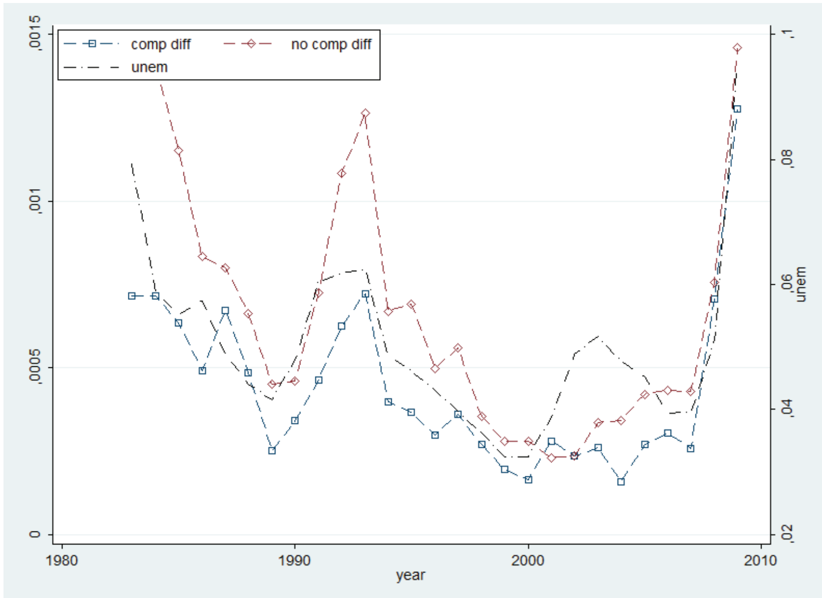


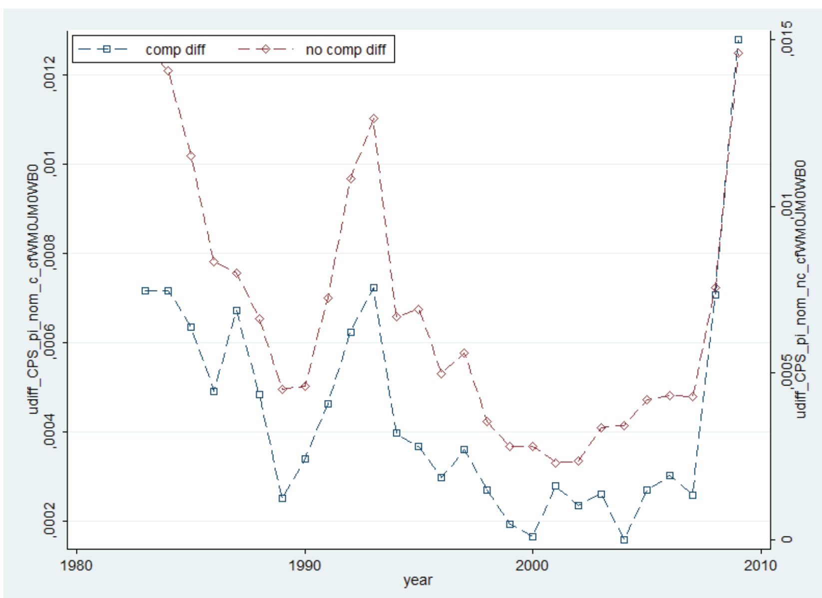
Contribution mismatch across industries to unemployment

The dashed line is the actual unemployment rate. The solid lines are counterfactual unemployment rates in the absence of dispersion in job finding rates. The labelled "no comp diff" is estimated without controlling for compensating differentials.

Figure 5

Cyclicality of structural unemployment across US states

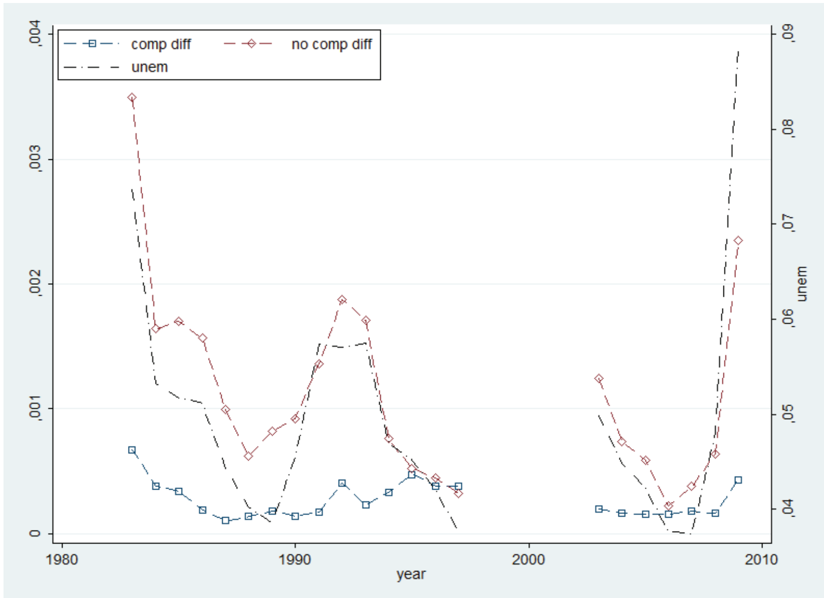


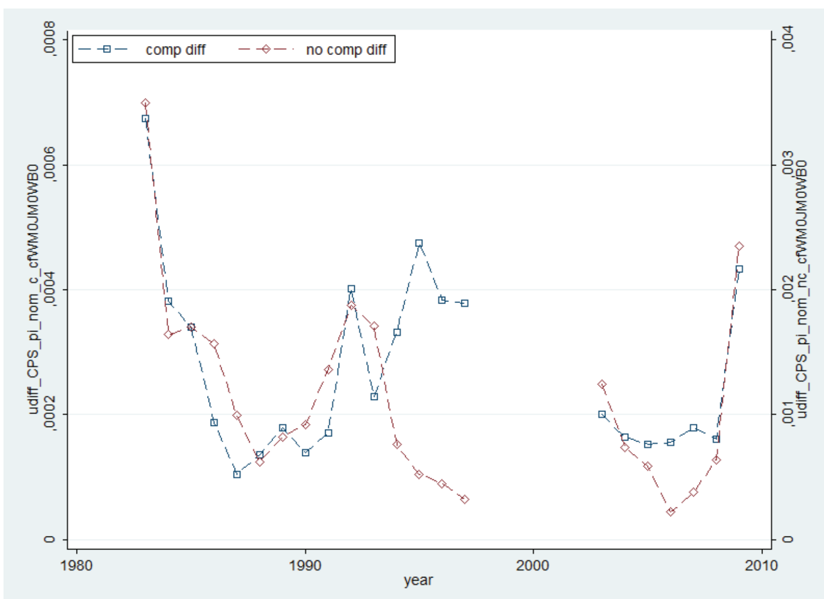


Structural unemployment due to mismatch across US states, calculated as actual unemployment minus the counterfactual unemployment rate in the absence of dispersion in job finding rates across states. The line labelled "no comp diff" shows structural unemployment without controlling for compensating differentials.

Figure 6

Cyclicality of structural unemployment across industries

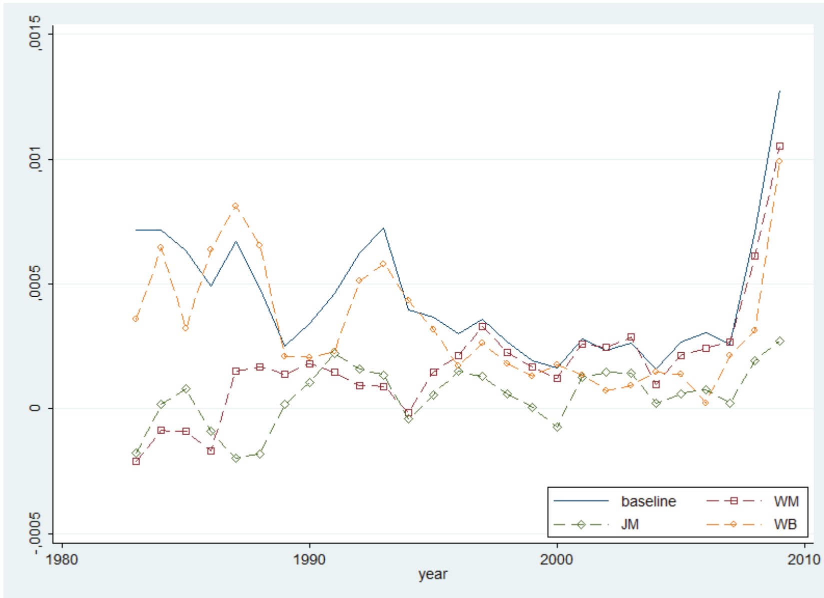




Structural unemployment due to mismatch across industries, calculated as actual unemployment minus the counterfactual unemployment rate in the absence of dispersion in job finding rates across industries. The line labelled "no comp diff" shows structural unemployment without controlling for compensating differentials.

Figure 7

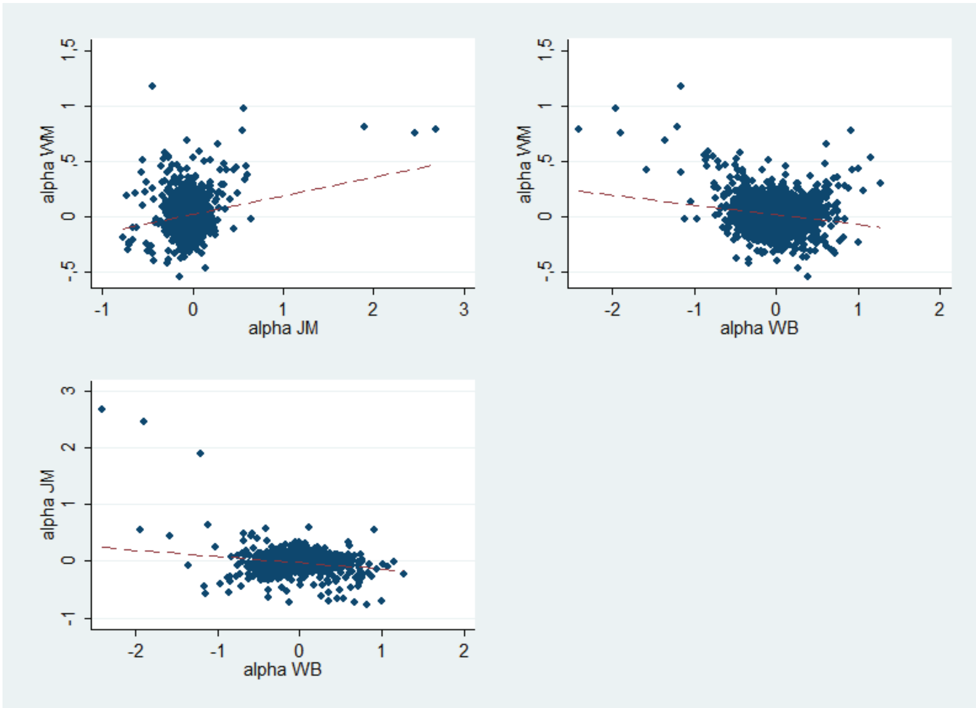
Sources of structural unemployment across US states



The solid line is our baseline estimate for structural unemployment, calculated as actual unemployment minus the counterfactual unemployment rate in the absence of dispersion in job finding rates across states. The other lines show the contribution of worker mobility costs (WM), job mobility costs (JM) and wage bargaining costs (WB).

Figure 8

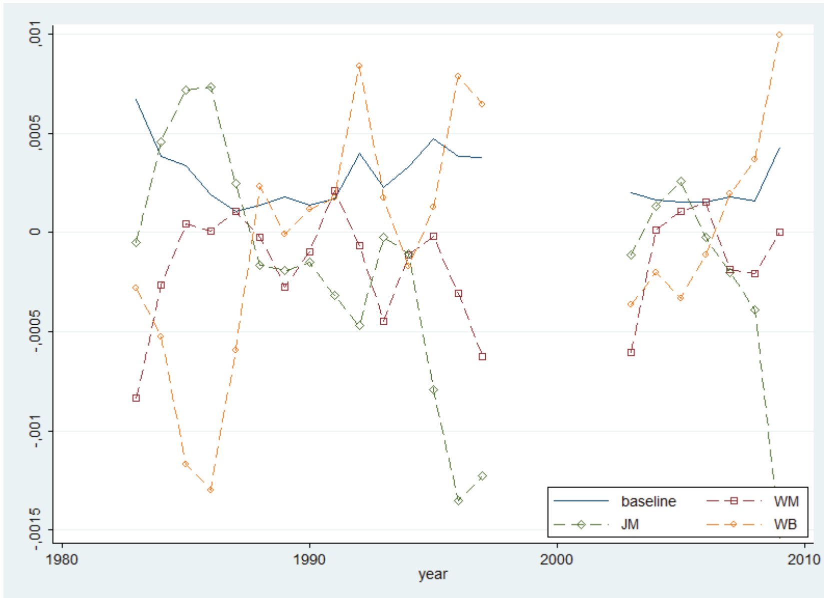
Adjustment costs across US states may reinforce of offset each other



Interactions between worker mobility costs, job mobility costs and wage bargaining costs across states. Pooled data for 1983-2009.

Figure 9

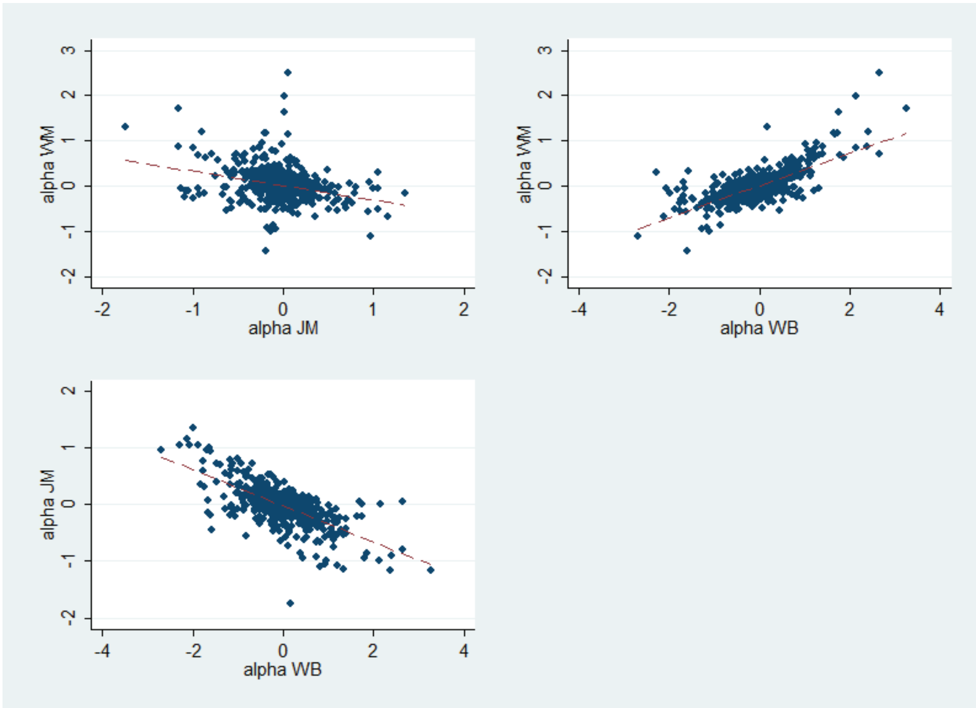
Sources of structural unemployment across industries



The solid line is our baseline estimate for structural unemployment, calculated as actual unemployment minus the counterfactual unemployment rate in the absence of dispersion in job finding rates across industries. The other lines show the contribution of worker mobility costs (WM), job mobility costs (JM) and wage bargaining costs (WB).

Figure 10

Adjustment costs across industries may reinforce of offset each other



Interactions between worker mobility costs, job mobility costs and wage bargaining costs across industries. Pooled data for 1983-2009.