Structural Unemployment

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There is an ongoing debate on whether the recent surge in unemployment in the US is due to cyclical or structural factors. The distinction is important because the policies required to reduce each type of unemployment are very different. We use a novel approach to empirically quantify the extent of structural unemployment and to shed light on its sources. We propose a simple model of a segmented labor market. Within each segment, search frictions generate unemployment. In addition, there is structural unemployment due to heterogeneity across segments. Four different types of adjustment costs give rise to structural unemployment: worker mobility costs, job mobility costs, wage setting frictions, and heterogeneity in matching efficiency. We construct data on job and worker surplus and job and worker finding rates and use them to estimate these adjustment costs and assess the contribution of each to unemployment. We find that, across US states, worker mobility costs are larger than job mobility costs. Across industries, mobility costs are very high for both workers and jobs. We then construct a time series for structural unemployment and its components. This helps us to understand the extent, to which unemployment is driven by structural factors in the current and past recessions.

Keywords: structural unemployment, heterogeneity, mismatch, worker mobility, job mobility, worker flows

JEL codes: E24 J6

Contents

1. Introduction

What role can monetary or fiscal stimulus policy play in reducing unemployment? The answer to this question depends crucially on the nature of unemployment. If unemployment is largely cyclical, driven by a lack of consumer demand for firms' products, then stabilization policy is effective. Several authors have suggested, however, that the recent surge in unemployment is at least partly structural in nature (Kocherlakota, 2010; Elsby et al., 2010; Barnichon and Figura, 2010).

Structural unemployment, as opposed to cyclical unemployment, is not due to an aggregate decline in productivity or lack of demand, but due to a mismatch between the availability of workers and the requirements of employers. This mismatch is caused by adjustment costs between sub-markets of the labor market. The distinction between these two types of unemployment is important, because structural unemployment cannot be solved using stabilization policy but requires active labor market policies. The distinction may also be important to understand changes in the nature of economic fluctuations, like the jobless recoveries, which have followed the most recent recessions (Groshen and Potter, 2003).

In this paper we aim to estimate the extent of structural unemployment and to quantify the underlying adjustment costs that cause structural unemployment. We consider a labor market that consists of multiple sub-markets or segments. Concretely, we think of the segmentation as being either geographical (US states) or by industry attachment. Within each segment, search frictions prevent the instantaneous matching of unemployed workers to vacant jobs. Frictional and cyclical unemployment result from these within-segment search frictions. Frictional unemployment is the unemployment rate that would persist if there were no differences across segments. Structural unemployment, on the other hand, is related to heterogeneity across segments and derives from frictions that prevent equalization of these differences.

The labor market within a segment 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. These four variables summarize all relevant information about the segment. In particular, we can use these variables to calculate the value to an unemployed worker and to a vacancy of searching in the segment.

Four adjustment processes introduce links between these four variables: worker mobility defines a relation between the job finding rate and workers' surplus; job mobility defines a relation between the worker finding rate and jobs' surplus; the wage adjustment process relates the jobs' and workers' surplus; the matching technology within a segment relates the worker and job finding rates. Figure 1 summarizes these relations.

$$\begin{tikzcd}[column sep=huge, row sep=huge]
\text{worker surplus } (\widehat{S_i^W}) \arrow[r, leftrightarrow, "\text{wage adjustment (NB)}"] \arrow[d, leftrightarrow, "\text{worker mobility (WM)}"'] & \text{job surplus } (\widehat{S_i^J}) \arrow[d, leftrightarrow, "\text{job mobility (JM)}"] \\
\text{job finding rate } (\widehat{p_i}) \arrow[r, leftrightarrow, "\text{matching function (MF)}"'] & \text{worker finding rate } (\widehat{q_i})
\end{tikzcd}$$

Figure 1: The four sources of structural unemployment and their relation to $\widehat{S_i^W}$, $\widehat{S_i^J}$, $\widehat{p_i}$, and $\widehat{q_i}$.

Frictions in any of the four adjustment mechanisms in Figure 1 increase unemployment above the level of frictional unemployment. We refer to this additional unemployment as structural. Thus, there are four sources of structural unemployment: worker mobility costs, job mobility costs, wage bargaining costs and heterogeneity in matching efficiency.

We estimate adjustment costs along these four margins and use our estimates to decompose unemployment into a frictional component (which includes cyclical unemployment) and four sources of structural unemployment. Out of the four possible sources of structural unemployment, we expect worker and job mobility costs to be the most important ones. In the current, preliminary, version of the paper, we have results only on those two adjustment costs. It is important to note that the decomposition of structural unemployment in its four components is not additive. For example, worker mobility costs only lead to more unemployment when there are also job mobility costs. The intuition is simple: if the workers cannot get to the jobs, but the jobs can get to the workers, we do not expect a lot of structural unemployment.

Our method to estimate adjustment costs in worker and job mobility is based on the idea of factor price equalization. Unemployed workers and vacancies are the input factors in job creation. We argue that in the absence of adjustment costs, worker mobility equalizes the value of being unemployed, and job mobility equalizes the value of a vacancy across segments of the labor market. Equalization of the value of being unemployed implies a negative relation between workers' surplus and the job finding rate, and therefore a negative relation between total match surplus and local labor market tightness. Equalization of the value of a vacancy implies a negative relation between firms' surplus and the worker finding rate, and therefore a positive relation between total match surplus and local labor market tightness. We interpret observed deviations from these relations in the data as evidence for worker and job mobility costs, which gives us an estimate of how large these costs are.

Data on the job and worker finding rates and workers' and firms' surplus from a match, which characterize each segment of the labor market, are not readily available. We construct these variables using data from the Current Population Survey (CPS) and from the Bureau of Economic Analysis (BEA). 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 characteristics when constructing our estimates. At the moment, our controls are rather crude: we construct all our estimates separately for four education cells (drop-outs, high-school, some college, and college or more) and then use re-weighted means of these cells. We are working on new results, using a richer set of controls for heterogeneity using not only education, but also other observable worker characteristics.

The preliminary results indicate that geographic mobility (across US states) is larger for jobs than for workers, but that neither jobs nor workers are mobile across industries. Estimates of mobility costs across states lines up well with geographic distances, giving us some confidence in the estimates. However, estimates overall seem too large. Possibly this is due to our poor controls for worker heterogeneity. By allowing for only four different worker types we probably only capture a minor part of the inter-segment differences in worker characteristics. That is, a substantial part of the variation in the surplus of having a job (think of this as wages) across local labor markets might be driven by differences in the worker composition, and not by barriers to mobility.

Our estimates of worker and job mobility costs can be used to answer the question what part of unemployment is due to structural factors. The model provides this mapping. Our identification strategy is purely cross-sectional and relies only on differences across different segments of the labor market at the same point in time. Therefore, we can do this exercise in all time periods for which data are available, generating a quarterly time series for structural unemployment. We are currently working on this. In this preliminary version of the paper, all results are based on an industry- and a state-cross-section that are constructed by pooling data from 2004 to 2007.

Using our time series for structural unemployment, we can test whether the fraction of unemployment that is structural increases in recessions. Such an exercise is especially interesting concerning the Great Recession of 2007. For example, Kocherlakota (2010) claims that the increase in unemployment in the current recession, unlike previous recessions, is mostly structural. Although his hypothesis was widely discussed among economists,[1] there is a lack of quantitative evidence. We provide such evidence. In addition, we go a step further and decompose structural unemployment in four components, driven by each of its four sources. This decomposition is important for prescriptions about where to focus policies to reduce structural unemployment.

Although recently there has been a revived interest in mismatch (Shimer, 2007; Alvarez and Shimer, 2011), there is little empirical work on the topic.[2] The few empirical studies that have been done, focus on shifts in the Beveridge curve (Barnichon and Figura, 2010; Blanchard and Diamond, 1989; Abraham, 1987; Lipsey, 1965). The paper that is most related to ours is Sahin et al. (2010). Sahin et al. (2010) use data on unemployment and vacancies to construct indices of structural unemployment. We see our work as complementary. The main difference in our approaches is that we use data on prices rather than quantities, as Sahin et al. (2010) do. Because of this, we have better data available and can construct longer time series for the United States. Moreover, we progress with respect to Sahin et al. (2010) by exploring the sources of structural unemployment.

This paper is organized as follows. In the next section we present an empirical model of mismatch and we show that structural unemployment is driven by four different kinds of adjustment costs. In section 3 we explain in detail how we construct the empirical counterparts of the variables that define a local labor market in our model. In section 4 we present the results.

2. An Empirical Model of Mismatch

The economy is segmented into N labor markets. There are at least two ways to think about the segmentation of the labor market. Firstly, in terms of geography: each labor market might represent a particular geographic location. Secondly, with regard to human capital: there might be different labor markets for different skills, occupations, or industries. In the first case, moving across segments actually means physically moving from one location to another. In the second case, it means to change ones skill-set or industry-affiliation.

Unemployed workers (looking for vacant jobs) and vacant jobs (looking for unemployed workers) are distributed across these labor markets. Mismatch takes place when unem-

[1] Krugman (2010); DeLong (2010)

[2] Older studies include work by Phelps (1994).

ployed and vacancies cannot match because they are searching in different labor markets. Because there is no matching, mismatch gives rise to unemployment. We refer to unemployment that is caused by mismatch as structural unemployment. Structural unemployment comes from heterogeneity and in that sense differs from cyclical or frictional unemployment, which are caused by aggregate conditions.

In the model, structural unemployment is due to mobility costs of workers and/or vacancies across segments of the labor market. To be more specific, mismatch can result from four different sources: lack of worker mobility, lack of job mobility, or from differences in matching efficiency or in the division of match surplus across segments. In the following, we describe these potential sources of mismatch in detail.

2.1. Worker Mobility

A worker is either employed or unemployed. If unemployed, he has to decide in which labor-market to look for a job. The probability to find a job in labor market i is denoted by p_i. That is, we explicitly allow for the likelihood to find a job to differ across labor markets. Unemployed workers receive an unemployment benefit b in each period. A crucial assumption we make is that the unemployment benefit does not depend on the market in which the worker was employed before or in which he is currently looking for a job.

If a worker is employed in labor market i, the surplus he receives from having a job is denoted by S_i^W. This surplus depends on a number of factors, among which are the wage and separation rate in sector i. We discuss in more detail how we measure the surplus in section 3. Again, we explicitly allow the surplus to differ across labor markets. The per-period value of looking for a job in labor market i given discount rate r is then

$$rU_i^W = b + p_i S_i^W \tag{1}$$

Under the assumption that there are no barriers to the mobility of workers it must hold that the per-period value of looking for a job is the same in all labor markets. That is, there are no arbitrage possibilities.

$$U_i^W = U_j^W \equiv \overline{U^W} \tag{2}$$

It follows

$$p_i S_i^W = r\overline{U^W} - b \tag{3}$$

Taking logs, we get

$$\widehat{S_i^W} = -\widehat{p_i} \tag{4}$$

where variables with hats denote deviations from their economy-wide mean. Notice that this equation is exact, not an approximation.

We refer to equation 4 as the **worker mobility curve (WM)**. The intuition is straightforward: the surplus of having a job in a specific labor market and the probability to find a job in this market are inversely related. If in one labor market employed workers have a higher surplus (e.g., due to higher wages) then – if there are no barriers to mobility – this advantage has to be compensated by a lower job-finding probability in this market.

Worker Mobility Costs

Assume now that workers have to pay a cost α^W to switch between labor markets segments. This implies that the difference in the per-period value of looking for a job in any pair of two sectors has to be smaller than α^W. If the difference would be bigger, the worker would switch to the labor market with the higher per-period value.

$$-\alpha^W < rU_i^W - rU_j^W < \alpha^W \qquad \text{for all } i, j \tag{5}$$

If the per-period value of looking for a job is symmetrically distributed around the economy-wide mean, this implies

$$-\frac{\alpha^W}{2} < rU_i^W - r\overline{U^W} < \frac{\alpha^W}{2} \qquad \text{for all } i \tag{6}$$

Remember that the per-period value of looking for a job in sector i can be written as $rU_i = b + p_i S_i^W$. Therefore,

$$-\frac{\alpha^W}{2} < p_i S_i^W - \overline{pS^W} < \frac{\alpha^W}{2} \qquad \text{for all } i \tag{7}$$

We can rewrite the variables as deviations from the mean.

$$-\widehat{p_i} - \frac{\alpha^W}{2\overline{pS^W}} < \widehat{S_i^W} < -\widehat{p_i} + \frac{\alpha^W}{2\overline{pS^W}} \qquad \text{for all } i \tag{8}$$

That is, if there are adjustment costs to worker mobility, the $(S^i, \widehat{\theta_i})$ pairs characterizing labor market segments will no longer going lie exactly on the WM curve but will be scattered around the curve. By measuring the extent of dispersion we can infer the worker mobility cost α^W, see Figure 2.

2.2. Job Mobility

A job is either filled or vacant. If vacant, there is a per-period cost k of having an open vacancy. We assume that this cost is the same for all labor markets. A firm with a vacancy has to decide in which labor market segment to search for a worker. The probability to find a worker in labor market i is denoted by q_i. As in the worker case, we explicitly allow for this likelihood to differ across labor markets.

If a job is filled in labor market i, the surplus from this job is denoted by S_i^J. This surplus is determined by several factors, including profits per employee and the separation rate in the labor market segment where the job exists. We discuss in detail how we measure job surplus in section 3. Again, we explicitly allow the surplus to differ across labor markets. The per-period value of having a vacancy in labor market i is therefore given by

$$rU_i^J = -k + q_i S_i^J \tag{9}$$

As in the worker case, under the assumption that there are no barriers to the mobility of jobs it must hold that the per-period value of a vacant job is the same in all labor markets.

$$U_i^J = U_j^J \equiv \overline{U^J} \tag{10}$$

It follows

$$q_i S_i^J = r\overline{U^J} + k \tag{11}$$

and, taking logs,

$$\widehat{S_i^J} = -\widehat{q_i} \tag{12}$$

We refer to equation 12 as the **job mobility curve (JM)**. The intuition is the same as for the worker mobility curve: the higher surplus of a filled job is in a labor market, then – under perfect mobility – the more difficult it must be to fill a job in this labor market.

Job Mobility Costs

We assume that there is a cost α^J for vacant jobs to switch labor markets. As in the worker case, we can write

$$-\widehat{q}_i - \frac{\alpha^J}{2p\overline{S^J}} < \widehat{S}^J_i < -\widehat{q}_i + \frac{\alpha^J}{2p\overline{S^J}} \qquad \text{for all } i. \tag{13}$$

Again, the higher the dispersion around the job mobility curve, the higher the barriers to mobility of vacant jobs, α^J, see Figure 2.

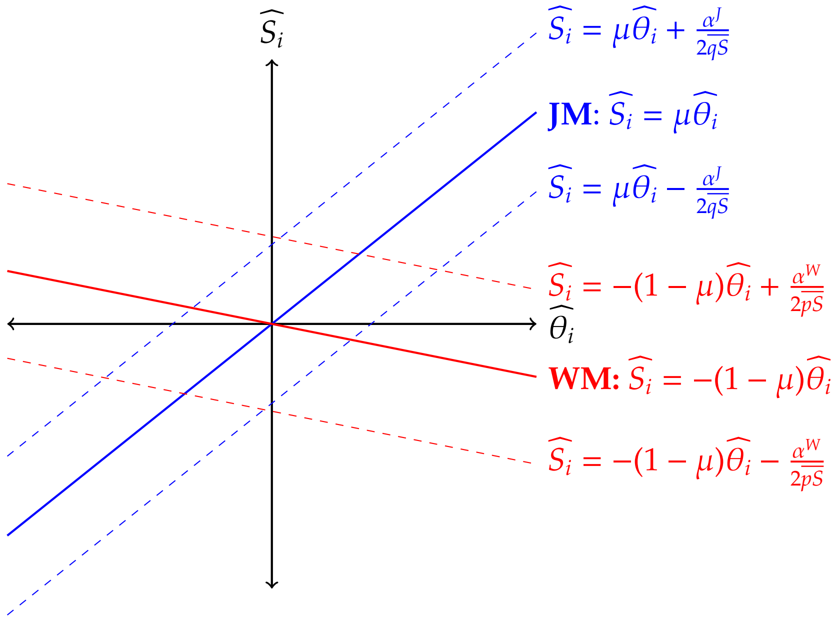

Figure 2: JM and WM curves with mobility cost bands (dashed lines)

2.3. Matching Function

The relation between the job finding probability p_i and the worker finding probability q_i is described by the matching function. Under a matching technology with constant returns to scale, both finding rates are functions of labor market tightness θ_i, the ratio of vacancies to unemployed workers in market i. Following most of the literature, we assume a matching function of the Cobb-Douglas form as a starting point. This assumption allows us to explicitly express p_i and q_i as a function of θ_i.

The number of matches that is produced in labor market i is given by

$$m_i = B_i u_i^{\mu} v_i^{1-\mu} \tag{14}$$

where v_i and u_i denote the number of vacancies and unemployed, respectively, μ is an elasticity and B_i a parameter reflecting the matching efficiency. We assume that μ is constant but matching efficiency B_i may vary across labor market segments. Using equation 14, we can express the job finding and worker finding probabilities as a function of the labor market tightness $\theta_i = \frac{v_i}{u_i}$

$$p_i = \frac{m_i}{u_i} = B_i\theta_i^{1-\mu} \Rightarrow \widehat{p_i} = (1-\mu)\widehat{\theta_i} + \hat{B}_i \tag{15}$$

$$q_i = \frac{m_i}{v_i} = B_i\theta_i^{-\mu} \Rightarrow \widehat{q_i} = -\mu\widehat{\theta_i} + \hat{B}_i \tag{16}$$

Combining equations 15 and 16, we get a relation between $\widehat{p_i}$ and $\widehat{q_i}$.

$$\mu\widehat{p_i} = -(1-\mu)\,\widehat{q_i} + \hat{B}_i \tag{17}$$

If the matching function is the same in in all labor market segments, job and worker finding probability must be inversely log-linearly related. In this case, equation 17 simplifies to

$$\mu\widehat{p_i} = -(1-\mu)\,\widehat{q_i} \tag{18}$$

We refer to equation 18 as the **matching functions curve (MF)**. The intuition is that if matching efficiency is the same in all labor market segments, aggregate matching efficiency is highest and therefore unemployment lowest, everything else equal.

Matching Function Heterogeneity

If the matching function varies across labor market segments, the MF curve does not hold exactly. Analogous to the expressions for worker and job mobility costs, we can represent deviations from the MF curve as an adjustment cost.

$$-(1-\mu)\,\widehat{q_i} - \frac{\alpha^M}{2} < \mu\widehat{p_i} < -(1-\mu)\,\widehat{q_i} + \frac{\alpha^M}{2} \tag{19}$$

Here, α^M represents the difference in matching efficiency between the labor market segments with the highest and lowest efficiency.

2.4. Wage Adjustment

The final relation that closes the model is between the surplus of a match to workers S_i^W and firms S_i^J. This relation is determined by our assumption on how match surplus is divided among the two parties. Since the wage is the instrument that is used to divide match surplus, this is an assumption on wage determination. A common assumption in the search and matching literature is generalized Nash bargaining. Under this assumption, total surplus S_i is shared according to a fixed proportion ϕ, often referred to as workers' bargaining power.

$$\frac{S_i^W}{\phi} = \frac{S_i^J}{1-\phi} = S_i \Rightarrow \widehat{S_i^W} = \widehat{S_i^J} = \widehat{S_i} \tag{20}$$

We refer to this relation as the **Nash bargaining curve (NB)**. The intuiton for this relation is that both worker and job surplus are proportional to the total surplus if the bargaining power parameter is the same across labor market segments.

Wage Adjustment Costs

Assume now that workers and firms would agree on the generalized Nash bargaining wage if they bargain, but there is a cost α^B attached to wage bargaining. Then, the surplus is only renegotiated if the payoff of doing so exceeds α^B.

$$-\alpha^B < \frac{S_i^W}{\phi} - \frac{S_i^J}{1-\phi} < \alpha^B \tag{21}$$

Assuming NB holds exactly for the economy-wide average surpluses to workers and firms, we can write

$$\widehat{S_i^J} - \frac{\alpha^B}{\bar{S}} < \widehat{S_i^W} < \widehat{S_i^J} + \frac{\alpha^B}{\bar{S}} \tag{22}$$

Figure 3 shows the Nash bargaining curve with the bargaining cost-bands. As in the worker and job mobility case, we can infer the bargaining costs α^B by measuring the dispersion in the relation between $\widehat{S_i^J}$ and $\widehat{S_i^W}$.

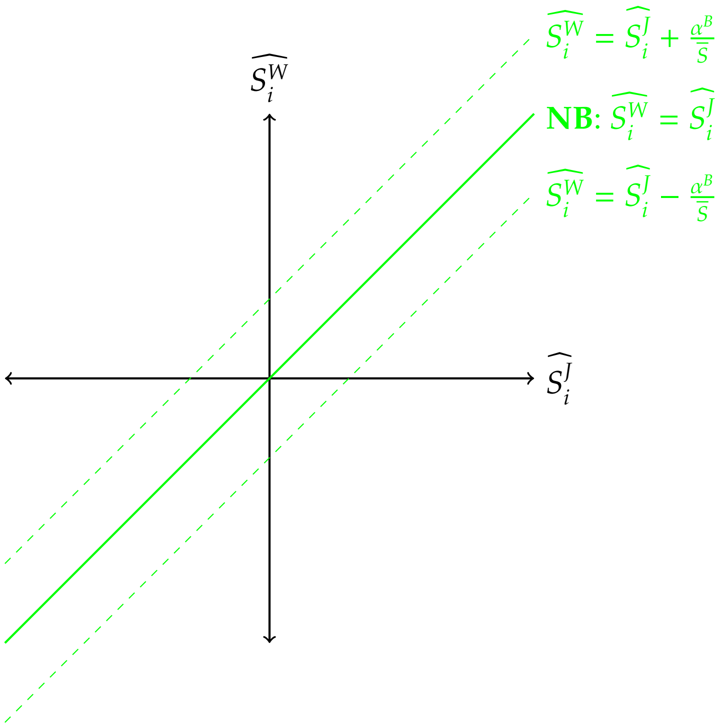

Figure 3: NB curve with bargaining cost bands (dashed lines)

2.5. Structural Unemployment

As described above, in our model there are four potential sources of structural unemployment: deviations from the WM, JM, MF, and NB curve. The relation between these curves and the objects $\widehat{S_i^J}$, $\widehat{S_i^W}$, $\widehat{p_i}$, and $\widehat{q_i}$ is summarized in Figure 1. In the following, the focus of our analysis will be on deviations from the WM and JM curve. We assume that the MF curve holds exactly. This allows us to write the WM and JM curves in terms of labor market tightness θ_i. However, because the empirical support for Nash bargaining is weak, we do not assume the NB curve holds and work with $\widehat{S_i^J}$ and $\widehat{S_i^W}$, which we can measure separately, rather than with total match surplus $\widehat{S_i}$. Thus, the worker and job mobility curves we work with, are the following.

$$\widehat{S_i^W} = -(1-\mu)\widehat{\theta_i} \tag{23}$$

$$\widehat{S_i^J} = \mu\widehat{\theta_i} \tag{24}$$

These two curves are shown in Figures 4 and 5.

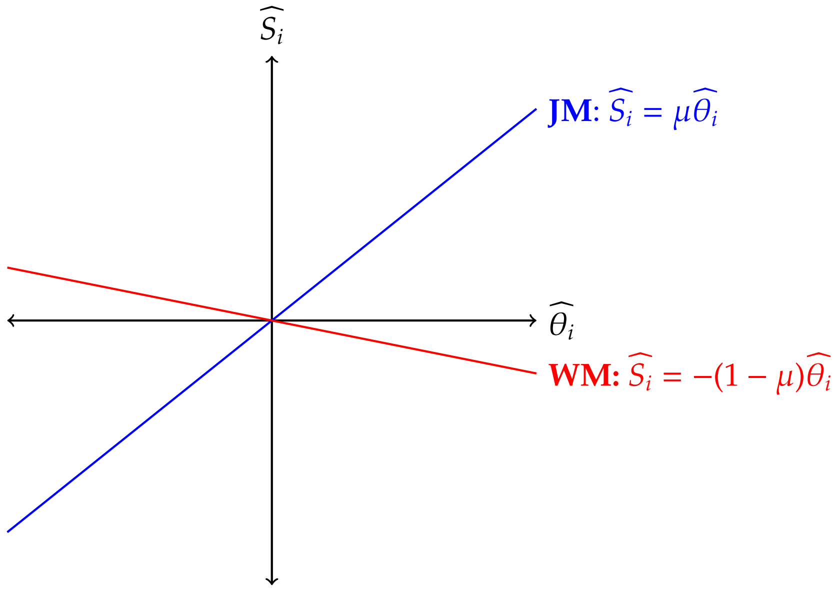

Figure 4: Job mobility (JM) and worker mobility (WM) curves

If jobs are mobile and workers are not, our model predicts a positive relation between match surplus and labor market tightness across labor market segments. If workers are mobile and jobs are not, we would expect a negative relation. Given data on surplus and tightness, we could now empirically explore – under the assumptions of our model – whether jobs or workers are mobile. In the case of perfect worker mobility, all data-points should lie on the downward sloping WM curve. In the case of perfect job mobility, all data-points should lie on the upward sloping JM curve. Note that in the case of joint perfect mobility of workers *and* jobs – the case that is implicitly assumed in the standard search model – all data-points should lie on the intersection of the WM and JM curves in Figure 4.

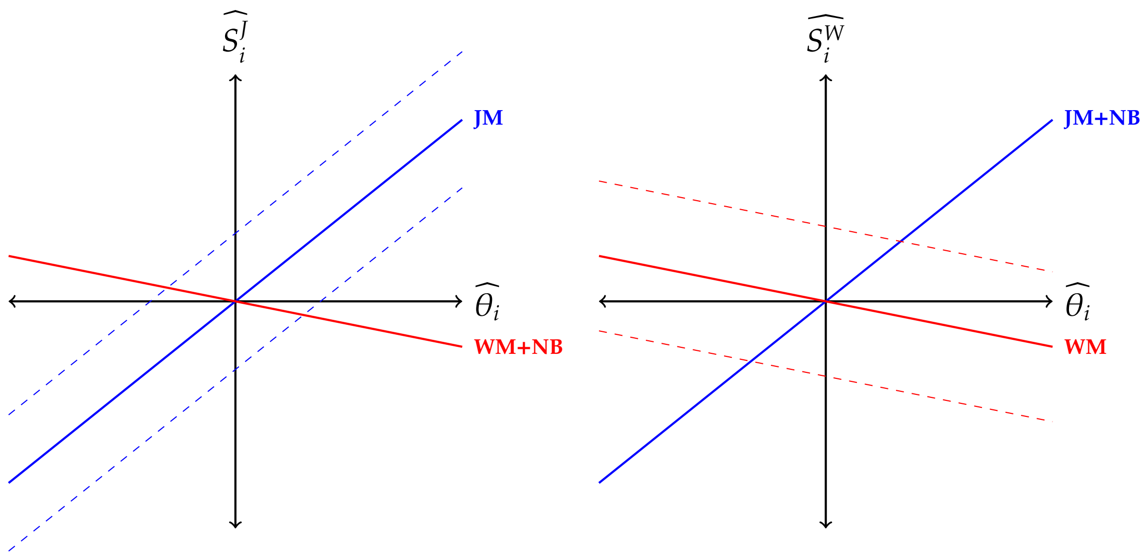

Figure 5: Job mobility curve (left) and wage mobility curve (right) without assuming Nash bargaining

Since we are not willing to assume wages are set through generalized Nash bargaining, we have to show the JM and WM curves in different coordinate systems, as in Figure 5. In the graph with $\widehat{S_i^J}$ on the Y-axis the interpretation of the WM curve is now slightly different. $\left(\widehat{S_i^J}, \widehat{\theta_i}\right)$ pairs should lie on this curve if the *joint* hypothesis of worker mobility and Nash bargaining $\left(\widehat{S_i^J} = \widehat{S_i^W}\right)$ holds. Along the same lines, in the right graph with $\widehat{S_i^W}$ on the Y-axis, the $\left(\widehat{S_i^J}, \widehat{\theta_i}\right)$ pairs should lie on the JM curve if the *joint* hypothesis of job mobility and Nash bargaining holds.

In the data, we observe deviations from the WM and JM curves, which we interpret as evidence for worker and job mobility costs as explained above. By measuring these deviations, we obtain estimates of the mobility costs. We then use those estimates to explore what part of unemployment is due to adjustment costs in worker and job mobility.

The mapping from mobility costs to unemployment is not immediate and we need to make additional assumptions on the initial dispersion in labor market tightness and match surplus across segments of the labor market. To see why, imagine that mobility costs are very large, but tightness and match surplus happen to be identical across segments of the labor market. In this case, the mobility costs are irrelevant, because neither workers nor jobs would move even in the absence of these costs. To circumvent this problem, we assume that idiosyncratic shocks are large enough, so that there is at least one segment of the labor market, for which there is an incentive for unemployed workers to leave and for firms to bring in more vacancies, and at least one other segment, for which there is an incentive for workers to move into and for firms to remove vacancies from. If we further assume that the dispersion of match surplus is sufficiently small across labor market segments, then we can show that the only thing that matters for dispersion in labor market tightness, and therefore for unemployment, is the smallest of the two mobility costs. Although the assumptions we need to show this result are somewhat restrictive, the result is likely to hold approximately in much more general cases.

The finding that, by and large, only the smaller of the two mobility costs matters for unemployment is intuitive. The fact that workers cannot move to where the jobs are is not a problem if the jobs can move to where the workers are. It is worth noting, however, that the result is only true for sufficiently large mobility costs. If jobs are perfectly mobile, but workers face mobility costs, there will still be a (small) amount of structural unemployment. The same is true if workers are perfectly mobile but firms find it costly to move vacancies.

3. Data and Measurement

To test the relations that we derived in the previous section, we need empirical counterparts of worker surplus S_i^W, job surplus S_i^W, the job-finding rate p_i, and the worker-finding rate q_i. In this section, we first explain how we construct these objects and then describe the data sources we use.

3.1. Worker Surplus

At time t, the worker surplus $S_{it}^W = W_{it} - U_{it}^W$ is the difference between the payoff from having a job in market i minus the payoff of looking for a job in market i. We assume that the job finding rate p_i and separation rate λ_i are not time-dependent. Then,

$$(1+r)W_{it} = w_{it} + \lambda_i \mathbb{E}_t U_{it+1}^W + (1-\lambda_i)\mathbb{E}_t W_{it+1} \tag{25}$$

$$(1+r)U_{it}^W = b + p_i \mathbb{E}_t W_{it+1} + (1-p_i)\mathbb{E}_t U_{it+1}^W \tag{26}$$

where w_i is the wage in segment i. Substracting the second equation from the first gives

$$(1+r)\underbrace{(W_{it} - U_{it})}_{S_{it}^W} = w_{it} - b + (1-\lambda_i - p_{it})\mathbb{E}_t\underbrace{[W_{it+1} - U_{it+1}]}_{S_{it+1}^W} \tag{27}$$

Solve forward

$$S_{it}^W = \frac{1}{1-\lambda_i - p_i}\sum_{\tau=1}^{\infty}\left(\frac{1-\lambda_i-p_i}{1+r}\right)^{\tau}\mathbb{E}_t\left(w_{it+\tau} - b\right) \tag{28}$$

and assume $E_t\left[w_{it+1}\right] = w_{it} \equiv w_i$. This implies

$$S_{it}^W = \frac{w_i - b}{r + \lambda_i + p_i} \tag{29}$$

The higher the wage in a labor market, the higher is the surplus of having a job in that market. Moreover, the more likely it is to lose that job in the future – that is, the higher is λ_i – the lower is the surplus. Also, the easier it is for an unemployed person in this market to find a job – the higher p_i – the smaller is the advantage of already having a job. Therefore, S_{it}^W is inversely related to p_i.

The expression for worker surplus is derived under the assumption that all workers are identical. When constructing the data, we therefore have to take care of the heterogeneity of workers in the real world by controlling for as many worker characteristics as possible. For example, wages in one labor market might be higher than in another because the average worker has a higher education. We try to control for these compositional effects by calculating $\widehat{\theta_i}$ and S_i^W for four different education groups (drop-outs, high-school, some college, college or more) and then using re-weighted estimates.

3.2. Job Surplus

At time t, the surplus of having a job filled $S_{it}^J = J_{it} - U_{it}^J$ is the difference between the payoff from having a job filled minus the payoff of having a vacant job. We assume that the worker finding rate q_i and separation rate λ_i are not time-dependent. Then,

$$(1+r)J_{it} = y_{it} - w_{it} + \lambda_i \mathbb{E}_t U_{it+1}^J + (1-\lambda_i)\mathbb{E}_t J_{it+1} \tag{30}$$

$$(1+r)U_{it}^J = -k + q_i \mathbb{E}_t J_{it+1} + (1-q_i)\mathbb{E}_t U_{it+1}^J \tag{31}$$

where $y_{it} - w_{it}$ is the the market-specific profit per employee. Substracting gives

$$(1+r)\underbrace{(J_{it} - U_{it}^J)}_{S_{it}^J} = y_{it} - w_{it} + k + (1-\lambda_i - q_{it})\mathbb{E}_t \underbrace{\left[J_{it+1} - U_{it+1}^J\right]}_{S_{it+1}^J} \tag{32}$$

Solve forward

$$S_{it}^W = \frac{1}{1-\lambda_i - q_i} \sum_{\tau=1}^{\infty} \left(\frac{1-\lambda_i - q_i}{1+r}\right)^{\tau} \mathbb{E}_t \left(y_{it+\tau} - w_{it+\tau} + k\right) \tag{33}$$

and assume $E_t\left[y_{it+1} - w_{it+1}\right] = y_{it} - w_{it} \equiv y_i - w_i$. This implies the following expression for job surplus

$$S_{it}^J = \frac{y_i - w_i + k}{r + \lambda_i + q_i} \tag{34}$$

We again need to control for heterogeneity when constructing the measure of job surplus from the data. Unfortunately, the lack of firm-level data makes this difficult, because the marginal profit of a new employee $y_i - w_i$ is an essential part of the job surplus. For the moment, we assume that the effect of education on the revenue y_i is proportional to the effect of education on the wage w_i, which we can measure. As in the case of worker surplus, we differentiate four different education groups and then use re-weighted estimates.

3.3. Labor Market Tightness

As mentioned above, we assume throughout the paper that the MF curve holds.[3] We can therefore derive an estimate of the labor market tightness θ_i as a function of p_i, which can be estimated from the Current Population Survey (CPS). Details on the sample are explained in section 3.4 below.

$$p_i = \frac{m_i}{u_i} = B\left(\frac{v_i}{u_i}\right)^{1-\mu} = B\theta_i^{1-\mu} \tag{35}$$

and therefore

$$\theta_i = \left(\frac{p_i}{B}\right)^{\frac{1}{1-\mu}} \tag{36}$$

When constructing labor market tightness from the data, we control for heterogeneity in the same way as we did for worker surplus.

3.4. Data Sources

To construct cross-sectional data on S_i^W, S_i^J and θ_i we need estimates of finding rates p_i, separation rates λ_i, wages w_i, and profits per employee $y_i - w_i$. We estimate p_i and λ_i using the basic monthly data from the Current Population Survey (CPS). Data on wages and profits come from the Bureau of Economic Analysis (BEA). We construct two cross-sections: one industry-cross-section and one state-cross-section. We pool data from 2004 to 2007. The data is based on men only. Moreover, for the industry-cross-section we drop “Agriculture”, “Mining”, “Utilities”, “Real estate and rental and leasing” because profits-per-employee are extremely large in these industries.

Finally, we need to assume values for some of the structural parameters in the model: the elasticity of the matching function μ, the unemployment benefit b, and the discount rate r. In our baseline specification we set $\mu = 0.75$. The unemployment benefit b is set to 60% of the wage in a labor market (Mortensen and Nagypal, 2007). Based on a yearly discount factor of 0.953 we set $r = 0.00402$. The per-period cost of a vacancy k and the efficiency parameter of the matching function B do quantitatively not matter for the results.

[3] In a future version of the paper we also want to empirically test the validity of the MF curve. However, for this we do not only need data on p_i but also on the worker-finding rate q_i. Data on q_i is in principle available from the Job Openings and Labor Turnover Survey (JOLTS). Unfortunately, disaggregated JOLTS data by region and industry is confidential and only available from year 2000 on. Therefore, due to the present lack of data on q_i, we do not have the possibility to empirically test the MF curve at this point in time.

4. Results

The basic idea of the empirical exercise in this paper is that – if there are no barriers to mobility – a worker's payoff of looking for a job in one sector cannot be higher than in any other sector. Technically speaking, the value $p_i S_i^W$ should not differ across labor markets. The same should hold for firms, that is, $q_i S_i^J$ should be the same across labor markets.

Of course, with real-world data we do not expect this to hold. Most likely there are some barriers to mobility for both workers and jobs. If a labor market is defined as an industry, we would expect that barriers to mobility for a worker should be highest across industries that differ substantially concerning their skill-requirements or their occupational composition.

Table 2 shows the 5 industry-pairs with the highest and the lowest difference in $p_i S_i^W$. The first 5 industry pairs should therefore be very different in their skill-requirements, whereas the last 5 should be quite similar. Table 3 shows the same exercise, but now labor markets are defined as states. The advantage of using state-data is that there is a good proxy for barriers to mobility across states: the distance between states. We see that the mean distance between the 5 state-pairs with the highest difference in the value of looking for a job is substantially higher than the mean distance between the 5 state-pairs with the lowest difference in $p_i S_i^W$. We take this as preliminary evidence to support our approach.

4.1. Worker and Job Mobility Costs

The WM and JM curves together with the actual observations for the state- and industry-cross-section are shown in Figure 6. The mobility-cost-bands (the dashed lines) are chosen in such a way that 90% of the observations lie within the bounds. It is apparent that the bands are much tighter in the two graphs on the right-hand side. That is, a first result is that both workers and jobs are substantially more mobile across states than across industries.

Estimates of the mobility costs are shown in Table 1. For workers, the numbers are estimates of $\frac{\alpha^W}{pS^W}$. That is, the mobility costs are expressed relatively to the option value of looking for a job in the "average" industry or state. Along the same lines, for jobs the numbers are estimates of $\frac{\alpha^J}{qS^J}$. It is apparent that the numbers are very large, i.e., mobility in general is very low.[4] The column $\frac{\textit{industries}}{\textit{states}}$ shows the relative mobility costs across industries and across states. As mentioned above, workers and jobs are more mobile geographically than across industries. However, this difference is much more pronounced for jobs than

[4] This may be because we are currently controlling for compositional effects using only 4 educational categories, see section 3. We are working on new results with more credible controls for worker heterogeneity.

for workers.

Table 1 also shows results for different subsamples and alternative parameterizations. Two sets of conclusions follow from this table. First, and somewhat surprisingly, we do not find a substantial impact of education on mobility. Second, unemployment benefits b have a large impact on the estimates of worker mobility whereas the effect of μ – the elasticity of the matching function – is small.

Figure 7 shows WM and JM curves together with linearly fitted values. Except for the industry-worker case, the WM/JM curve matches the regression line very well. This finding lends support to our approach.

4.2. Structural Unemployment and its Sources

In order to assess the effect of mobility costs on unemployment, we need to make assumptions on the initial (before mobility) degree of dispersion in labor market tightness and match surplus. To see why, imagine that mobility costs are very large, but tightness and match surplus happen to be identical across segments of the labor market. In this case, the mobility costs are irrelevant, because neither workers nor jobs would move even in the absence of these costs.

We assume that idiosyncratic shocks are large enough, so that there is at least one segment of the labor market, for which there is an incentive for unemployed workers to leave and for firms to bring in more vacancies, and at least one other segment, for which there is an incentive for workers to move into and for firms to remove vacancies from. Under this assumption, and if we further assume that the dispersion of match surplus is sufficiently small across labor market segments, we can show that the only thing that matters for dispersion in labor market tightness, and therefore for unemployment, is the smallest of the two mobility costs. We are working on a more general way to formalize the mapping between worker and job mobility costs and unemployment, which will allow us to how much structural unemployment results from the adjustment costs observed in the data.

[Results to be added]

4.3. Cyclicality of Structural Unemployment

Our estimates of the worker and job mobility costs are based exclusively on cross-sectional variation in the data (across states or industries). This means that we can repeat the analysis separately for different years. In particular, it will be interesting to shed light on the difference of the extent of structural unemployment between boom and recession years.

In particular, we may be able to shed light on the claim, mentioned in the introduction, that the 2007 Great Recession is of a more structural nature than previous recessions.

[Results to be added]

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A. Appendix

	worker mobility cost			job mobility cost		
	industries	**states**	$\frac{\text{industries}}{\text{states}}$	**industries**	**states**	$\frac{\text{industries}}{\text{states}}$
baseline	2.44	1.01	2.42	2.99	0.73	4.09
high school	2.69	1.08	2.49	3.15	0.86	3.66
$\geq$ college	2.90	1.24	2.34	2.79	0.77	3.62
$\mu = 0.55$	2.41	1.01	2.39	2.74	0.64	4.28
$\mu = 0.65$	2.42	1.01	2.39	2.70	0.67	4.03
$b = 0.7$	3.19	1.35	2.36	2.99	0.73	4.09
$b = 0.8$	4.68	2.03	2.30	2.99	0.73	4.09
S_i^W: $p_i = \overline{p}$	2.27	1.08	2.10	2.99	0.73	4.09

Table 1: Estimated Mobility Costs

5 industry pairs with largest $\widehat{p_i S_i^W} - \widehat{p_j S_j^W}$	$\widehat{p_i S_i^W}$	$\widehat{p_j S_j^W}$	$\widehat{p_i S_i^W} - \widehat{p_j S_j^W}$
Chemical manufacturing - Social assistance	1.65	-1.39	3.04
Computer and electronics man. - Food services & drinking places	1.44	-1.20	2.64
Finance - Accommodation	1.17	-0.83	2.00
Broadcasting and Telecomm. - Retail Trade	1.15	-0.77	1.92
Publishing industries (exc. internet) - Hospitals	1.09	-0.75	1.84
5 industry pairs with smallest $\widehat{p_i S_i^W} - \widehat{p_j S_j^W}$			
Nonmetallic mineral product man. - Wholesale trade	0.6876	0.6866	0.0010
Forestry, logging, ... - Other services (exc. government)	-0.6495	-0.6534	0.0040
Educational services - Hospitals	-0.7422	-0.7467	0.0046
Transportation & warehousing - Transportation equipment man.	0.2935	0.2826	0.0109
Motion picture & sound recording - Professional & techn. services	0.5312	0.5150	0.0163

Table 2: Difference of payoff of looking for work in two industries

5 state-pairs with largest $\widehat{p_i S_i^W} - \widehat{p_j S_j^W}$	$\widehat{p_i S_i^W}$	$\widehat{p_j S_j^W}$	$\widehat{p_i S_i^W} - \widehat{p_j S_j^W}$	distance (km)
District of Columbia - Montana	1.42	-0.66	2.08	2834
New York - South Dakota	0.59	-0.65	1.24	2152
Connecticut - North Dakota	0.47	-0.64	1.11	2296
Delaware - Kansas	0.35	-0.51	0.86	1981
New Jersey - Mississippi	0.35	-0.5	0.85	1593
mean distance				**2171**
5 state-pairs with smallest $\widehat{p_i S_i^W} - \widehat{p_j S_j^W}$				
Rhode Island - Georgia	-0.0647	-0.0649	0.0002	1459
Indiana - Florida	-0.1646	-0.1651	0.0005	1482
Delaware - New Jersey	0.3501	0.3492	0.0009	160
South Carolina - Utah	-0.3797	-0.3811	0.0014	2731
Tennessee - Montana	-0.2865	-0.2880	0.0015	2345
mean distance				**1435**

Table 3: Difference of payoff of looking for work in two state vs. distance between states

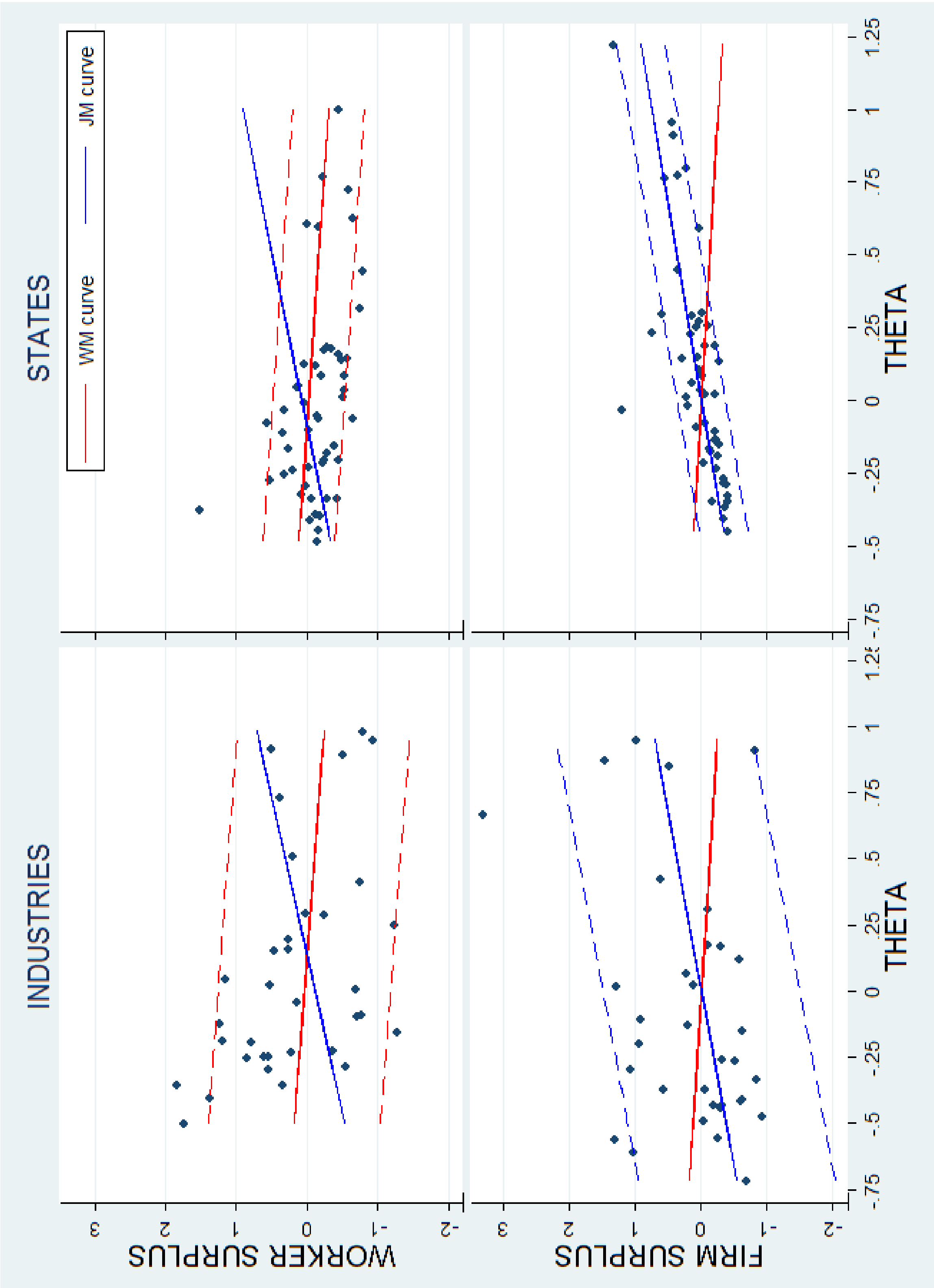

Figure 6: WM and JM curves, observations, and fitted mobility-cost bands by industries and states

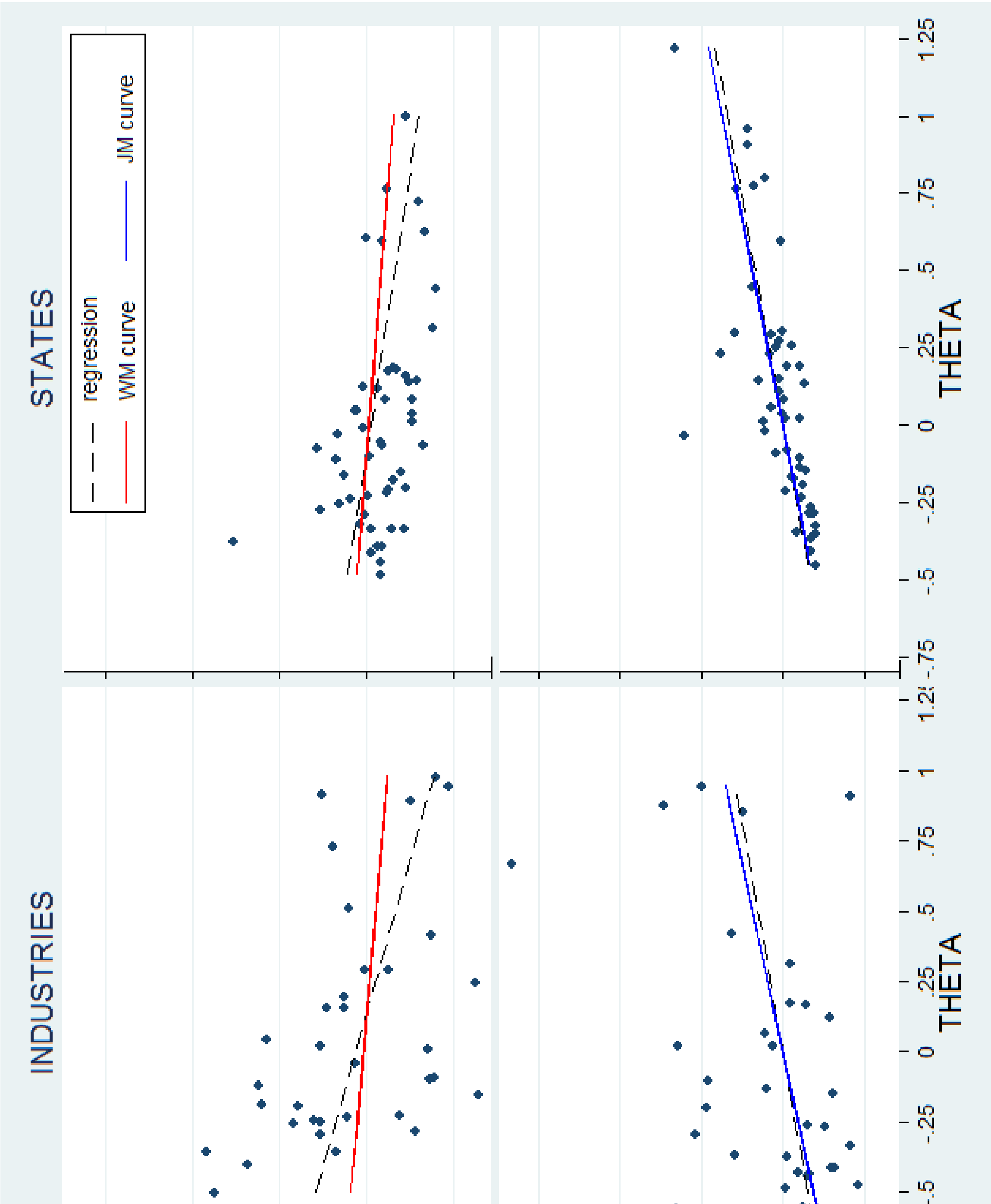

Figure 7: WM and JM curves, observations, and fitted values (dashed lines) by industries and states