A Multisector Equilibrium Search Model of Labor Reallocation*

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Abstract

It is well documented that some unemployment is caused by slow intersectoral labor reallocation. Whether or not the contribution of sectoral reallocation to unemployment responds to increases in the dispersion of sectoral shocks is less clear. In this paper, I argue that the answer to this question depends crucially on how we think about intersectoral worker flows. In a model where gross worker flows exceed net worker flows, shocks that require net reallocation may have little impact on the total number of movers. Relatively unproductive sectors experience an increase in the outflow of labor, while relatively productive sectors experience a decline in the outflow of labor. In the aggregate, the effect on the total number of movers is ambiguous - only a structural model can predict which force will dominate. To this end, I develop a multisector search model of intersectoral labor reallocation that features gross flows in excess of net flows. In a two-sector calibration of the model to construction and non-construction, I examine how the dispersion of sectoral shocks during the Great Recession contributed to unemployment due to frictional intersectoral mobility. Contrary to a long-standing argument articulated in Lilien (1982), the dispersion of shocks hardly increased unemployment due to sectoral reallocation. Consistent with the argument outlined above, while the outflow of labor from construction increased, the inflow decreased relative to the benchmark in which shocks are symmetric.

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1 Introduction

The 2008 recession and its linkages to the housing boom and bust have brought renewed attention to the importance of intersectoral mobility frictions in explaining aggregate unemployment. Some have argued that the increased need for reallocation of construction workers to other sectors of the economy has contributed to the high and persistent level of unemployment in the United States.[1] When workers need to reallocate themselves to other sectors and this process is time-consuming, unemployment might rise as workers carry out this slow transition. This hypothesis is the basis for theories of the natural rate of unemployment such as Lucas and Prescott (1974), and explanations for its fluctuations articulated in Lilien (1982).

There is ample evidence that some unemployment is caused by slow intersectoral labor reallocation: a significant fraction of unemployed workers are in the process of transitioning to new sectors, and these workers experience longer unemployment spells relative to workers who remain in sectors where they were last employed.[2] What is less clear is whether the fraction of unemployment explained by slow reallocation responds to changes in the dispersion of sectoral shocks. Supporters of this argument seem to have in mind that an increase in the dispersion of sectoral shocks necessitates net labor reallocation, thereby increasing unemployment due to frictional intersectoral mobility.

In this paper, I show that this chain argument ignores a key link. Whether increases in net labor mobility increase unemployment due to reallocation depends crucially on how we think about the flow of labor across sectors. In a model where gross intersectoral flows equal net intersectoral flows, any change in the desired allocation of labor increases unemployment due to movers. Conversely, if gross flows are in excess of net flows, shocks that require net reallocation may have little impact on the total number of movers. Relatively unproductive sectors experience an increase in the outflow of labor, while relatively productive sectors

[1] See, for example, Kocherlakota (2010) and Plosser (2011).

[2] See, for example, Murphy and Topel (1987), Loungani and Rogerson (1989), or Shin and Shin (2008).

experience a decline in the outflow of labor. In the aggregate, the effect on the total number of movers is ambiguous. Only a well-calibrated structural model, which incorporates gross flows that are not equal to net flows, can determine the overall effect on the number of movers.

To this end, I develop a multisector search model of labor reallocation which features gross flows in excess of net flows. My model economy consists of multiple sectors, each with many workers and firms. In each sector, firms and workers are matched according to a standard matching technology. Matches separate at an exogenous rate and unemployed workers choose to stay or move to other sectors. The choice is determined by sectoral job finding rates and wages, but also by an idiosyncratic taste component. If a worker decides to move to another sector, she spends additional time in unemployment before she becomes available to the new sector's labor market. Importantly, the framework distinguishes between unemployment due to movers and unemployment due to stayers. This provides a precise measure of unemployment due to sectoral reallocation.

While I develop the model in a general multiple sector setting, to analyze the 2008 recession I tailor the empirical implementation to two sectors, construction and non-construction. I calibrate several model parameters to match sectoral labor market objects from micro data sources. Using Simulated Method of Moments, I estimate the remaining parameters to match sectoral level data on movers and stayers. I estimate the history of sectoral shocks from 1977-2012 by using the model's second order approximation around its deterministic steady state. Using data on employment in construction and the rest of the economy, I recover the sectoral shocks consistent with observed sectoral employment dynamics over this time period. I then use the calibrated model and the recovered shocks to study unemployment dynamics under several counterfactual scenarios.

In the first counterfactual, I confirm the hypothesis that intersectoral reallocation contributes to aggregate unemployment and quantify the magnitude of its contribution. I analyze the evolution of aggregate unemployment in the absence of intersectoral mobility frictions, holding the realized sectoral shocks fixed. I find that barriers to intersectoral labor mobility generate ten percent of aggregate unemployment, of which roughly two thirds can be attributed to longer unemployment spells for movers. The remaining third can be attributed to labor misallocation. When moving costs are eliminated, workers move to sectors where their productivity is highest. This movement provides firms with incentives to post more vacancies, which in turn leads to lower unemployment. This estimate is a lower bound since the model does not account for the movement of labor within the broad industry grouping of non-construction.

I then turn my attention to the 2008 recession and ask how the dispersion of sectoral shocks during the Great Recession contributed to unemployment due to sectoral reallocation. Taking intersectoral mobility frictions as given, I study what would have happened if the realized shocks across construction and non-construction were more symmetric and the need for net labor reallocation eliminated. Contrary to a long-standing argument articulated in Lilien (1982), I find that the dispersion of shocks hardly increased unemployment due to reallocation. While the outflow of labor from construction increased, the inflow decreased relative to the benchmark case with symmetric shocks. The results support the idea that total gross reallocation, and thus aggregate unemployment due to intersectoral mobility, does not necessarily move one-for-one with net reallocation. In the aggregate, changes in sectoral flows cancel out leaving the total number of movers relatively unchanged.

The remainder of the paper is organized as follows. Section 2 discusses some related work. Section 3 develops the proposed model and its main features. Section 4 calibrates and estimates the model using sectoral level labor market data and evidence on movers and stayers taken from several micro data sources. Section 5 performs the counterfactuals described above. Section 7 concludes and describes how the model can be applied to other topics and ongoing work.

2 Literature

The theory in this paper is a hybrid of three literatures on sectoral mobility and unemployment: the islands models of Lucas and Prescott (1974), the search models of Mortensen and Pissarides (1994), and models of labor mobility that draw from Discrete Choice Theory such as Artuc, et.al. (2010), Kline (2008), and Kennan and Walker (2011). Bridging these models together produces properties that are desirable in studying the quantitative importance of intersectoral labor mobility frictions in unemployment. I discuss how the model presented here relates to each of these literatures in turn. I then discuss papers that are closely related to the analysis I perform that relates to the recent recession.

I model labor mobility between distinct markets that is time-consuming in a way that is similar to the island model of Lucas and Prescott (1974) and extensions of that model such as Alvarez and Shimer (2011). In these models, each market belongs to a continuum of markets in which a law of large numbers holds. While this assumption provides tractability, it implies that sectoral shocks do not have aggregate implications. Since my model consists of a discrete number of islands where this law no longer holds, it becomes amenable to quantitative analysis in which sectoral shocks have meaningful implications for aggregate statistics. I can study environments in which certain sectors are in permanent decline, or cases in which some sectors are hit by larger shocks than others. Chang (2011) has a search-theoretic model of sectoral reallocation, but the theoretical analysis is limited to two sectors. Carrillo-Tudela and Visschers (2011), on the other hand, have a model of sectoral reallocation among many distinct markets, but these markets are again subject to a law of large numbers and thus exposed to the same aforementioned criticism.

I model unemployment within an island or sector using the search models of Mortensen and Pissarides (1994) in which workers and job-openings match via a constant returns to scale matching function. Since a model with a single sector precludes any discussion of intersectoral mobility frictions, I introduce multiple sectors and costly intersectoral labor mobility between them. If an aggregate shock is experienced differentially across sectors - a hypothesis supported by empirical work in Abraham and Katz (1986) - the model generates much slower dynamics relative to the single-sector benchmark since an aggregate shock will lead to slow labor reallocation. Finally, the measured efficiency of the matching function in my model is endogenous and will depend on the total number of movers, which in turn will depend on the state of the economy and how much reallocation is taking place. In the standard one-sector search model, match efficiency is exogenous.

Lastly, I model the worker's sectoral choice problem using methods developed in the discrete choice literature as in Kline (2008), Artuc, et. al. (2011), and Kennan and Walker (2011), all of whom take advantage of the Type I Extreme Value Distributions to formulate worker flows. Formulating idiosyncratic worker shocks as taste shocks (or shocks to moving costs) generates gross worker flows in excess of net worker flows, a feature of the data that is quantitatively large and usually ignored.[3] In several counterfactual experiments, I show that the presence of gross flows in excess of net flows is an important feature of a model which tries to infer the effect of time-consuming labor mobility on unemployment. The composition of inflows and outflows across sectors can change in response to shocks rather than just the total number of movers.

The model provides a theoretical framework for thinking about the relationship between unemployment and vacancies in the face of sectoral shifts, a relationship studied by Lilien (1982) and Abraham and Katz (1986). These papers are largely empirical and test informal hypotheses. The model presented here formalizes these theories, but remains general enough to incorporate permanent sectoral declines as well as aggregate movements in demand that might impact sectors differentially over the cycle. While this paper focuses on the types of shocks described in Abraham and Katz (1986), the model would predict that permanent sectoral declines coincide with permanent sectoral switches, while movements in aggregate demand that are experienced differentially by sectors over the cycle induce more temporary

[3]For descriptive statistics on gross and net flows, see Section 4.

movements across sectors. The results also challenge the basic premise in Lilien (1982) that posits a direct link between net reallocation and unemployment. My results suggest that the relevant statistic is gross reallocation, since some changes in net reallocation are accomplished through the composition of gross flows across sectors.

The application of this paper is related to recent papers by Sahin, et al. (2012), and Herz and van Rens (2011). These papers seek to measure the extent to which unemployment in the Great Recession is structural or caused by mismatch between available jobs and workers. Since I model labor mobility costs in a decentralized equilibrium, I can ask whether or not the observed unemployment patterns are constrained efficient, where the social planner is subject to the same frictions workers face when reallocating themselves across sectors. If the planner faces the same mobility costs and matching frictions as workers face, the observed level of unemployment is a constrained efficient response of the economy in the face of sectoral shocks, provided that the Hosios (1994) condition holds.

The counterfactuals I run for the recent recession in which I eliminate the relative boom and bust in construction are similar to exercises in Charles, Hurst, and Notowidigdo (2012). There are two main differences. First, I do not include manufacturing as a separate sector, although this can certainly be added. Second, I do not have a labor force participation margin, though this could also be integrated easily. However, since my model provides a general equilibrium framework to analyze sectoral shocks, I can observe what happens counterfactually to aggregate productivity when shocks to certain sectors are shut off. Theoretically, the removal of the housing boom and bust in Charles, Hurst, and Notowidigdo (2012) does not hold aggregate demand fixed. Some of their results may be driven by the simple change in the aggregate frontier in the economy rather than the removal of the shock to the housing sector. In the counterfactuals I run, I examine a removal of the housing boom and bust that holds the aggregate frontier of the economy fixed. This isolates the effect of reallocation on unemployment by disallowing any changes in aggregate productivity.

3 Model

Each sector produces a homogeneous intermediate good using a linear production function whose only input is labor. The intermediate goods are aggregated via a CES aggregator to produce a final consumption good. In what follows, I suppress the time indices until they become necessary for clarity.

Every period, workers draw idiosyncratic sector-specific taste shocks that impact their mobility decisions. These shocks are assumed to be independently and identically distributed over time and across sectors.[4] If a worker chooses to switch sectors, she must pay an additional cost of extra time in unemployment associated with switching sectors. This state, which I refer to as move unemployment, is distinct from stay unemployment in that workers in move unemployment have no prospect of getting hired.[5] The state of move unemployment captures the time workers must spend retraining (if an island is viewed as a sector) before acquiring the necessary skills to be employable in a new sector, or the time spent moving to a new location (if an island is viewed as a geographical location).[6] The empirical counterparts that will discipline these objects are movers and stayers which we can observe retrospectively using several household surveys.[7]

3.1 Final Goods Production

The N islands of the economy each produce an intermediate good y_n every period that is aggregated into a final good Y by final goods producers for consumption via the following

[4]The taste shocks can be equally interpreted as utility costs to mobility since workers moving from n to j will lose $\varepsilon_j - \varepsilon_n$ utils.

[5]These notions are distinct from the notions of search and rest unemployment developed by Alvarez and Shimer (2011). Stayers in this model will still be actively searching for work on their island. Rest unemployed workers in Alvarez and Shimer (2011) remain on their island even though there is no immediate prospect for work.

[6]In the model calibration, I think of this state as people who remain in the labor force but switch sectors. One could easily introduce a separate choice of non-participation in this setup and analyze non-employment rather than unemployment.

[7]See Loungani and Rogerson (1989) and Murphy and Topel (1987) for studies of movers and stayers using the PSID and CPS respectively.

CES aggregator:

$$Y = \left[\sum_{n \in N} (\tau_n)^{\frac{1}{\sigma}} (y_n)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

where σ represents the elasticity of substitution between goods and τ_n represents sector n's share of production in the final good so that $\sum_{n \in N} \tau_n = 1$. If we let P denote the price of the final consumption good and p_n denote the price of each intermediate good, it follows that the optimal demand for each intermediate good y_n by final goods producers is given by:

$$y_n = \frac{Y \tau_n}{\left(\frac{p_n}{P}\right)^{\sigma}}$$

where $P = \left[\sum_{n \in N} \tau_n (p_n)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$ is the "ideal" price index. Each island or sector thus faces a downward sloping demand curve. Finally, workers spend all their income on consumption of the final good.

3.2 Intermediate Goods Production and Sectoral Labor Markets

Each island produces an intermediate good with a linear production function whose only input is labor. One unit of labor in sector n produces μ_n units of output. Detrended log labor productivity in each sector follows an AR(1) process so that:

$$\log(\mu_n') = \kappa_n \log(\mu_n) + \zeta_n \nu_n'$$

where κ_n represents the monthly autocorrelation of detrended log labor productivity in sector n, $\nu_n \sim N(0,1)$ represents the innovations to log labor productivity in sector n, and ζ_n controls the variance of the series. I allow for correlations in the shocks across sectors as discussed in more detail in Section 4.[8]

While the final goods market is competitive, the labor markets within each island are

[8] Alternatively, I could have assumed there is one aggregate component of productivity and a sector-specific component that is independent across sectors. The two versions are equivalent since what ultimately matters is changes in relative sector sizes.

subject to standard search frictions; therefore, each sector will have an associated unemployment rate. For each island n, let l_n denote the labor force size. The labor force will consist of employed workers e_n and unemployed workers of two types: movers and stayers. Stayers s_n will be unemployed workers who are searching for work in sector n. Movers m_{nj} will be unemployed workers who were last in sector n, but are moving to search for work in some sector j.[9] Thus, the total labor force size on sector n will be given by:

$$l_n = s_n + \sum_{j \epsilon N} m_{nj} + e_n$$

The probability that stayers on island n meet jobs on island n is determined by the sector-specific matching function $\Gamma_n(v_n, s_n)$, where v_n represents the total number of vacancies on island n. The fact that the matching function takes only stayers as inputs from the unemployment pool highlights the difference between the two states of unemployment. Stayers have the skills necessary to be hired instantaneously - they remain unemployed simply because it takes time for their resumes to reach potential employers. Movers, on the other hand, are still in the process of acquiring the skills necessary to become attractive hires. I make the standard assumption that Γ_n is constant returns to scale and has the particular form:

$$\Gamma_n(v_n, s_n) = \Upsilon_n \cdot (v_n)^{1-g} (s_n)^g \tag{3.1}$$

where $g \in (0, 1)$ is the elasticity of the matching function and Υ_n represents the sector-specific match efficiency. Letting $\theta_n = \frac{v_n}{s_n}$ denote the island labor market tightness, the probability that vacancies in sector n turn into jobs is given by $q_n(\theta_n) = \frac{\Gamma_n(v_n, s_n)}{v_n}$. The probability that job seekers find jobs in sector n is given by $f_n(\theta_n) = \frac{\Gamma_n(v_n, s_n)}{s_n}$. Therefore, the transition probabilities satisfy the standard relationship $f_n(\theta_n) = q_n(\theta_n)\theta_n$.

[9] I choose to include these workers as part of sector n to more closely mimic what we observe in the data. In the CPS, we observe an unemployed workers sector of last employment, but cannot observe which sector they are moving to until they actually find a job. I discuss this in more detail in Section 4.

In the spirit of Kline (2008), Kennan and Walker (2011), and Artuc, et. al (2011), all workers draw a vector ε of sector-specific idiosyncratic taste shocks $\varepsilon_n \sim Gumbel(-\rho\gamma, \rho)$ every period.[10] The shocks are independently and identically distributed over time and across sectors.[11] I interpret these taste shocks as anything that might keep workers in a sector or geographic region that is unrelated to wages or the ease of finding a job. For example, a worker might be unable to find a job as an artist, but she continues to search for work as an artist because this is what she enjoys doing most. In a spatial interpretation of the model, the tastes might include things like marriage or housing that would keep someone tied to a certain locale.

At the end of every period and after realizing their tastes, unemployed workers are able to move to the sector of their choice. This assumption ensures both that there are always some workers who will find it beneficial to change sectors (positive gross flows), and that labor mobility is multi-directional (gross flows in excess of net flows), even in the absence of sectoral productivity shocks. I abstract from endogenous quits in response to these shocks, and discuss this assumption in more detail below.

The timing of the model is as follows. Time is discrete, and the economy begins with an allocation of workers in employment, stay unemployment, and move unemployment across all sectors $n \in N$, given sectoral productivities $\{\mu_n\}_{n=1}^N$. Employed workers work and earn wage w_n and unemployed workers earn their value of leisure b. Afterward, separation of employed workers, absorption of movers into new sectors, and job-finding of stayers occur. Only after these labor market events occur do workers realize their taste shocks for the next period and make a move decision. After this intersectoral reallocation has taken place, the process starts over again after a new draw of sectoral productivity in each sector $\{\mu'_n\}_{n=1}^N$

[10] The Gumbel distribution is also known as the Type I Extreme Value Distribution. Without loss of generality, I set the mean of this distribution to 0, which requires setting the shape parameter to $-\rho\gamma$ where $\gamma \sim .5772$ is Euler's constant.

[11] A more plausible version of the model would be to have taste shocks that are correlated over time for an individual, which would significantly slow down the adjustment of labor in response to sectoral shocks. However, to solve this model one would need to keep track of the distribution of taste shocks within each sector as an additional state variable.

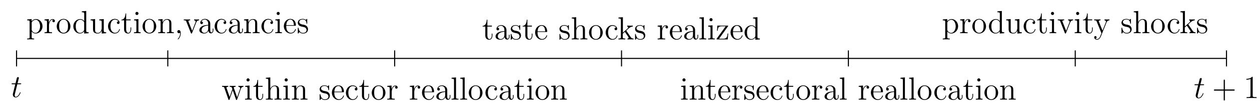


Figure 1: Model Timeline

has been realized. Figure 1 shows the timeline of the model graphically.

3.3 Workers

There are three distinct states of the labor force: employment, stay unemployment, and move unemployment. Let W_n, S_n, and M_{nj} represent their respective values. If δ_n represents the exogenous separation probability in sector n and w_n represents the worker's wage, the value of a job to an employed worker i in sector n (net of idiosyncratic taste shocks) is given by:

$$
\begin{aligned}
(3.2) \qquad W_n(\Omega) = w_n &+ [1-\delta_n]\beta \mathbf{E}_{\Omega',\varepsilon'}\left\{\left(W_n(\Omega') + \varepsilon'_{n,i}\right)\right\} \\
&+ \delta_n \beta \mathbf{E}_{\Omega',\varepsilon'}\left\{\max\left(S_n(\Omega') + \varepsilon'_{n,i}, \max_{k\neq n\in N} M_{nk}(\Omega') + \varepsilon'_{k,i}\right)\right\}
\end{aligned}
$$

where $\Omega = \{s_n, e_n, m_{nj}, \mu_n \; \forall n, j \in N\}$ represents the state of the economy and $\varepsilon'_{n,i}$ represents worker i's taste draw for next period in sector n.[12] The present value of being an employed worker i in sector n is the earned wage w_n plus the continuation value. With probability $1-\delta_n$, the worker remains employed in sector n. With probability δ_n the worker separates into stay unemployment, but is able to choose between remaining stay unemployed in n and becoming move unemployed from sector n to some other sector k. Note that I do not allow workers to quit their jobs and search for other sectors, either through move unemployment or through job-to-job transitions. However, this assumption is not as restrictive as it might seem. First, one can think of quits as being represented by the exogenous breakup governed by δ_n. I later calibrate δ_n to the sectoral separation probability in the Current Population Survey. Whether some of the workers who separate self-select into unemployment or not is

[12] In what follows, I show that the value functions do not depend on i.

not crucial for my results. Second, job-to-job transitions matter only insofar as I load all net reallocation on the currently unemployed. While this is likely to bias my estimate for net movements of unemployed workers upward (some net reallocation in the data surely takes place through job-to-job transitions), this does not lead me to overestimate the amount gross movements for the unemployed since I calibrate these flows to match observed flows in the data.[13]

The value of being a stay unemployed worker in sector n for worker i (net of idiosyncratic taste shocks) is given by:

$$
\begin{aligned}
(3.3)\qquad S_n(\Omega) = b + f_n(\theta_n)\beta\mathbf{E}_{\Omega',\varepsilon'}\left\{\left(W_n(\Omega') + \varepsilon'_{n,i}\right)\right\} \\
+ [1 - f_n(\theta_n)]\beta\mathbf{E}_{\Omega',\varepsilon'}\left\{\max\left(S_n(\Omega') + \varepsilon'_{n,i}, \max_{k\neq n\in N} M_{nk}(\Omega') + \varepsilon'_{k,i}\right)\right\}
\end{aligned}
$$

where b is the value of leisure for the unemployed. Unemployed workers earn a current period return of b, plus the expected future value of stay unemployment. With probability $f_n(\theta_n)$ these workers find a job in sector n. With probability $1 - f_n(\theta_n)$ these workers do not find a job and choose between remaining stay unemployed in sector n or becoming move unemployed from sector n to some other sector k. Finally, the value of being move unemployed from sector n to sector j (net of idiosyncratic taste shocks) is given by:

$$
(3.4)\qquad M_{nj}(\Omega) = b + \beta\mathbf{E}_{\Omega',\varepsilon'}\left\{\max\left(S_j(\Omega') + \varepsilon'_{j,i}, \max_{k\neq n\in N} M_{jk}(\Omega') + \varepsilon'_{k,i}\right)\right\}
$$

In the current period, movers earn the value of leisure for unemployed. After one period, the worker is absorbed and becomes a stayer in j, but can choose whether or not to remain a stayer in j or become a mover from sector j to some other sector k. Thus, movers will

[13] Moreover, this only makes my point stronger: if net movements do not predict movements in gross mobility when net mobility is large, they will also not predict gross mobility when net movements are smaller. In addition, if I allowed workers to search on the job, each worker would have a different outside option which would in turn imply that the value functions are individual specific, significantly complicating the numerical solution of the model.

spend one extra period in unemployment relative to stayers.[14]

To simplify the terms within the expectations in equations (3.2), (3.3), and (3.4), I use results from McFadden (1978) exploiting Type I Extreme Value Theory and integrate out future taste shocks:

$$W_n(\Omega) = w_n + [1-\delta_n]\beta \mathbf{E}_{\Omega'}\left\{W_n(\Omega')\right\} + \rho\delta_n\beta\mathbf{E}_{\Omega'}\left\{\log\left[\sum_{k\in N}\exp(\widetilde{S}_{nk}(\Omega')/\rho)\right]\right\} \tag{3.5}$$

$$S_n(\Omega) = b + f_n(\theta_n)\beta \mathbf{E}_{\Omega'}\left\{W_n(\Omega')\right\} + \rho[1-f_n(\theta_n)]\beta\mathbf{E}_{\Omega'}\left\{\log\left[\sum_{k\in N}\exp(\widetilde{S}_{nk}(\Omega')/\rho)\right]\right\} \tag{3.6}$$

$$M_{nj}(\Omega) = b + \rho\beta\mathbf{E}_{\Omega'}\left\{\log\left[\sum_{k\in N}\exp(\widetilde{S}_{jk}(\Omega')/\rho)\right]\right\} \tag{3.7}$$

Now all value functions are independent of the worker's future taste shocks, significantly simplifying the numerical computation of the model.[15]

The worker's problem in unemployment is to choose whether to remain stay unemployed or to become move unemployed and transition to some other sector. To simplify notation, define $\widetilde{S}_{nj}$ as follows:

$$\widetilde{S}_{nj} = \begin{cases} S_n & \text{for } j = n \\ M_{nj} & \text{for } j \neq n \end{cases}$$

The probability, then, that a worker facing the reallocation choice in n chooses to become move unemployed and move to some sector j from n at time t is given by:

$$\pi_{nj} = Pr\left(\widetilde{S}_{nj}(\Omega') + \varepsilon'_{j,i} > \widetilde{S}_{nk}(\Omega') + \varepsilon'_{k,i} \;\; \forall k \in N\right)$$

[14]In earlier versions of this paper there was an absorption parameter α_{nj} governing the length of time it takes workers to move from sector n to sector j. One could calibrate this parameter to relative durations of movers and stayers in the data. However, since the data I use on movers and stayers suggest that movers spend one month extra in unemployment relative to stayers, the calibration would call for setting $\alpha_{nj} = 1$.

[15]See Appendix section A for a derivation.

which reduces to:[16]

$$\pi_{nj} = \frac{1}{\sum_{k\in N}\exp(\frac{\widetilde{S}_{nk}(\Omega')-\widetilde{S}_{nj}(\Omega')}{\rho})} \tag{3.8}$$

The move probabilities specified in Equation 3.8 are the standard Logit probabilities from Discrete Choice Theory. The move probabilities imply that, on average, workers move in response to differences in sectoral payoffs. Furthermore, we can write the value of being a stayer in sector n as a function of these move probabilities:

$$S_n(\Omega) = b + f_n(\theta_n)\beta\mathbf{E}_{\Omega'}W_n(\Omega') + [1-f_n(\theta_n)]\beta\mathbf{E}_{\Omega'}S_n(\Omega') + \rho[1-f_n(\theta_n)]\beta\mathbf{E}_{\Omega'}\left\{\log\left[\pi_{nn}^{-1}\right]\right\}$$

Therefore, the value of being a stayer in sector n can be decomposed into the value of finding a job in sector n, the value of being a stayer next period in sector n, and the option value of remaining in sector n. The last-mentioned is given by the expected difference in sectoral payoffs next period, or the gain from being able to move from n to some j next period:

$$\pi_{nn}^{-1} = \sum_{k\in N}\exp(\frac{\widetilde{S}_{nk}(\Omega')-S_n(\Omega')}{\rho})$$

3.4 Firms

Turning to the decisions of the firms, the value of a job to a firm is given by:

$$J_n(\Omega) = p_n\mu_n - w_n + \beta\mathbf{E}_{\Omega'}\left\{[1-\delta_n]J_n(\Omega') + \delta_n V_n(\Omega')\right\} \tag{3.9}$$

A firm earns $p_n\mu_n$, but must pay the worker a wage w_n. With probability $[1-\delta_n]$ the match remains. With probability δ_n the match exogenously blows up and the firm gets V_n. The

[16] See McFadden (1978) for a derivation.

value of a vacancy to a firm is given by:

$$V_n(\Omega) = -c_n + \beta \mathbf{E}_{\Omega'} \left\{ q_n(\theta_n) J_n(\Omega') + [1 - q_n(\theta_n)] V_n(\Omega') \right\} \tag{3.10}$$

where c_n represents the flow cost of posting a vacancy in sector n. Free entry every period in each sector drives the value of a vacancy in all sectors $n \in N$ to zero.

3.5 Wages

To close the model, I assume that wages are rigid and fixed at their efficient deterministic steady state level.[17] I choose a rigid wage model over a flexible wage model so that the model will be able to more closely match unemployment fluctuations.[18]

In this setting, the efficient wage will be equal to the Nash bargained wage where firms and workers bargain over match surplus $W_n - S_n + J_n - V_n$ when the Hosios (1994) condition holds.[19] If η is the worker's bargaining power and it is set equal to the elasticity of matching function g, efficient wages in the deterministic steady state will be given by:

$$\bar{w}_n = (1-\eta)b + \eta \overline{p}_n \mu_n + \eta c_n \overline{\theta}_n + (1-\eta)\rho\beta[1 - \delta_n - f_n(\overline{\theta}_n)] \mathbf{E}_{\Omega'} \left\{ \log(\overline{\pi}_{nn}^{-1}) \right\} \tag{3.11}$$

where the bars above variables denote the variable's value in the deterministic steady state. This wage resembles the standard wage equation in Pissarides (2001), for example, but has an extra positive term which accounts for the fact that workers are not allowed to move. As such, they must be compensated for the value of search in unemployment.

[17] I relegate the derivation of the efficient wage equation to Appendix Section B.

[18] We know from Shimer (2005) that wage rigidity significantly improves the ability of the model to match unemployment fluctuations. Another option would be to follow the calibration strategy outlined in Hagedorn and Manovskii (2008). Since real wages are, if anything, only mildly procyclical (Shimer 2012), the rigid wage assumption seems suitable. Appendix Section C discusses the implications of the rigid wage assumption for the model calibration and other possible calibration strategies.

[19] See Appendix Section D for the characterization and solution for the planner's problem.

3.6 Inflows and Outflows

I am now able to characterize the stock of employed, stay unemployed, and move unemployed in each sector n at the beginning of period $t+1$. The stock of employed workers in sector n at time $t+1$ is given by:

$$e_n' = e_n[1-\delta_n] + s_n f_n(\theta_n) \tag{3.12}$$

That is, $1-\delta_n$ employed workers on island n from last period remain employed, while $f_n(\theta_n)$ stayers in n find a job. The stock of stayers in sector n at time $t+1$ is given by:

$$s_n' = \pi_{nn}\left[s_n\left[1-f_n(\theta_n)\right] + \delta_n e_n + \sum_{k\in N} m_{kn}\right] \tag{3.13}$$

A fraction $\pi_{nn}[1-f_n(\theta_n)]$ of stayers in n from last period do not find a job and choose to remain stayers. The inflow consists of $\pi_{nn}\delta_n e_n$ employed workers from last period who lose their jobs and choose to remain stay unemployed, and movers searching in n from all other sectors k who get absorbed into sector n and choose to remain stayers in n. Finally, the stock of movers in sector n moving to sector j at time $t+1$ is given by:

$$m_{nj}' = \pi_{nj}\left[e_n\delta_n + s_n[1-f_n(\theta_n)] + \sum_{k\in N} m_{kn}\right] \tag{3.14}$$

That is, $\pi_{nj}\delta_n e_n$ employed workers in sector n lose their job and choose to become move unemployed in n, moving toward sector j. A fraction $[1-f_n(\theta_n)]\pi_{nj}$ stayers in n do not find a job and choose to become move unemployed in n to some sector j. Finally, some movers from sector k who get absorbed in n choose to turn their search efforts to some sector j rather than remaining stayers in sector n.

3.7 Equilibrium

Letting the final consumption good be the numeraire of this economy, and normalizing the total labor force size to one, an equilibrium is an allocation $\{s_{n,t}, m_{nj,t}, e_{n,t}, \theta_{n,t} \;\; \forall n, j \in N\}_{t=1}^{\infty}$ and a set of prices $\{p_{n,t}, \forall n \in N\}_{t=1}^{\infty}$, value functions $\{W_{n,t}, S_{n,t}, M_{nj,t} \;\; \forall n, j \in N\}_{t=1}^{\infty}$, and move probabilities $\{\pi_{nj,t} \;\; \forall n, j \in N\}_{t=1}^{\infty}$, such that given $\left\{s_n^0, m_{nj}^0, e_n^0 \;\; \forall n, j \in N\right\}$, wages $\{\bar{w}_n\}_{n=1}^{N}$, and the evolution of sectoral productivities $\{\mu_{n,t}\}_{n=1}^{N}$:

1. The free entry condition holds for all sectors $n \in N$, $V_n = 0$, which implies:

$$\frac{c_n}{\beta q_n(\theta_{n,t})} = \frac{p_{n,t}\mu_{n,t} - \bar{w}_n}{1 - \beta(1 - \delta_n)} \qquad \forall n \in N$$

2. Unemployed workers $\{s_{n,t}, m_{nj,t}\}_{n=1}^{N}$ choose where to search to maximize utility so that move probabilities satisfy Equation (3.8)

3. Given $\{s_{n,t}, m_{nj,t}, e_{n,t}\}_{n=1}^{N}$, firms in each sector $n \in N$ optimally post vacancies v_n so as to maximize profits

4. The evolution of employment in each sector $n \in N$ follows Equation (3.12)

5. The evolution of stay unemployment in each sector $n \in N$ follows Equation (3.13)

6. The evolution of move unemployment in each sector $n \in N$ follows Equation (3.14)

7. The intermediate goods market clears in every sector:

$$y_{n,t} = \mu_{n,t} e_{n,t} = \frac{Y_t \tau_n}{(p_{n,t})^{\sigma}} \qquad \forall n \in N$$

8. Value functions in each sector $\{W_{n,t}, S_{n,t}, M_{nj,t} \;\; \forall n, j \in N\}$ are given by Equations (3.5), (3.6), and (3.7).

3.8 Model Features

The model exhibits positive gross flows of unemployed workers across sectors, even absent sectoral productivity shocks. Since workers draw idiosyncratic shocks every period, there will always be a positive number of workers finding it optimal to switch sectors. This feature of the model accords well with the data, in which gross flows of workers across sectors are always positive and larger than net flows. For example, the CPS monthly data I use to categorize unemployed workers suggest that, on average, approximately ten percent of unemployed workers in any given month will find work in a sector other than their sector of last employment.[20] This is about five times larger than the average net flows of unemployed workers observed in the data.

Second, the model displays slow adjustment of sectoral labor allocations and thus aggregate unemployment in response to sectoral shocks. The impulse responses from the calibrated model suggest that when the economy is hit by a 1 standard deviation shock in one sector, the half-life of aggregate unemployment is 40 months. The logic is simple: consider a two sector economy that is in a steady state where sectoral productivities are constant and net flows are zero. In response to a permanent shock which changes the desired allocation of labor across sectors, the economy does not adjust instantaneously since some workers still find it optimal to stay where they are given their current realizations of taste shocks. Net flows increase as a fraction of workers move to the relatively more productive sector, which then lowers the difference in values of unemployment across sectors. In the next period when taste shocks are drawn again, there is still positive net reallocation, but net reallocation declines as the difference in values across sectors declines. This process continues until the new desired allocation is achieved and net flows return to zero.

Third, consistent with evidence found in Loungani and Rogerson (1989), the model will feature an inflow of labor into cyclically sensitive sectors during booms and an outflow of

[20] This statistic is for the two-sector disaggregation to construction and non-construction. The number would likely increase at a higher level of disaggregation.

labor from cyclically sensitive sectors during recessions. The intuition becomes clear when we examine the move probabilities: since workers care about differences in sectoral payoffs, sectors that are hit relatively worse during recessions will on average experience more workers deciding to leave. These same sectors will, on average, experience inflows during booms when they become relatively more productive.

Finally, the model features countercyclical reallocation. When sectoral payoffs become lower through lower job-finding probabilities during recessions, the taste component becomes more prominent in the move decision faced by workers. That is, more workers move when the opportunity cost of moving is low so that the aggregate number of movers will be higher during recessions.[21]

4 Calibration

In this section I calibrate the model at a monthly frequency. I work with two sectors ($N = 2$), construction (C) and non-construction (NC). I choose this dichotomy so that I can analyze the movements in unemployment in construction in the counterfactual exercises that are specific to the 2008 recession. Given this two-sector calibration, there are 21 parameters governing the system, summarized in Table 1.

4.1 Calibrated Parameters

To reduce the number of parameters to be estimated, I fix the following parameters. I choose a monthly discount rate of $\beta = 0.997$, which corresponds to an annual interest rate of 4 percent, and an elasticity of substitution of $\sigma = 2.00$. Broda and Weinstein (2006) find that the median elasticity for three-digit sectors is about 2.2. I choose an elasticity lower than this median because the level of disaggregation here is lower.

I calculate sectoral separation probabilities using sectoral monthly labor force data from

[21] The evidence presented in Murphy and Topel (1987) suggests that total unemployment due to reallocation is acyclic, whereas Loungani and Rogerson (1989) find that reallocation plays a slightly larger role in explaining unemployment fluctuations and is modestly countercyclical. In the model, the degree of countercyclicality displayed by reallocation will ultimately be governed by the variance of the taste shocks, as described in more detail in Section 4.

Table 1: Parameters

parameter	description
σ	elasticity of substitution
β	discount rate
τ_n	sectoral ces demand shares $\{C, NC\}$
$\bar{\mu}_n$	mean sectoral labor productivity $\{C, NC\}$
g	vacancy share in matching function
η	worker's bargaining power
Υ_n	sectoral match efficiency $\{C, NC\}$
b	value of leisure for unemployed
δ_n	sectoral separation probability $\{C, NC\}$
ρ	variance of taste shocks
c_n	sectoral vacancy creation cost
ζ_n	sectoral variance parameter in AR(1) process $\{C, NC\}$
κ_n	sectoral autocorrelation parameter in AR(1) process $\{C, NC\}$
ϕ	correlation between sectoral innovations in AR(1) processes ν_n

the CPS. Following Shimer (2005), the empirical monthly separation probability is calculated via:

$$\delta_n(t) = \frac{u_n^{short}(t+1)}{e_n(t)[1 - .5\widehat{f_n}(t)]}$$

where $u_n^{short}(t+1)$ corresponds to the level of short term unemployed workers from sector n (workers who separated from their job within the last month), $e_n(t)$ corresponds to the level of employment in sector n at time t, and $\widehat{f_n}(t)$ corresponds to the monthly job finding probability of workers last employed in sector n.[22] I find that the mean monthly separation probability from 1976-2002 for construction is $\delta_c = 0.05$, while the mean monthly separation probability for non-construction over the same time period is $\delta_{nc} = 0.03$. I fix the sectoral separation parameters at these values.

The parameters τ_n, the CES demand shares, will govern the employment shares across sectors. I choose these to match the average share of employment in construction and non-construction from 1976-2002. I set τ_C =0.07 and τ_{NC} =0.93 , and assume that mean labor productivity $\bar{\mu}_n$ in each sector is equal to one.[23] I fix $\eta = g$ so that the worker's bargaining

[22]This job finding probability is not the same as f in the model. $\widehat{f_n}$ is the job finding probability of all workers who were last employed in sector n, regardless of whether they subsequently become movers or stayers.

[23]Without data on intermediate goods prices, I cannot separately identify τ_n from μ_n. Since shocks to

power is equal to the elasticity of the matching function and the Hosios (1994) condition holds if wages were flexible, as described in Section 3.5.

I fit the AR(1) process for detrended log productivity in each sector, μ_n, by matching data on sectoral employment dynamics.[24] Recall that the process for detrended log sectoral productivity is as follows:

$$\log(\mu_n') = \kappa_n \log(\mu_n) + \zeta_n \nu_n'$$

The variance of the detrended log employment rate in construction is 0.0178, while in non-construction its value is 0.0057. The monthly autocorrelations (κ_C, κ_{NC}) for the detrended log employment rates are .93 and .89 respectively. Assuming $\nu_n \sim N(0,1) \;\; \forall n \in \{C, NC\}$, solving for the implied ζ_n results in setting $\zeta_C = 0.013$, $\kappa_C = 0.76$, $\zeta_{NC} = 0.004$, and $\kappa_{NC} = 0.90$.[25] Finally, set the correlation between ν_{μ_C} and $\nu_{\mu_{NC}}$ to 0.80 to match the correlation in the data, 0.78 . This reduces the system to seven parameters which need to be estimated, $H = [b \;\; \Upsilon_C \;\; \Upsilon_{NC} \;\; \rho \;\; c_C \;\; c_{NC} \;\; g]$.

4.2 Estimated Parameters

I estimate the remaining parameters using Simulated Method of Moments (SMM). Before launching into the SMM estimation of the remaining parameters, I describe here how I construct model moments that will be equivalent to moments we observe in the data. Respondents in the CPS are interviewed for four consecutive months, and then interviewed for another 4 consecutive months 8 months after the first rotation. When we follow these respondents, we can observe their sector of last employment, but we cannot observe where

these variables move all the endogenous variables in the same way (except for intermediate goods prices), I do not focus on separately identifying the two parameters in each sector. Thus, the shocks to labor productivity I identify are really combinations of supply and demand shocks, represented by shocks to τ_n and μ_n. Furthermore, the model allows one normalization anyway: since doubling the parameters $\{b, c_n, \mu_n, \rho\}$ doubles all the value functions and output, but does nothing to the allocation of workers across sectors, I am permitted to normalize one of the μ_n regardless.

[24] One could also include these parameters as part of the Simulated Method of Moments procedure described below, but given the computational intensity of the algorithm, I begin by calibrating them independently.

[25] See the Appendix Section E for a detailed derivation of how to recover the implied parameters governing the AR(1) processes.

Table 2: Average Monthly Gross Flows of Unemployed Workers: 1976-2008

	C	NC
C	0.69	0.30
NC	0.06	0.94

they are searching. Therefore, limiting the sample to workers who were in the labor force throughout the first four month period, I identify movers in the CPS in any given month to be any unemployed workers who were last employed in some sector n who subsequently find a job in sector j within the months I can follow them.[26]

Table 2 reports summary statistics from the CPS on movers out of total unemployment. The matrix shows the fraction of unemployed workers within a given month who were last employed in some sector $n \in \{C, NC\}$ (represented by the matrix rows) and subsequently find employment in sector $n \in \{C, NC\}$ (represented in columns). For example, on average 94 percent of unemployed workers who were last employed in non-construction find work in non-construction when they subsequently find a job.[27]

In my model, there are some workers labeled as "movers" from n to j who will ultimately find a job in a sector other than j. For example, suppose a stayer in sector n receives a vector of taste shocks in period t that compels her to become a mover from n to j. She reaches sector j in period $t+2$, but randomly gets a vector of taste shocks that compel her to move back to sector n. To be consistent with the definitions in the CPS, if this unemployed worker never finds employment in a new sector, we should not count her as a mover. Thus, I must correctly determine the fraction of model movers who are the data equivalent of movers described above. Similarly, I must categorize a worker as belonging to sector n only when her sector of last employment was sector n.

Fortunately, the model setup allows me to do this easily. To do so, I take the simulated

[26]Some unemployed workers do not find a job within this four month period and cannot be categorized as movers or stayers. I assume all these unclassified workers are stayers (approximately thirty percent of unemployed). In future work, I intend to exploit the full-panel structure of the CPS and to allow right-censored unemployment spells of workers to be categorized as censored. Importantly, I follow this same categorization of the unclassified workers in my model simulations, as described in detail below.

[27]The counterpart to this number in construction is lower by virtue of the level of disaggregation.

model and create a dataset equivalent to the CPS as follows. Using the simulated time path for the value functions, I take random Gumbel draws of the taste shocks for two sectors for one million people over 250 months (approximately 20 years).[28] The realized taste shocks for each individual combined with the value functions are all that is necessary to compute decision rules for each unemployed worker according to Equation 3.8. Once I follow the decision rules, I can track each worker's employment history and categorize every unemployed person in the sample as *data* movers or stayers (as opposed to *model* movers and stayers) and the sectors they belong to in the same way as was done in the CPS. To deal with the fact that in the beginning of this simulated CPS sample I do not know where workers were last employed, I drop the first half of the sample. This is long enough to be able to completely categorize a worker's sector of last employment. In what follows, all moments that are reported are the moments taken from this simulated dataset so that the model moments and moments calculated from the data are equivalent.

I estimate the remaining seven parameters (the value of leisure in unemployment, one match efficiency per sector, one vacancy flow cost per sector, the variance of the taste-shocks, and the elasticity of the matching function) using the Simulated Method of Moments. The moment condition is of the form:

$$E[G(H_0)] = 0$$

where H_0 is the true value of $H = [b \;\; \Upsilon_C \;\; \Upsilon_{NC} \;\; \rho \;\; c_C \;\; c_{NC} \;\; g]$. The SMM estimator is then given by:

$$\widehat{H} = \arg\min_{H}[G(H)'\mathbf{W}G(H)] \tag{4.1}$$

where $\mathbf{W}$ is a 7 by 7 weighting matrix and $G(H)$ is the 7 by 1 vector of moments that are a function of the parameters to be estimated, H. The seven moment conditions used to estimate the parameters are as follows. The match efficiencies as well as the vacancy

[28]I use one million people to eliminate small simulation errors due to the draws from the T1EV.

creation costs will in part determine the unemployment rates and mover rates across sectors, so I include these as moments in the SMM procedure. All else equal, a higher match efficiency will lead to a lower unemployment rate and a lower mover rate as job-finding probabilities rise. Next, the parameter ρ governs how likely it is for unemployed workers to decide to move when faced with the reallocation decision, so I choose to match the fraction of movers out of unemployed workers in each sector.[29] Finally, the elasticity of the matching function will determine the relationship between labor market tightness and job-finding probabilities in time series data. Thus, the moment I choose to match is the coefficient on labor market tightness from the following regression in the CPS:

$$\ln\left(\frac{h_{nt}}{u_{nt}}\right) = \ln(\Phi_t) + \ln(\tilde{\Upsilon}_n) + (1-\tilde{g})\ln\left(\frac{v_{nt}}{u_{nt}}\right)$$

where $\tilde{\Upsilon}_n$ is the sector-specific match-efficiency parameter estimated in the data, Φ_t is the time-varying match-efficiency, h_{nt} are the number of hires in sector n at time t, v_{nt} is the number of vacancies in sector n at time t, and u_{nt} is the number of unemployed workers in sector n at time t. I can run a similar regression with my simulated CPS dataset.

I use the method of Simulated Annealing to search for the parameters that minimize the

[29] In future work, I plan to use the responsiveness of labor mobility to differences in sectoral payoffs as the moment to calibrate ρ. Higher values of ρ correspond to less responsive labor mobility to differences in sectoral job-finding probabilities. Letting $X = M_{nj}(\Omega') - S_n(\Omega')$

$$\frac{\partial \pi_{nn}}{\partial [X]} = -\frac{1}{\rho}\frac{\exp(\frac{X}{\rho})}{\left[\sum_{k\in N}\exp(\frac{X}{\rho})\right]^2}$$

The limit of this derivative as ρ goes to infinity is given by

$$-\left[\lim_{\rho\to\infty}\frac{1}{\rho}\right]\left[\lim_{\rho\to\infty}\frac{\exp(\frac{X}{\rho})}{\left[\sum_{k\in N}\exp(\frac{X}{\rho})\right]^2}\right] = 0*1 = 0$$

Thus, if the variance of the shocks is large, there will be several workers realizing taste shocks that will induce mobility regardless of sector differences in job-finding probabilities and wages. Any changes in these differences will not change the move decisions of workers. On the other hand, if the variance in taste shocks is small, there will be a large number of workers close to the cutoff point for movement. In this case, even slight changes in sectoral job-finding probabilities will induce labor mobility so that labor mobility will be more responsive to movements in sectoral productivity over the cycle.

Table 3: Estimated Parameter Values

Υ_C	Υ_{NC}	b	c_C	c_{NC}	g	ρ
0.70	0.69	0.40	0.51	0.46	0.64	0.40

Table 4: Results from SMM Estimation

	Model	Data
stayer share of unemployed, construction	0.78	0.69
stayer share of unemployed, non-construction	0.96	0.94
unemployment rate, construction	0.12	0.09
unemployment rate, other	0.05	0.05
job-finding probability, construction	0.38	0.41
job-finding probability, non-construction	0.49	0.40
aggregate matching function regression	0.63	0.64

moment function given by Equation 4.1. The algorithm is explained in detail in the online appendix of Dell (2011). Tables 3,4, and 5 report the results from the estimation as well as other moments not targeted in the estimation respectively.

5 Counterfactual Experiments

In this section, I use the calibrated version of my model to asses the importance of slow intersectoral labor reallocation in explaining aggregate unemployment. I then study how changes in the dispersion of sectoral shocks impact unemployment due to sectoral reallocation.

In Section 5.2, I compare unemployment in the model with moving costs (the "true" model) to unemployment when intersectoral labor reallocation is frictionless. This allows me to gauge the importance of intersectoral mobility frictions in explaining observed aggregate unemployment. I then turn my focus to the recent recession in which the dispersion of shocks across sectors may have been large given the linkages of the recession to the boom

Table 5: Other Moments

	Model	Data
relative durations (movers/stayers)	1.53	1.57
employment share, construction	0.07	0.07

and bust in the housing market. I analyze the Lilien (1982) hypothesis and examine how unemployment due to sectoral reallocation would have changed if the shocks had been more symmetric, behaving more like an aggregate shock rather than a shock that required net reallocation of labor across sectors. This is described in Sections 5.3 through 5.4.

5.1 Recovering the Shocks

To run these counterfactuals, I first recover the shocks that hit construction and non-construction from 1977-2012 that are consistent with observed sectoral employment dynamics in the data, conditional on the estimated parameters from Section 4. I take a second order approximation of the model around its deterministic steady state which gives an approximate rule for how the model's endogenous variables respond following exogenous shocks to sectoral productivities.[30] Recall that the evolution of sectoral labor productivities follows:

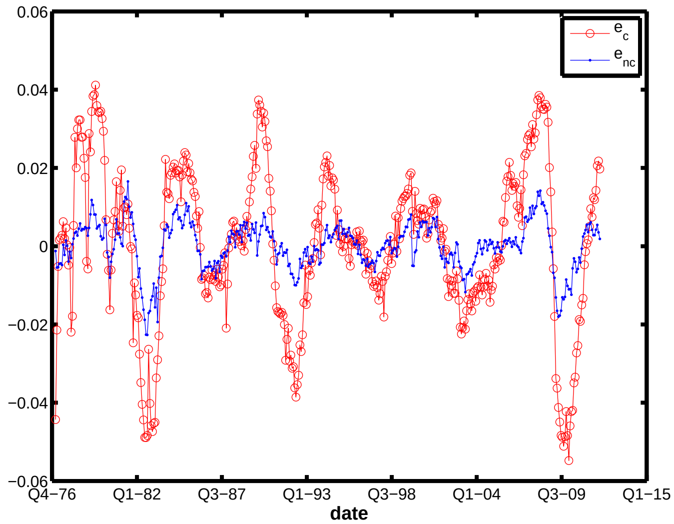
$$\log(\mu_n') = \kappa_n \log(\mu_n) + \zeta_n \nu_n'$$

Thus, combining the second order approximation with a time series on two of the model's endogenous variables implies that solving for the underlying shocks reduces to solving a system of two non-linear equations for every period t in the shocks, $\nu_{\mu_{C,t}}$ and $\nu_{\mu_{NC,t}}$. Given the time-series on employment in construction and the rest of the economy, I assume the economy was in a steady state in January 1977 and back out the time path of sectoral shocks consistent with observed sectoral employment dynamics. The time series for employment can be found in Figure 2 while the recovered paths of sectoral productivity can be found in Figure 3.[31] A more complete description of how I recover the shocks is described in the

[30]In particular, I first solve for the shocks using a first order approximation of the model, and use these recovered shocks as the starting values for the search with the second order approximation. I use the second order approximation because it is more accurate, especially in episodes when there were large swings in employment from the steady state.

[31]The sectoral employment series I use is employment relative to the aggregate labor force. Since the model generated e_n is employment in each sector relative to the total labor force when the labor force is normalized to 1, the aforementioned series will be equivalent to its model counterpart and I can use the second order approximation directly.

Figure 2: Time Series of Sectoral Employment

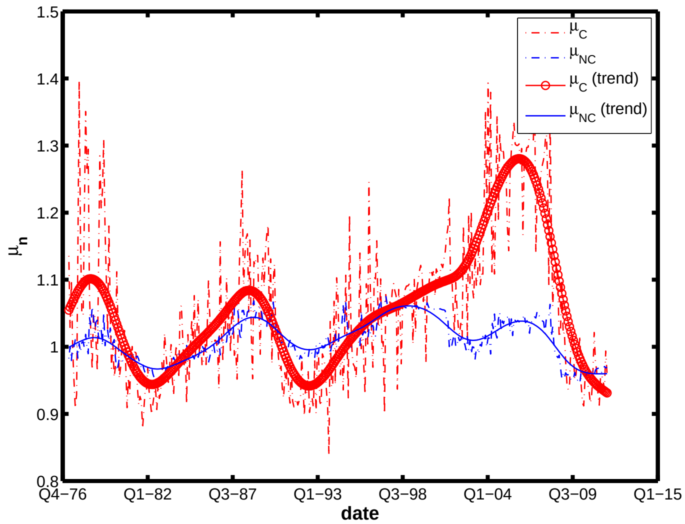


Notes: Both series were constructed using data on employment from the Current Employment Statistics and labor force data from the CPS. To be consistent with the model, the series created is employment in each sector relative to the total labor force. The red line represents the cyclical component of hp-filtered monthly employment in construction relative to the total labor force, with smoothing parameter 14400. The blue line represents the cyclical component of hp-filtered monthly employment in non-construction relative to the total labor force, with smoothing parameter 14400.

Appendix, Section F.

Since I fit the labor productivity shocks to movements in employment, construction labor productivity displays larger variance over the cycle. The shocks are able to pick up the housing market boom, which drew many workers into construction. This phenomenon corresponds to the larger deviation in sectoral productivities beginning in the early 2000s. The estimated paths of sectoral productivity are consistent with the idea that sectoral shocks became more dispersed in the recent recession. The standard deviation of the shocks beginning in 2002 is approximately four times larger than the average historic standard deviation. Thus, the recent recession provides a good natural phenomenon to study the importance of sectoral shock dispersion in generating aggregate unemployment. Since the dispersion became large relative to historical standards, if sectoral shocks are important in generating aggregate unemployment, their importance should be detectable in the recent cycle.

Figure 3: Estimated Paths of Sectoral Productivity



Notes: The red line represents the hp-filtered trend of monthly labor productivity in construction with smoothing parameter 14400. The blue line represents the hp-filtered trend of monthly labor productivity in non-construction with smoothing parameter 14400. The dotted lines represent represent their unfiltered values.

5.2 Counterfactual 1: Frictionless Benchmark

In this exercise, I ask how much unemployment is caused by the presence of intersectoral mobility frictions in the form of extra time spent unemployed. Given the two-sector calibration, the measured fraction of unemployment attributed to these frictions will be a lower bound, as the estimate does not account for the labor mobility between sectors I have lumped into non-construction. Nonetheless, the exercise provides an idea of the magnitudes of overall unemployment from this channel.

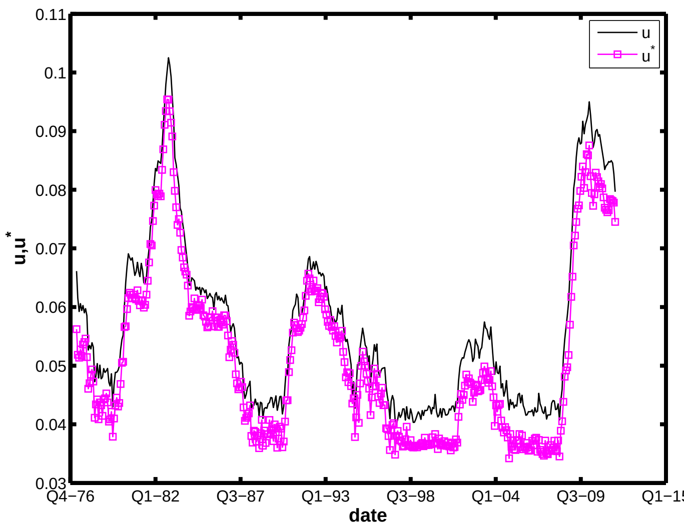
I solve the model in which labor mobility across sectors takes no extra time, thus removing the state of *model* move unemployment.[32] Workers are now choosing between stay unemployment between sectors. In this two sector case, the relevant probability of moving becomes:

$$\pi_{12} = \frac{1}{1 + \exp(S_1 - S_2)} = 1 - \pi_{21}$$

[32] That is, there will still be *data* movers, but I remove the notion of extra time spent in unemployment in the model.

I then construct the second order approximation of the model without moving time around its deterministic steady state, and use the approximation combined with the recovered shocks from Section 5.1 to trace out the path of unemployment when labor can move freely across sectors. Figure 4 depicts both the realized path of unemployment as well as the path of unemployment in the hypothetical world with no moving costs.

Figure 4: Hypothetical Aggregate Unemployment Rate without Moving Costs



Notes: The black line represents the unemployment rate constructed using the estimated shocks found in 5.1 combined with the second order approximation of the true model, which mimics the dynamics of unemployment in the data. The pink line connected by squares represents the hypothetical unemployment rate in the model without moving time using the same estimated shocks.

The overall level of unemployment in the hypothetical economy in which moving takes no extra time is always lower than the unemployment in the "true" economy.[33] On average, the unemployment rate falls by 0.55 percentage points. This reduction comes from two different channels. First, holding the number of movers fixed, but lowering their unemployment duration lowers unemployment as the flow into employment increases. Second, the absence of moving costs allows for a more efficient allocation of labor, as workers who previously did not move choose to reallocate to the more productive sector. The better allocation of labor

[33] I have also done a similar exercise in which I do not permit mobility in response to sectoral shocks, which is equivalent to the case of infinite moving costs. This economy also features lower unemployment. Since workers are often moving due to tastes and this process takes time, eliminating the possibility of intersectoral mobility also lowers unemployment. The results from this exercise can be found in Appendix Section H.

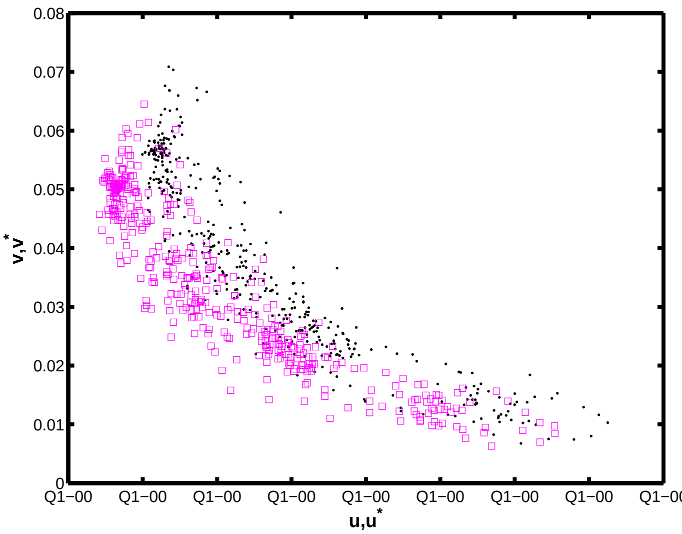
incentivizes vacancy creation and thus lowers unemployment.

To tease out the importance of these two effects, I compute a simple calculation. I take all movers in the "true" model, and then assume these workers find a job according to the sectoral job finding probabilities of stayers in that model. I find that 0.36 percentage points of unemployment (approximately sixty five percent of the decline) can be attributed to the decline in unemployment duration associated with these movers. The remaining 0.19 percentage points can be attributed to the more efficient allocation of labor following the elimination of moving costs. Note that while the first channel is something that is directly measurable in data, the latter is one which requires a structural model to estimate.

I also examine how these types of moving costs impact the Beveridge curve relationship (the relationship between vacancies and unemployment) as well as the matching function one would estimate from the data. Figure 5 plots the relationship between vacancies and unemployment in the hypothetical world without moving costs as well as in the world with moving costs. The world with moving costs is associated with an outward shift of the Beveridge curve relative to the frictionless world so that the vacancy rate is approximately one percentage point higher at every level of unemployment; the job-finding probability is 11.90 percent lower at every level of labor market tightness.

Thus, the model has the power to generate endogenous shifts in the Beveridge curve. While I focus on a two-sector calibration with one extra period of unemployment for switchers, one can imagine that an N-sector calibration where switching time is origin-and-destination specific would lead to constant inward and outward shifts of the Beveridge curve. The amount of movers as a fraction of unemployment will change depending on (i) how costly it is to switch sectors, and (ii) which sectors are getting shocked. If relative demand shifts occur between sectors that are closely related in terms of human capital so that moving takes no extra time, this might induce an inward shift. Conversely, if relative demand shifts occur between sectors that are more different so that moving takes longer, this would induce an outward shift.

Figure 5: Hypothetical Aggregate Beveridge Curve without Moving Costs



Notes: The black dots represents the unemployment rate and vacancy rate constructed using the estimated shocks found in 5.1 combined with the second order approximation of the model with moving time. The pink squares represent the hypothetical unemployment rate and vacancy rate in the model without moving time using the same estimated shocks.

5.3 Counterfactual 2: Symmetric Shocks in the 2008 Recession

Lilien (1982) argues that the empirical correlation between dispersion in employment growth, a proxy for the dispersion in sectoral shocks, and aggregate unemployment is evidence that some unemployment is due to the slow movement of labor across sectors in response to sectoral shifts. The underlying assumption is that an increase in the dispersion of sectoral shocks leads to an increase in net reallocation of labor which in turn increases aggregate unemployment through higher unemployment duration for movers. According to this logic, we might expect that the recent recession, which affected the construction sector relatively worse than other sectors of the economy, increased the need for net reallocation and thus unemployment due to movers.[34] As the estimated time-path for sectoral shocks suggests, the dispersion of shocks indeed increased in the last recession relative to historical standards.

To evaluate the validity of the Lilien (1982) hypothesis in the most recent downturn, I

[34] Abraham and Katz (1986) argue that the correlation between the dispersion of shocks and unemployment is not necessarily evidence of sectoral shifts; the correlation can arise if sectors have different cyclical sensitivities to an aggregate shock. This paper does not seek to distinguish between the origin of the shocks and thus the roots of the empirical correlation studied in Lilien (1982).

ask what would have happened to move unemployment if shocks to labor productivity in construction and non-construction were more symmetric. Specifically, I construct a hypothetical path for productivity in the two sectors so that (i) aggregate employment (and thus unemployment) are equal to the same values as in the true economy over the length of the recession and (ii) the employment shares in construction and non-construction are constant beginning in 2008.[35] If we define aggregate productivity $\tilde{\mu}_t$ as:

$$\tilde{\mu}_t = \left[\sum_{n \in N} \tau_n \mu_{n,t}^{\sigma-1} \right]^{\frac{1}{\sigma-1}}$$

then the counterfactual shocks are constructed so that:

$$1 = \sum_{n \in N} \tau_n \left(\frac{\mu_{n,t}}{\tilde{\mu}_t} \right)^{\sigma-1} = \sum_{n \in N} \hat{\tau}_n$$

In this way, the hypothetical shocks will lead to an economy in which the unemployment rate is the same as in the true economy, but there is no need for net reallocation.[36]

The hypothetical paths of sectoral productivity can be found in Figure 6. The shocks which would have been necessary to keep net reallocation at zero are more symmetric. Hypothetical labor productivity in construction is higher relative to its estimated productivity, while hypothetical labor productivity in non-construction is relatively lower, bringing the two productivity levels closer together.

[35]The first restriction guarantees that the depth of the recession the same. The second restriction removes any need for net reallocation of labor.

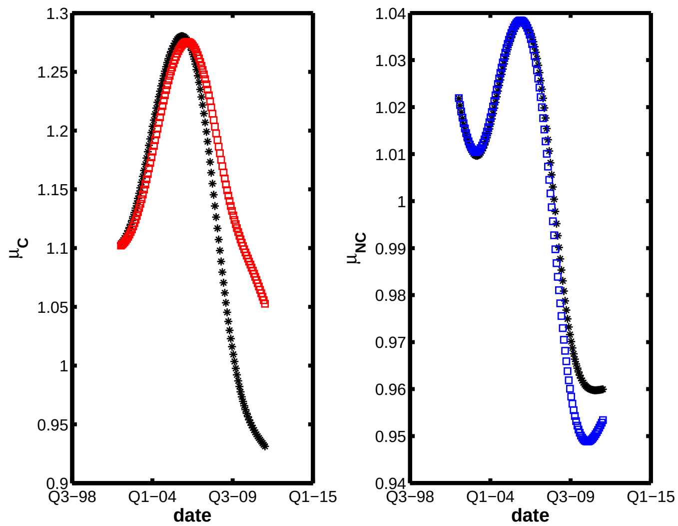
[36]Note that, letting $\tilde{e}_t$ denote aggregate employment, we can write aggregate output as:

$$Y_t = \tilde{\mu}_t \tilde{e}_t \left[\sum_{n \in N} \tau_n^{\frac{1}{\sigma}} \left(\frac{\mu_{n,t} e_{n,t}}{\tilde{\mu}_t \tilde{e}_t} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

which is equivalent to:

$$Y_t = \tilde{\mu}_t \tilde{e}_t \left[\sum_{n \in N} \hat{\tau}_n^{\frac{1}{\sigma}} \left(\frac{e_{n,t}}{e_t} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

Figure 6: Estimated and Hypothetical Paths of Sectoral Productivity



Notes: The black starred line in the left panel represents the estimated path of sectoral productivity in construction, while the red line with circles in the left panel represents the hypothetical path of sectoral productivity in construction. The black starred line in the right panel represents the estimated path of sectoral productivity in non-construction, while the blue line with circles in the right panel represents the hypothetical path of sectoral productivity in non-construction.The hypothetical shocks are constructed so that aggregate unemployment remains the same, but sectoral employment shares in the hypothetical world remain constant beginning in 2008, as described in Section 5.3.

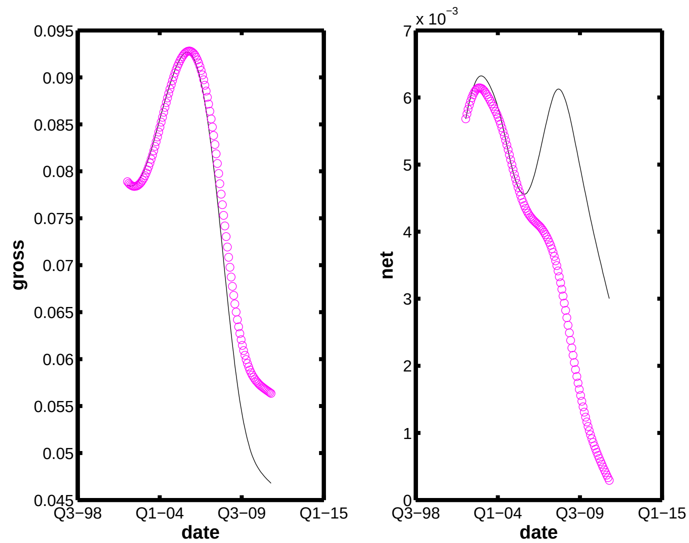
Figure 7 plots the realized and hypothetical path of unemployment due to gross movers (move unemployment) and the fraction of unemployment due to net movers in both the hypothetical and true scenario.[37] By construction, the fraction of unemployment due to net movers depicted in the right panel of Figure 7 tends to zero since the shocks require no net reallocation. Net reallocation does not immediately jump to zero because some leftover reallocation must take place depending on where the economy begins.[38] Gross reallocation, on the other hand, does not tend to zero. In this scenario, gross reallocation in the hypothetical world where shocks are more symmetric increases by an average of one percentage point relative to the true scenario in which shocks are more dispersed.[39]

[37] If gross reallocation is given by $m_{12} + m_{21}$, then net reallocation is given by $|m_{12} - m_{21}|$.

[38] I return to the position of the economy beginning in 2008 in the next section.

[39] The reason for the increase is because, in such a model, whenever the sectors become more similar to one another, gross reallocation increases.

Figure 7: Fraction of Unemployment Due to Gross Reallocation (Move Unemployment) and Net Reallocation

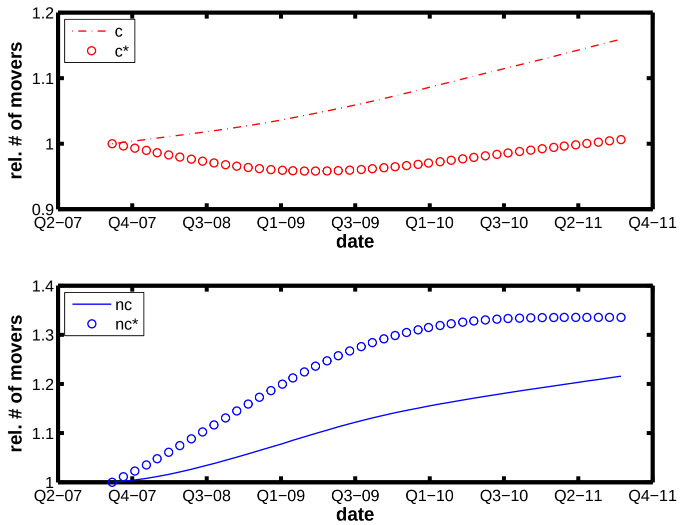


Notes: The black solid line in the left panel represents the move unemployment rate constructed using the estimated shocks found in 5.1, while the black dashed line in the right panel represents the fraction of unemployment due to net movers constructed using the same estimated shocks. The pink line connected by circles in the left panel represents the hypothetical move unemployment rate in the hypothetical scenario, while the pink line connected by circles in the right panel represents the hypothetical fraction of unemployment due to net movers.

What is the reason a decline in net reallocation is not associated with a similar decline in gross reallocation? The intuition is as follows. Consider a world in which gross reallocation is large; therefore, at any point in time, workers are moving back and forth simultaneously between these two sectors. When a shock comes that requires net labor reallocation from construction to non-construction, this reallocation does not necessarily occur through a simple increase in the number of movers from construction to non-construction. Instead, some who may have previously moved from non-construction to construction no longer move, while more people move from construction to non-construction. In the aggregate, the level of total movers may remain unchanged. That is, when gross reallocation is not equal to net reallocation, some of the response to sector-specific shocks works through changes in the composition of gross reallocation.

To see this, I plot the number of movers in both construction and non-construction in the hypothetical and true scenario relative to their initial values before the new shock (when they are equal) in Figure 8. As the intuition describes, the world with more symmetric shocks features both fewer movers from construction to non-construction as well as more movers from non-construction to construction.

Figure 8: Estimated and Hypothetical Number of Movers in Construction and Non-Construction



Notes: The solid lines represent the estimated path of movers in construction (red, upper panel) and non-construction (blue, lower panel). The dotted line represents the hypothetical path of movers in construction (red) and non-construction (blue). The hypothetical shocks are constructed so that aggregate unemployment remains the same in the two counterfactuals and the employment shares in the hypothetical world remain constant beginning in 2008, as described in Section 5.3. All values are expressed relative to their values in 2008m1, in which the hypothetical and estimated paths are initially the same.

While the effect on the aggregate number of movers is small, the dispersion of sectoral shocks plays a significantly more important role in explaining sectoral employment dynamics. While the total number of movers remains relatively unchanged, the number of movers within sectors responds to relative negative (positive) sectoral shocks. This result is consistent with evidence found in Loungani and Rogerson (1989), in which total gross reallocation is relatively acyclic, while the number of movers within sectors displays a prominent cyclical pattern. That is, the flow of labor into cyclically more sensitive sectors increases during booms and declines during recessions. Since these flows cancel out in the aggregate, total gross reallocation over the cycle is relatively acyclic.

5.4 Counterfactual 3: Symmetric Shocks in the pre-2008 Housing Boom

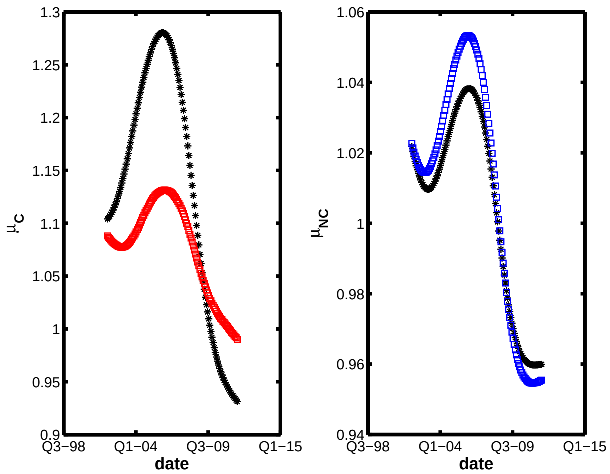
In the previous counterfactual, net reallocation does not immediately fall to zero when changes in the desired allocation of labor are removed. The time it takes for the economy to reach a point of zero net reallocation depends on the allocation of labor relative to the desired allocation of labor dictated by the realized sectoral productivities. Therefore, taking the Lilien (1982) logic one step further, the housing boom might have been responsible for some unemployment if it induced a large fraction of labor to move to construction in the boom period that only needed to reallocate again during the bust. That is, the housing boom maybe have induced an allocation of labor beginning in 2008 that was even further from its desired level.

In this section, I perform a similar exercise as the previous counterfactual, except I solve for the path of shocks that would keep sectoral employment shares constant beginning in 2002, when the housing boom started to take off.[40] This would lower the need for net reallocation during the recession, and, according to the Lilien (1982) hypothesis, would also lead to less unemployment due to reallocation. The hypothetical paths for sectoral productivity for this exercise can be found in Figure 9.

Consistent with the results from earlier experiments, while the housing boom increased the need for net reallocation during the recession, it hardly increased the amount of unemployment due to movers. Aggregate gross reallocation over the entire period is basically unchanged. The first result might be surprising since the counterfactual effectively shuts down large intersectoral net labor movements. Again, the underlying reason is that these net flows were happening through the composition of gross reallocation and not through its level. Second, gross reallocation would have been lower during the housing boom and slightly higher during the bust. The reason for the asymmetry is that the construction sector was

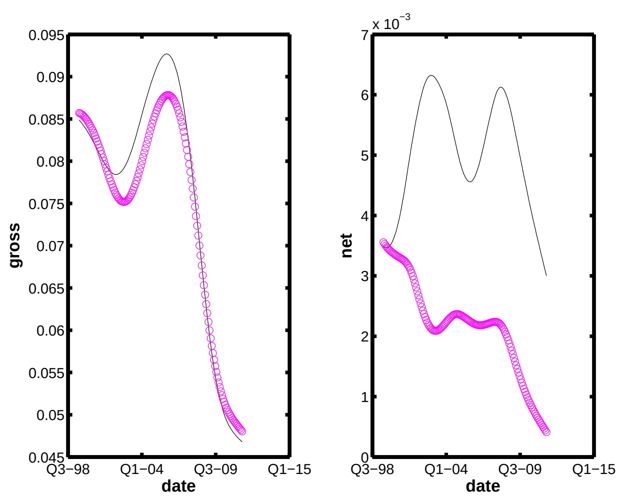
[40]The rise in house prices started earlier, but I want to analyze the interaction between the housing boom that occurred at the same time as the boom period prior to the recession.

Figure 9: Estimated and Hypothetical Paths of Productivity in construction and non-construction



Notes: The black solid line represents the estimated path of sectoral productivity in construction, while the red starred line represents the hypothetical path of sectoral productivity in construction. The hypothetical shocks are constructed so that aggregate unemployment remains the same in the two counterfactuals, but so the employment shares in the hypothetical world remain constant beginning in 2002, as described in Section 5.3.

Figure 10: Estimated and Hypothetical Paths of Gross Reallocation (Move Unemployment)



Notes: The black solid line in the left panel represents the move unemployment rate constructed using the estimated shocks found in 5.1. The pink line connected by circles represents the hypothetical move unemployment rate.

large between 2002 and 2007. In the counterfactual construction is significantly smaller thus reducing the number of workers flowing into and out of that sector.[41] The reason for the slight increase in gross reallocation during the recession is similar. Note, however, that the effect for the recession is much smaller compared to Figure 7 owing to the fact that Figure 7 starts at the housing buildup, whereas this counterfactual does not allow for the buildup.

These three counterfactuals combined suggest that (i) intersectoral mobility frictions are an important determinant of aggregate unemployment in the face of sectoral shocks, and that (ii) the importance of slow intersectoral labor reallocation in explaining aggregate unemployment does not necessarily increase when the dispersion of sectoral shocks increases. While asymmetric shocks induce more movers out of the sector hit relatively worse, they also induce less movement from relatively better off sectors. In the aggregate, the total amount of unemployment due to reallocation is ambiguous. In the above examples, gross reallocation as a fraction of unemployment is largest when sectors are more similar, which means that a decline in the dispersion during the boom period and a decline in dispersion during the bust period have counterfactually different impacts on unemployment due to sectoral reallocation.

The results also point to a different cause for the correlation between the dispersion in sector specific shocks and aggregate unemployment found in Lilien (1982). Given that aggregate reallocation in my counterfactuals does not grow with the dispersion of sectoral shocks, this suggests that the misallocation channel discussed in 5.2 is responsible for the observed correlation. That is, it is not the direct time of movers spent in unemployment, but rather the misallocation induced by moving frictions that drives up aggregate unemployment in response to sectoral shifts.

6 An Illustrative Example

I have argued that a shock that requires net reallocation across sectors does not necessarily increase gross reallocation and therefore move unemployment. An important question is

[41]This is the same force driving the results behind the increase in gross flows in Counterfactual 2.

whether or not this result is robust under different scenarios in which the size of the sector getting hit is larger, or the shock itself is more permanent. Consider a simplified version of the model. Suppose the economy consists of two sectors $n = \{1, 2\}$ and movers do not need to spend additional time in unemployment. Instead, movers are immediately absorbed within one period. Then, the assignment of unemployed workers is a repeated static choice. An unemployed worker in sector 1 chooses to move or stay according to

$$\max\{S_1 + \varepsilon_1, S_2 + \varepsilon_2\}$$

In the steady state, gross (G) and net (N) flows are given by:

$$G = \pi_{12}U_1 + \pi_{21}U_2$$

$$N = |\pi_{12}U_1 - \pi_{21}U_2| = 0$$

where

$$\pi_{12} = \frac{1}{1 + \exp[S_1 - S_2]} = 1 - \pi_{21}$$

and U_n for $n \in \{1, 2\}$ represents the level of unemployment in sector n. From the above, we can write that in steady state:

$$\frac{\pi_{12}}{\pi_{21}} = \frac{U_2}{U_1} = \exp[S_2 - S_1] = \bar{d}$$

Now consider a shock that increases S_2 relative to S_1 so that $X = S_2 - S_1$ increases, but corresponds to the same level of aggregate unemployment. Letting $U_2 = \bar{d}U_1$,

$$\frac{\partial G}{\partial X} = \frac{\exp(S_1 - S_2)}{[1 + \exp(S_1 - S_2)]^2}U_1 - \frac{\exp(S_1 - S_2)}{[1 + \exp(S_1 - S_2)]^2}\bar{d}U_1$$

$$\frac{\partial N}{\partial X} = \frac{\exp(S_1 - S_2)}{[1 + \exp(S_1 - S_2)]^2}U_1 + \frac{\exp(S_1 - S_2)}{[1 + \exp(S_1 - S_2)]^2}\bar{d}U_1$$

We know that $\frac{\partial N}{\partial X} > 0$, but $\frac{\partial G}{\partial X}$ will depend on the sign of $1 - \bar{d}$. Putting the two together:

$$|\frac{\partial G}{\partial X}| = \frac{\partial N}{\partial X}| \left[\frac{1-\bar{d}}{1+\bar{d}}\right] |$$

Note that total gross reallocation only increases when $\bar{d} < 1$, or equivalently $S_2 - S_1 < 0$. Therefore, gross reallocation and net reallocation only move in the same direction when the larger sector receives the relatively worse shock. Further, when sectors sizes are more similar ($S_2 \sim S_1$), the impact of relative sectoral shocks on gross flows is smaller. In particular, the case where the two sectors are exactly equal is when the change in sectoral flows will exactly cancel out in the aggregate.

The key to understanding these results is that net reallocation always operates through the composition of gross reallocation. If sectors are exactly of equal size, the increased outflow out of the adversely shocked sector is exactly offset by the decreased outflow from the favorably shocked sector. If sectors are of different size, the compositional change may increase or decrease gross allocation. In a long time series of construction and the rest of the economy, we should see that net reallocation is not correlated with gross reallocation.

7 Conclusion

This paper develops a tractable multisector equilibrium search model of labor reallocation to study the importance of intersectoral mobility frictions in explaining aggregate unemployment. In a version of the model calibrated to construction and non-construction, I find that intersectoral mobility frictions in the form of higher unemployment durations for movers significantly contribute to unemployment. First, these frictions impede the efficient movement of labor across sectors in response to sector-specific shocks. Second, they increase average unemployment duration in the aggregate by increasing the unemployment duration for those who choose to move in response to those shocks. Together, these two forces generated ten percent of aggregate unemployment on average over the last 35 years. Given the two sector calibration, this is likely a lower bound for the importance of these types of mobility frictions.

I then ask whether the importance of labor reallocation in explaining aggregate unemployment changed in the recent recession, when differences in sectoral shocks were pronounced. In accordance with the argument put forth in Lilien (1982), one might expect that the concentration of the recession in sectors closely tied to the housing market increased the need for reallocation of workers in sectors hit by relatively acute shocks. This in turn would increase aggregate unemployment. While the nature of the sectoral shocks in the 2008 recession did require net labor reallocation, I find no significant increase in unemployment due to movers relative to a benchmark case in which the shocks were less dispersed. I similarly study the importance of the housing boom in generating a large degree of misallocation given the nature of the shocks during the recession. The recession essentially overturned the pre-recession run-up in the share of unemployment in construction, so the housing boom is responsible for a large need for net reallocation. Consistent with the results from earlier experiments, while the housing boom increased the need for net reallocation during the recession, it hardly increased the amount of unemployment due to movers.

These results highlight the importance of accounting for gross labor reallocation rather than net reallocation when quantifying the impact of reallocation on unemployment. First, if the relevant cost of intersectoral mobility is extra time in unemployment, the total number of movers is a more appropriate statistic than the net number of movers. Second, since net reallocation does not necessarily move in the same direction as gross reallocation, it might overstate the importance of intersectoral mobility in generating unemployment. While the model I develop is quite stylized, the intuition is quite general and unlikely to be an artifact of the modeling assumptions in this paper. That is, in any model with gross flows exceeding net flows, there is no reason to suspect that the total number of movers in the economy will necessarily move when net reallocation increases.

While I use the model to focus on the most recent recession and its uniqueness in terms of its relationship to the housing boom and construction workers, it has broader applications. For example, one could use the model to study the effect of trade liberalization on unemployment dynamics in manufacturing and services. Artuc, et. al. (2010) have a similar setup, but they study the impact of trade liberalization on employment and wage dynamics. Given their emphasis on the welfare effects of trade liberalization, a natural extension would be to include unemployment, since these costs can be large and significant contributions to welfare losses, at least in the short run.[42] While there are several papers that have begun to study the effects of trade liberalization on the labor market, to my knowledge none have incorporated its impact on unemployment dynamics.[43]

One could also amend the model to think about more simple forms of mobility costs by removing the state of move unemployment and introducing a utility cost that might be sector or location specific, as in Kline (2008).[44] This formulation of the model could be used in several studies. For example, one could measure mobility costs across different dimensions (space, sectors, or both) and think about how these costs might have changed over time, both in absolute terms and relative to one another. This line of inquiry might be useful in understanding why interstate migration in the U.S. has declined drastically since the 1980s. This decline may be driven by a decline in intersectoral moving costs that allows workers to more easily adjust to local shocks by changing sectors rather than locations.[45] As another example, one could estimate spatial moving costs over time, and ask whether they have increased in the recent recession to test the "house lock" hypothesis.

As I have emphasized earlier, permanent sectoral declines can be integrated into the framework I have developed. In work in progress, I introduce a third sector - manufacturing - which has experienced a steady decline in its overall employment share in the past thirty years. Understanding differences between permanent sectoral declines and temporary movements in relative sectoral productivities is a topic beyond the scope of this paper. However, thinking about these differences as well as the interaction between permanent declines and

[42] See Davis and Wachter (2011), for example.

[43] See, for example, Kamborouv (2009) and Dix-Carneiro (2010).

[44] The model becomes computationally simple when the extra state variable of move unemployment is removed.

[45] In work in progress with Erik Hurst and Kerwin Charles, we explore such a hypothesis.

the business cycle is an interesting avenue for future work.

A Derivation of Equations (3.5), (3.6), and (3.7)

We begin with the value of employment for a worker in an arbitrary sector n:

$$W_n(\Omega) = w_n + \beta \mathbf{E}\left\{[1-\delta_n](W_n(\Omega') + \varepsilon'_{n,i}) + \delta_n \max\left(S_n(\Omega') + \varepsilon'_{n,i}, \max_{k \neq n \in N} M_{nk}(\Omega') + \varepsilon'_{k,i}\right)\right\}$$

Integrating out the idiosyncratic taste shocks gives:

$$\beta \mathbf{E}\left\{\delta_n \max\left(S_n(\Omega') + \varepsilon'_{n,i}, \max_{k \neq n \in N} M_{nk}(\Omega') + \varepsilon'_{k,i}\right)\right\}$$

$$= \beta \mathbf{E}_\Omega \mathbf{E}_\varepsilon \left\{\delta_n \max\left(S_n(\Omega') + \varepsilon'_{n,i}, \max_{k \neq n \in N} M_{nk}(\Omega') + \varepsilon'_{k,i}\right)\right\}$$

where the first expectation is taken over the aggregate state, and the second refers to the expectation over the idiosyncratic taste shocks. Simplifying further we get:

$$\beta \mathbf{E}_\Omega \mathbf{E}_\varepsilon \left\{\delta_n \max\left(S_n(\Omega') + \varepsilon'_{n,i}, \max_{k \neq n \in N} M_{nk}(\Omega') + \varepsilon'_{k,i}\right)\right\}$$

$$= \beta \delta_n \mathbf{E}\left\{\rho \log[\sum_{k \in N} \exp(\widetilde{S}_{nk}(\Omega')/\rho)]\right\}$$

where I use the fact that the expectation of a T1EV($-\rho\gamma$,ρ) variable is zero.

B Derivation of the Wage Equation Under Nash Bargaining

First derive the surplus for the worker, $W_n - S_n$:

$$W_n(\Omega) - S_n(\Omega) = w_n - b + \beta[1-\delta_n - f_n(\theta_n)]E\left\{W_n(\Omega') - \rho \log\left[\sum_{k \in N} \exp(\widetilde{S}_{nk}(\Omega'))\right]\right\} \tag{B.1}$$

Applying the wage sharing rule $(1-\eta)[W_n - S_n] = \eta J_n$ and substituting in for $J_n(\Omega)$ gives:

$$(1-\eta)(w_n - b) + (1-\eta)\beta[1-\delta_n - f_n(\theta_n)]E\left\{W_n(\Omega') - \rho\log\left[\sum_{k\in N}\exp(\widetilde{S}_{nk}(\Omega')/\rho)\right]\right\}$$
$$= \eta(p_n - w_n) + \eta\beta(1-\delta_n)E\{J_n(\Omega')\}$$

Solving for w_n gives:

$$\begin{aligned} w_n &= (1-\eta)b + \eta p_n \\ &\quad - (1-\eta)\beta[1-\delta_n - f_n(\theta_n)]E\left\{W_n(\Omega') - \rho\log\left[\sum_{k\in N}\exp(\widetilde{S}_{nk}(\Omega')/\rho)\right]\right\} \\ &\quad + \eta\beta(1-\delta_n)J_n(\Omega') \end{aligned}$$

Using the wage sharing rule for next period, $(1-\eta)\left[W_n(\Omega') - S_n(\Omega')\right] = \eta J_n(\Omega')$ gives:

$$\begin{aligned} w_n &= (1-\eta)b + \eta p_n \\ &\quad - (1-\eta)\beta[1-\delta_n - f_n(\theta_n)]\mathbf{E}\left\{W_n(\Omega') - \log\left[\sum_{k\in N}\exp(\widetilde{S}_{nk}(\Omega')/\rho)\right]\right\} \\ &\quad + (1-\eta)\beta(1-\delta_n)\mathbf{E}\{W_n(\Omega') - S_n(\Omega')\} \end{aligned}$$

Adding and subtracting $(1-\eta)\beta[1-\delta_n - f_n(\theta_n)]S_n(\Omega')$ gives:

$$\begin{aligned} w_n &= (1-\eta)b + \eta p_n \\ &\quad - (1-\eta)\beta[1-\delta_n - f_n(\theta_n)]\mathbf{E}\left\{W_n(\Omega') - S_n(\Omega') + S_n(\Omega') - \rho\log\left[\sum_{k\in N}\exp(\widetilde{S}_{nk}(\Omega')/\rho)\right]\right\} \\ &\quad + (1-\eta)\beta(1-\delta_n)\mathbf{E}\{W_n(\Omega') - S_n(\Omega')\} \end{aligned}$$

Using the free entry condition, we know that $\beta\mathbf{E}\{J_n(\Omega')\} = \frac{c_n}{q_n(\theta_n)}$ so that:

$$\begin{aligned} w_n &= (1-\eta)b + \eta p_n + \eta c_n\theta_n \\ &\quad - (1-\eta)\beta[1-\delta_n - f_n(\theta_n)]\mathbf{E}\left\{S_n(\Omega') - \rho\log\left[\sum_{k\in N}\exp(\widetilde{S}_{nk}(\Omega')/\rho)\right]\right\} \end{aligned}$$

which is equivalent to:

$$\text{(B.2)}\quad w_n = (1-\eta)b+\eta p_n+\eta c_n\theta_n-\rho(1-\eta)\beta[1-\delta_n-f_n(\theta_n)]\mathbf{E}\left\{\log\left[\frac{\exp(S_n(\Omega')/\rho)}{\sum_{k\in N}\exp(\widetilde{S}_{nk}(\Omega')/\rho)}\right]\right\}$$

Using the equation for the probability of remaining a stayer on island n, we can also write this as:

$$w_n = (1-\eta)b + \eta p_n + \eta c_n\theta_n - \rho(1-\eta)\beta[1-\delta_n - f_n(\theta_n)]\mathbf{E}\log\left[\pi_{nn}\right]$$

C Alternative Model Calibrations

I have chosen a calibration of the model in which wages are rigid in order to better match unemployment fluctuations in the data. There are other routes I could have chosen in the model calibration, two of which I describe below. However, since my counterfactual exercises will ultimately recover productivity shocks which match fluctuations in unemployment, either calibration strategy is valid.

To highlight the last point, consider a version of the model where I allow wages to be fully flexible, the Hosios (1994) condition holds, and the value of leisure is relatively low compared to the market wage. In this version of the calibration, the shocks I estimate in section 5.1 will be large, given the evidence introduced in Shimer (2005). Since I use an approximation of the model around its deterministic steady state in my counterfactuals, this route is less appealing as the approximation will be less accurate in the face of large shocks to productivity, especially like the ones we observe in the last recession.

Hagedorn and Manovskii (2008) show that it is possible to generate fluctuations in unemployment in the MP model with flexible wages, given a different calibration strategy for the bargaining power (η) and the value of leisure (b). The authors show that what really matters in this setting is the sensitivity of firm accounting profits ($p_n - w_n$) to movements in productivity. This alternative calibration strategy would require data on vacancy creation costs by sector ($\{c_C, c_{NC}\}$). Given these values, I could estimate the values of non-market activity and the worker's bargaining power to match the elasticities of sectoral wages to sectoral productivity shocks and the average job-finding probabilities in each sector. This would lead to a higher value of leisure and a lower bargaining power η. However, since this would require matching the elasticity of wages in two sectors, I would also need to have two different values of non-market activity which would in turn affect the level of intersectoral labor mobility. Therefore, I choose the simpler route of rigid wages.

D Efficiency

A natural question is whether or not the equilibrium allocations are efficient. In this section, I set out the social planner's problem and compare its properties with the decentralized equilibrium. In this multisector model, the key equilibrium objects are the number of vacancies posted by firms, as well as the move decisions of workers. Thus, the question here is whether or not wages, intermediate goods prices, and move probabilities found in the decentralized equilibrium lead to the same outcomes chosen by a social planner, in which case the decentralized equilibrium is constrained efficient. I assume that the planner, in deciding how many vacancies to post, does not take into account the effect of his cutoff choice on the pool of people who will be able to make move decisions.[46] Finally, the planner is subject to the same moving frictions and search frictions outlined in the decentralized economy. In what

[46] If I instead let the planner internalize the effect of market tightness on the pool of workers making a move decision, wages that decentralize the planner's solution are lower than the nash-bargained wages. Since firms do not account for how their vacancy choices will impact the pool of workers making move decisions today, they over-post vacancies. The planner would like to keep some workers unemployed so that they can capitalize on taste-shock differences. Since this is an artifact of the way I model taste shocks, I assume that the planner, like the firms, does not take into account the effect of that choice on the pool of people who will be able to make move decisions.

follows, I draw heavily from results previously derived in Cameron, et. al. (2007). However, since the models are different in significant ways I re-derive their results when necessary.

Following the proof given in Cameron, et. al. (2007), define $D^{ij}(\varepsilon;\Omega)$ to be a function which gives the fraction of workers who are unemployed with idiosyncratic shocks $\varepsilon = \{\varepsilon_1, ..., \varepsilon_N\}$ in sector i making a move decision who will move to sector j given the state of the economy Ω. Of course, the necessary constraint is that:

$$\sum_{j=1}^{N} D^{ij}(\varepsilon;\Omega) = 1 \;\; \forall i \in N$$

The social planner wishes to solve :

(D.1)

$$\max_{\{D_t^{nk}\}_{t=0}^{\infty}} \;\; \mathbf{E}_{\{\Omega_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \left[\sum_{n \in N} \left(\{s_n[1 - f_n(\theta_{n,t})] + e_n\delta_n + \sum_{j \in N} m_{nj,t}\} \int \cdots \int \sum_{k=1}^{N} D^{nk} \varepsilon_k \prod_{k=1}^{N} h(\varepsilon_k) \mathrm{d}\varepsilon_k \right) \right.$$
$$\left. + \max_{\{\theta_{n,t}\}_{t=0}^{\infty}} \sum_{n \in N} \left(\left\{ (\tau_n)^{\frac{1}{\sigma}} (\mu_{n,t} e_{n,t})^{\frac{\sigma-1}{\sigma}} \right\} - s_{n,t}\theta_{n,t}c_n + b[s_{n,t} + \sum_{j \neq n \in N} m_{nj,t}] \right) \right]$$

over θ_n and D^{nk} $\forall n, k \in N$ subject to:

$$e_{n,t+1} = e_{n,t}[1 - \delta_n] + s_{n,t} f_n(\theta_{n,t})$$

$$s_{n,t+1} = \left(1 - \sum_{k \neq n \in N} \int \cdots \int D^{nk} \prod_{k=1}^{N} h(\varepsilon_k) \mathrm{d}\varepsilon_k \right) \left[s_{n,t} \left[1 - f_n(\theta_{n,t})\right] + \delta_n e_{n,t} + \sum_{j \in N} m_{jn,t} \right]$$

$$m_{nk,t+1} = \int \cdots \int D^{nk} \prod_{k=1}^{N} h(\varepsilon_k) \mathrm{d}\varepsilon_k \left[e_{n,t}\delta_n + s_{n,t}[1 - f_n(\theta_{n,t})] + \sum_{j \in N} m_{jn,t} \right]$$

The first term in the planner's problem represents the value of taste-shocks, conditional on move-decisions of workers. The last terms the current period return from output and the value of leisure, net the cost of keeping vacancies posted. Form the Lagrangean L:

(D.2)

$$\max_{\{D_t^{nk},\lambda_{n,t+1}\}_{t=0}^{\infty}} \quad \mathbf{E}_{\{\Omega_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \Bigg\{ \Bigg(\sum_{n\in N} \{s_n[1-f_n(\theta_{n,t})] + e_n\delta_n + \sum_{j\in N} m_{nj,t}\} \int \cdots \int \sum_{k=1}^{N} D^{nk}\varepsilon_k \prod_{k=1}^{N} h(\varepsilon_k)\mathrm{d}\varepsilon_k \Bigg)$$

$$\max_{\{\theta_{n,t}\}_{t=0}^{\infty}} \sum_{n\in N} \Bigg(\Big\{ (\tau_n)^{\frac{1}{\sigma}} (\mu_{n,t}e_{n,t})^{\frac{\sigma-1}{\sigma}} \Big\} - s_{n,t}\theta_{n,t}c_n + b[s_{n,t} + \sum_{j\neq n\in N} m_{nj,t}] \Bigg)$$

$$\beta\lambda_{e_{n,t+1}} \left[e_{n,t+1} - e_{n,t}[1-\delta_n] - s_{n,t}f_n(\theta_{n,t})\right]$$

$$\beta\lambda_{s_{n,t+1}} \left[s_{n,t+1} - \Big(1 - \sum_{k\neq n\in N} \tilde{D}^{nk} \Big) [s_{n,t}[1-f_n(\theta_n)] + \delta_n e_{n,t} + \sum_{j\in N} m_{jn,t}] \right]$$

$$\beta\lambda_{m_{nj,t+1}} \left[m_{nk,t+1} - \tilde{D}^{nk}[e_{n,t}\delta_n + s_{n,t}[1-f_n(\theta_{n,t})] + \sum_{j\in N} m_{jn,t}] \right] \Bigg\}$$

where $\lambda_{n,t+1} = \{\lambda_{e_{n,t+1}}, \lambda_{s_{n,t+1}}, \lambda_{m_{nj,t+1}}\}$ and

$$\tilde{D}^{nk} = \int \cdots \int D^{nk} \prod_{k=1}^{N} h(\varepsilon_k)\mathrm{d}\varepsilon_k$$

The first order conditions for $\theta_{n,t}$ are given by:

$$\{\theta_{n,t}\}: \quad -\frac{c_n}{\beta f'(\theta_{n,t})} = \lambda_{e_{n,t+1}} - \lambda_{s_{n,t+1}} \left[1 - \sum_{k\in N} \tilde{D}^{nk} \right] - \lambda_{m_{nj,t+1}} \sum_{k\in N} \tilde{D}^{nk} \tag{D.3}$$

Letting $X = \int \cdots \int D^{nk}\varepsilon_k \prod_{k=1}^{N} h(\varepsilon_k)\mathrm{d}\varepsilon_k$, the FOC for $e_{n,t}$ and $s_{n,t}$ are given by:

$$\begin{aligned} \{e_{n,t}\}: \quad & p_{n,t}\mu_{n,t} - \beta\lambda_{e_{n,t+1}}[1-\delta_n] - \beta\lambda_{s_{n,t+1}}\delta_n \left[1 - \sum_{k\in N} \tilde{D}^{nk} \right] \\ & -\beta\lambda_{m_{nj,t+1}}\delta_n \sum_{k\in N} \tilde{D}^{nk} + \delta_n X = 0 \end{aligned} \tag{D.4}$$

(D.5)

$$\{s_{n,t}\}: \quad -c_n\theta_{n,t} + b - \beta\lambda_{e_{n,t+1}}[f_n(\theta_{n,t})] - \beta\lambda_{s_{n,t+1}}[1 - f_n(\theta_{n,t})]\left[1 - \sum_{k\in N}\tilde{D}^{nk}\right] -$$

$$\beta\lambda_{m_{nj,t+1}}[1 - f_n(\theta_{n,t})]\sum_{k\in N}\tilde{D}^{nk} + [1 - f_n(\theta_n)]X = 0$$

Now subtract D.5 from D.4 to get:

$$p_{n,t}\mu_{n,t} + c_n\theta_{n,t} - b = \beta[1 - \delta_n - f_n(\theta_{n,t})]\left(X + \lambda_{e_{n,t+1}} - \lambda_{s_{n,t+1}}\left[1 - \sum_{k\in N}\tilde{D}^{nk}\right] - \lambda_{m_{nj,t+1}}\sum_{k\in N}\tilde{D}^{nk}\right)$$

Combining this with D.3 gives:

$$-\frac{c_n}{\beta f'(\theta_{n,t})} = \frac{p_{n,t}\mu_{n,t} + c_n\theta_{n,t} - b - \beta[1 - \delta_n - f_n(\theta_{n,t})]X}{\beta[1 - \delta_n - f_n(\theta_{n,t})]}$$

Recall that $f_n'(\theta_{n,t}) = (1 - g)q_n(\theta_{n,t})$. Substituting this in gives:

$$\frac{c_n}{\beta q_n(\theta_{n,t})} = \frac{gc_n\theta_{n,t} + (1 - g)\left[\{p_{n,t}\mu_{n,t} - b - \beta[1 - \delta_n - f_n(\theta_{n,t})\}X\right]}{1 - \beta[1 - \delta_n]}$$

Set $\eta = g$ so that the Hosios (1994) condition holds. Then the above condition is the same as job creation condition for the firm provided that:

$$X = \rho\mathbf{E}\log\left[\pi_{nn}\right]$$

Proposition 1. *Any equilibrium maximizes the planner's problem, provided that the Hosios (1994) condition holds, $g = \eta$.*

Proof. Fix the initial allocation of labor $\left\{s_n^0, m_{nj}^0, e_n^0 \;\; \forall n, j \in N\right\}$. Following the proof in Cameron, et. al. (2007), for any date $t > 0$, define the public history variable $H_t = \{\Omega_0, ..., \Omega_t\}$ and for any worker define the history of private shocks $H_t' = \{\varepsilon_0, ..., \varepsilon_t\}$. The decision for moving can be written as a function $d_t^{ij}(H_t, \varepsilon_t)$ where $d_t^{ij}(H_t, \varepsilon_t) = 1$ if a workers is in sector i making a move decision after aggregate history H_{t-1} and faces idiosyncratic shocks

ε_t moves to j and $d_t^{ij}(H_t, \varepsilon_t) = 0$ otherwise. From this rule along with indicator functions for separation and job-finding, we can figure out the allocation $\{s_{n,t}, m_{nj,t}, e_{n,t} \ \ \forall n, j \in N\}$ at date t from H_{t-1} and the location of every workers from H_{t-1} and H'_{t-1}. We can now summarize this information by writing three vector-valued functions. Call the first $\pi_t^j(H_{t-1}; H'_{t-1}, i)$ where $\pi_t^j = 1$ if a person is in sector j at time t and $\pi_t^j = 0$ otherwise. Call the second $\xi_t(H_{t-1}; H'_{t-1}, i)$ where $\xi_t = 1$ if a person is employed at time t and $\xi_t^j = 0$ otherwise. Finally, call the third $\xi_t^s(H_{t-1}; H'_{t-1}, i)$ where $\xi_t^s = 1$ if a person is a stayer at time t and $\xi_t^s = 0$ otherwise.

Define the following indicators function. Let $\mathbf{I}_\delta = 1$ if an employed worker separates, $\mathbf{I_f} = 1$ if a stayer finds a job. Now suppose that the functions $\tilde{D}^{ij}$ with associated moving functions, allocations, and location functions $\tilde{d}^{ij}$, $\tilde{\Omega}$, and $\tilde{\pi}$ respectively. Consider an alternative feasible allocation $\hat{D}^{ij}, \hat{d}^{ij}, \hat{\pi}$ and $\hat{\Omega}$. From final goods producer optimization, it must be that:

(D.6)
$$\begin{aligned} &\mathbf{E}_{\{\Omega\}_{t=0}^{\infty}} \beta^t \sum_{n \in N} \left\{ (\tau_n)^{\frac{1}{\sigma}} (\tilde{y}_{n,t})^{\frac{\sigma-1}{\sigma}} \right\} - \sum_{n \in N} \tilde{p}_{n,t}(\tilde{y}_{n,t}) \tilde{y}_{n,t} \\ \geq\ &\mathbf{E}_{\{\Omega\}_{t=0}^{\infty}} \beta^t \sum_{n \in N} \left\{ (\tau_n)^{\frac{1}{\sigma}} (\hat{y}_{n,t})^{\frac{\sigma-1}{\sigma}} \right\} - \sum_{n \in N} \tilde{p}_{n,t}(\tilde{y}_{n,t}) \hat{y}_{n,t} \end{aligned}$$

From worker optimality, it must be that:

$$
\begin{aligned}
&\mathbf{E}_{\{\Omega\}_{t=0}^{\infty}}\beta^t \sum_{n\in N}\tilde{\pi}_t^n(H_{t-1};H'_{t-1};i)\,(\\
&\tilde{\xi}(H_{t-1};H'_{t-1};i)\cdot\left\{\tilde{w}_t^n+\mathbf{I}_\delta\varepsilon_t^n+[1-\mathbf{I}_\delta]\sum_{k\in N}\tilde{d}_t^{nk}(H_t,\varepsilon_t)\right\}\\
&+\tilde{\xi}_t^s(H_{t-1};H'_{t-1};i)\cdot\left\{b+\mathbf{I}_\mathbf{f}\varepsilon_t^n+[1-\mathbf{I}_\mathbf{f}]\sum_{k\in N}\tilde{d}_t^{nk}(H_t,\varepsilon_t)\right\}\\
&\left[1-\tilde{\xi}_t^s(H_{t-1};H'_{t-1};i)-\tilde{\xi}_t(H_{t-1};H'_{t-1};i)\right]\cdot\left\{b+\sum_{k\in N}\tilde{d}_t^{nk}(H_t,\varepsilon_t)\right\}\Bigg)\\
&\geq \mathbf{E}_{\{\Omega\}_{t=0}^{\infty}}\beta^t \sum_{n\in N}\hat{\pi}_t^n(H_{t-1};H'_{t-1};i)\,(\\
&\hat{\xi}(H_{t-1};H'_{t-1};i)\cdot\left\{\tilde{w}_t^n+\mathbf{I}_\delta\varepsilon_t^n+[1-\mathbf{I}_\delta]\sum_{k\in N}\hat{d}_t^{nk}(H_t,\varepsilon_t)\right\}\\
&+\hat{\xi}_t^s(H_{t-1};H'_{t-1};i)\cdot\left\{b+\mathbf{I}_\mathbf{f}\varepsilon_t^n+[1-\mathbf{I}_\mathbf{f}]\sum_{k\in N}\hat{d}_t^{nk}(H_t,\varepsilon_t)\right\}\\
&\left[1-\hat{\xi}_t^s(H_{t-1};H'_{t-1};i)-\hat{\xi}_t(H_{t-1};H'_{t-1};i)\right]\cdot\left\{b+\sum_{k\in N}\hat{d}_t^{nk}(H_t,\varepsilon_t)\right\}\Bigg)
\end{aligned}
\tag{D.7}
$$

Summing this over all workers gives:

$$
\begin{aligned}
&\sum_{n\in N}\tilde{e}_{n,t}\tilde{w}_{n,t}+b[\tilde{s}_{n,t}+\sum_{j\in n}\tilde{m}_{jn,t}]+\left(\tilde{e}_{n,t}\delta_n+\tilde{s}_{n,t}[1-f_n(\tilde{\theta}_{n,t})]+\sum_{j\neq n\in N}\tilde{m}_{jn,t}\right)\times\\
&\int\cdots\int\sum_{k\in N}\left(\tilde{D}^{nk}\varepsilon_k\right)\prod_{k=1}^{N}(h(\varepsilon_k)\mathrm{d}\varepsilon_k)\\
&\geq\sum_{n\in N}\hat{e}_{n,t}\tilde{w}_{n,t}+b[\hat{s}_{n,t}+\sum_{j\in n}\hat{m}_{jn,t}]+\left(\hat{e}_{n,t}\delta_n+\hat{s}_{n,t}[1-f_n(\hat{\theta}_{n,t})]+\sum_{j\neq n\in N}\hat{m}_{jn,t}\right)\times\\
&\int\cdots\int\sum_{k\in N}\left(\hat{D}^{nk}\varepsilon_k\right)\prod_{k=1}^{N}(h(\varepsilon_k)\mathrm{d}\varepsilon_k)
\end{aligned}
\tag{D.8}
$$

Finally, from the intermediate firm's optimality condition, we have that:

$$\begin{aligned}
&\mathbf{E}_{\{\Omega\}_{t=0}^{\infty}}\beta^t \sum_{t=0}^{\infty} \mathbf{I_v}\left(-c_n\right) + \mathbf{I_j}[\tilde{p}_{n,t}(\tilde{y_{n,t}})\mu_{n,t} - \tilde{w}_{n,t}] \\
&\geq \mathbf{E}_{\{\Omega\}_{t=0}^{\infty}}\beta^t \sum_{t=0}^{\infty} \mathbf{I_v}\left(-c_n\right) + \mathbf{I_j}[\tilde{p}_{n,t}(\tilde{y}_{n,t})\mu_{n,t} - \tilde{w}_{n,t}]
\end{aligned} \tag{D.9}$$

Adding Equation D.6, D.9, and Equation D.8, and canceling terms gives:

$$\begin{aligned}
&\mathbf{E}_{\{\Omega\}_{t=0}^{\infty}}\beta^t \sum_{n\in N}\left\{(\tau_n)^{\frac{1}{\sigma}}(\tilde{y}_{n,t})^{\frac{\sigma-1}{\sigma}}\right\} + \sum_{n\in N} b[\tilde{s}_{n,t} + \sum_{j\in n}\tilde{m}_{jn,t}] - c_n\tilde{v}_{n,t} \\
&+ \left(\tilde{e}_{n,t}\delta_n + \tilde{s}_{n,t}[1 - f_n(\tilde{\theta}_{n,t})] + \sum_{j\neq n\in N}\tilde{m}_{jn,t}\right) \times \int\cdots\int \sum_{k\in N}\left(\tilde{D}^{nk}\varepsilon_k\right)\prod_{k=1}^{N}(h(\varepsilon_k)\mathrm{d}\varepsilon_k) \\
&\geq \mathbf{E}_{\{\Omega\}_{t=0}^{\infty}}\beta^t \sum_{n\in N}\left\{(\tau_n)^{\frac{1}{\sigma}}(\hat{y}_{n,t})^{\frac{\sigma-1}{\sigma}}\right\} + \sum_{n\in N} b[\hat{s}_{n,t} + \sum_{j\in n}\hat{m}_{jn,t}] - c_n\hat{v}_{n,t} \\
&+ \left(\hat{e}_{n,t}\delta_n + \hat{s}_{n,t}[1 - f_n(\hat{\theta}_{n,t})] + \sum_{j\neq n\in N}\hat{m}_{jn,t}\right) \times \int\cdots\int \sum_{k\in N}\left(\hat{D}^{nk}\varepsilon_k\right)\prod_{k=1}^{N}(h(\varepsilon_k)\mathrm{d}\varepsilon_k)
\end{aligned} \tag{D.10}$$

Provided that $\eta = g$ so that the level of vacancies are the same as in the planner's problem, the move decisions of workers maximize the planner's problem. $\square$

E Calibrating Sectoral AR(1) Parameters

I have assumed that detrended log labor productivity in each sector follows:

$$\log(\mu'_n - \bar{m}u_n) = \kappa_n \log(\mu_n - \bar{m}u_n) + \zeta_n \nu'_n$$

Therefore, the variance for detrended log labor productivity will be given by:

$$\mathbf{Var}\left[\log(\mu_n - \bar{m}u_n)\right] = \frac{\zeta_n^2}{1 - \kappa_n^2}$$

where I use the assumption that $\nu_n \sim N(0, 1)$. The autocorrelation is simply κ_n. I thus set each κ_n to the autocorrelations of the detrended log sectoral employment series in the data,

Table 6: Detrended Log Sectoral Employment in the Data

	C	NC
monthly autocorrelation	0.928	0.890
variance(*1000)	0.317	0.032

reported in Table 6. Given these values for κ_n, I can back out the implied value for ζ_n that would make the variance of my AR(1) match the variance of the detrended log employment series. Letting hats denote my own estimates of these numbers,

$$\hat{\zeta}_n = \mathbf{Var}\left[\log(e_n)\right] \cdot \left[1 - \hat{\kappa}_n^2\right]$$

Now we have pinned down $\{\kappa_n, \zeta_n\}$ for $n \in \{C, NC\}$. The only thing left to pin down is the parameter ϕ which governs the correlation between $\log(\mu_C)$ and $\log(\mu_{NC})$. Given the above AR(1) assumption, the following holds:

$$\mathbf{Cov}\left[log(\mu'_C) - \kappa_C log(\mu_C), log(\mu'_{NC}) - \kappa_{NC} log(\mu_{NC})\right] = \zeta_C \cdot \zeta_{NC} \mathbf{Cov}\left[\nu'_C, \nu'_{NC}\right]$$

Thus, given the ζ_n described above, I set $\phi = 0.80$.

F Recovering the Shocks

F.1 First Order Approximation

To fix ideas, start with the first order approximation of the model. In the two sector version, I have 26 endogenous variables, of which 8 are state variables. Let T_{26X1} denote these endogenous variables and let R_{8X8} denote the state variables. Then the first order approximation solves for a linear relationship between T, R, and the innovations in the model ν_n:

$$\left[T_{t+1} - \bar{T}\right] = \bar{T} + \mathbf{A_1}\left[R_t - \bar{R}\right] + \mathbf{A_2}\nu_{t+1}$$

where ν is a $2X1$ vector of the two innovations to sectoral productivity.[47] Thus, to recover the innovations, take the following steps:

1. Start in period $t = 0$ in the steady state so that $R_t - \bar{R} = 0$. In my calculations, I use January 1977 as the steady state.

2. Using data on employment in the two sectors in February 1977 (date $t+1$) and the first order approximation implies that there is exactly one solution for ν_{t+1} that would produce the observed employment in $t+1$. Solve for the implied ν_{t+1}

3. Once you have uncovered ν_{t+1}, use the first order approximation again to solve for the remaining endogenous variables in T. Now we have the vector T_{t+1} and thus R_{t+1}.

4. Repeat steps 2 through 3 until the end of the series

F.2 Second Order Approximation

Because the time series on employment tends to deviate from its mean values over some periods, I choose to use a second order approximation to more accurately match the data. The algorithm is the same as described above, except that the approximation is no longer linear - there might be multiple shocks that can generate the same employment data. Therefore, I carry out the first order approximation as above, and use the recovered shocks there as starting values in the search for the true shocks under the second order approximation. The second order approximation has the form:

$$\begin{aligned}\left[T_{t+1} - \bar{T}\right] = \Big([\bar{T} + .5\mathbf{A_0}^2 + \mathbf{A_1}\left[R_t - \bar{R}\right] + \mathbf{A_2}\nu_{t+1} \\ + .5\mathbf{A_3}\left[\left(R_t - \bar{R}\right) \otimes \left(R_t - \bar{R}\right)\right] + .5\mathbf{A_4}\left[(\nu_{t+1}) \otimes (\nu_{t+1})\right] + \mathbf{A_5}\left[\left(R_t - \bar{R}\right) \otimes (\nu_{t+1})\right]\Big)\end{aligned}$$

1. Start in period $t = 0$ in the steady state so that $R_t - \bar{R} = 0$. Again, I use January 1977 as the steady state.

[47] I use Dynare to numerically solve my model and thus recover the different $\mathbf{A}$ coefficients.

2. Using data on employment in the two sectors, the second order approximation, and the recovered shocks from the first order approximation, solve for the implied ν_{t+1}

3. Once you have uncovered ν_{t+1}, use the approximation again to solve for the remaining endogenous variables in T. Now we have the vector T_{t+1} and thus R_{t+1}.

4. Repeat steps 2 through 3 until the end of the series

G Simulated Method of Moments

The updating algorithm I use in Simulated Method of Moments is Simulated Annealing as described in Kirkpatrick, Gellat, and Vecchi (1983). The algorithm is useful for non-convex problems in which gradient methods might produce local minima. This procedure allows the objective function to increase in value at some points over the search. I begin with the identity weighting matrix. I then carry out the following procedure:

1. Guess an initial value for the parameters.

2. Simulate the model and retrieve the time series for value functions.

3. Using the value functions, simulate Gumbel draws for individuals to create a "Simulated CPS" dataset.

4. Calculate the moments of the "Simulated CPS" dataset that are comparable to the actual CPS as described in Section 4.

5. Form the moment function.

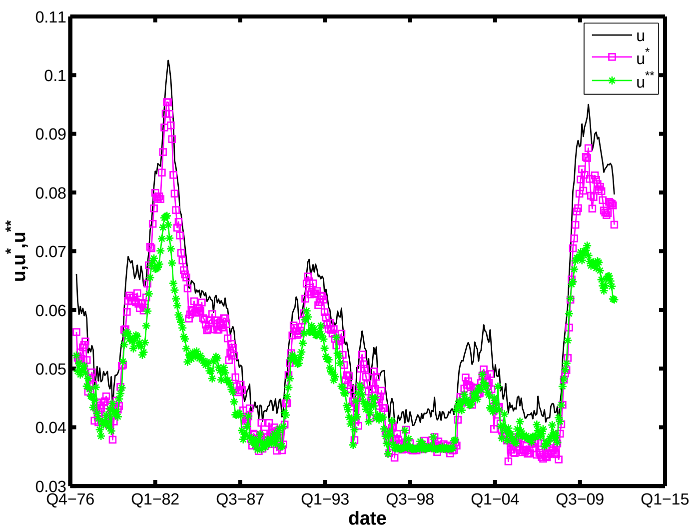
6. Update the parameters space.

7. After the algorithm has converged once, compute the optimal weighting matrix as described in Gourieroux and Monfort (1997) and rerun these steps (but substituting the parameters achieved on the first iteration for the initial guess) until convergence is achieved again.

H Infinite Moving Costs

Counterfactual 1 measures the contribution of intersectoral reallocation frictions on aggregate unemployment by solving for the hypothetical path of unemployment when labor mobility is frictionless. In this section, I solve for the hypothetical path of unemployment when labor mobility between sectors is infinitely costly so that no workers can move. This scenario boils down to solving two separate standard MP models (one per sector) and then aggregating their unemployment rates to solve for aggregate unemployment. Figure **??** plots three evolutions of unemployment: the "true" economy, the economy where labor mobility is frictionless, and the economy in which labor mobility is infinitely costly.

Figure 11: Estimated and Hypothetical Path of Unemployment: Infinite Moving Costs



Notes: The black line represents the unemployment rate constructed using the estimated shocks found in 5.1 combined with the second order approximation of the true model, which mimics the dynamics of unemployment in the data. The pink line connected by squares represents the hypothetical unemployment rate in the model without moving time using the same estimated shocks. The green line represents the hypothetical unemployment rate in the model with infinite moving costs.

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