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Occupation-industry mismatch in the cross section and the aggregate

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Abstract

I define occupations that are employed in more industries as “broader” occupations. I study the implications of broadness for mismatch of the unemployed and vacancies across occupations and industries. I empirically find that workers in broader occupations are better insured against industry specific shocks. A recent literature has found that mismatch did not significantly contribute to the rise in unemployment during the Great Recession. I build a general equilibrium model that uses occupational broadness as a microfoundation of mismatch. The model uncovers a general equilibrium channel that realigns the strong crosssectional effects of mismatch with its missing aggregate impact. I argue that mismatch across occupations and industries cannot significantly contribute to aggregate unemployment fluctuations.

Resume

Jeg definerer erhvervsgrupper, der dækker flere brancher, som “bredere” erhvervsgrupper. Jeg undersøger på erhvervsgruppeniveau breddens konsekvenser for mismatch mellem ledige arbejdstagere og ledige stillinger på tværs af erhvervsgrupper og brancher. Jeg finder empirisk belæg for, at arbejdstagere i bredere erhvervsgrupper er bedre forsikret mod branchespecifikke stød. Nyere litteratur viser dog, at mismatch ikke bidrog signifikant til stigningen i ledigheden under den sidste recession. Jeg konstruerer en generel ligevægtsmodel, der bruger erhvervsgruppernes bredde som en et mikrofundament for mismatch. Modellen viser en generel ligevægtskanal, som forener de stærke tværsnitseffekter af mismatch med den manglende effekt på aggregeret niveau. Jeg argumenterer for, at mismatch på tværs af erhvervsgrupper og brancher ikke kan bidrage signifikant fluktuationer i den aggregerede ledighed.

Key words

Research

JEL classification

E24; J22; J24; J63; J64

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Occupation-industry mismatch in the cross section and the aggregate*

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Abstract

Occupations that are used in many industries are "broad". Workers in broader occupations can respond to adverse shocks to their industry by moving to better-faring industries. When changing industries, they negatively affect other workers in the destination sector through a "relocation externality". I show empirically that workers in broader occupations were better insured against industry-specific shocks during the Great Recession. I then build a dynamic general equilibrium model that features occupations that are heterogeneous in their broadness. In the model, recessions that affect less broad occupations generate more mismatch. These recessions however do not lead to larger unemployment fluctuations than recessions that affect broader occupations. This is because the calibrated relocation externality is quite strong: roughly every job saved due to the direct effect of broadness translates to one job lost due to the relocation externality. I conclude that mismatch across occupations and industries cannot significantly contribute to aggregate unemployment fluctuations (JEL E24, J22, J24, J63, J64).

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1 Introduction

Between 2007 and 2009, the United States experienced one of the largest downturns in the post-war era. During that period, the unemployment rate increased from 4.5% to 10%. Simultaneously, the job-finding rate decreased persistently and the Beveridge curve shifted outwards – the same number of vacancies and unemployed workers led to fewer hires than before. One explanation for this dramatic disruption of the labor market was the mismatch between labor supply and labor demand.

The construction sector was particularly severely affected: around 20% of construction workers became unemployed in 2008.[1] Yet, many new job openings were in sectors that were traditionally not easily accessible to former construction workers, for example in the IT industry. Şahin, Song, Topa, and Violante (2014) describe this misalignment of jobseekers and vacancies across submarkets as "mismatch", and refer to the excess unemployment that is due to this misalignment as "mismatch unemployment". A shock that affects labor demand across submarkets of the economy unequally creates persistent mismatch if relocation frictions then prevent a subsequent adjustment of labor supply.

Both industries and occupations are candidate dimensions for mismatch.[2] Industries are affected unequally by aggregate business cycles (Lilien, 1982), and the Great Recession affected some industries much more than others. Figure 1 shows that occupations too were affected unequally by this recession, even after controlling for industry and other factors.[3]

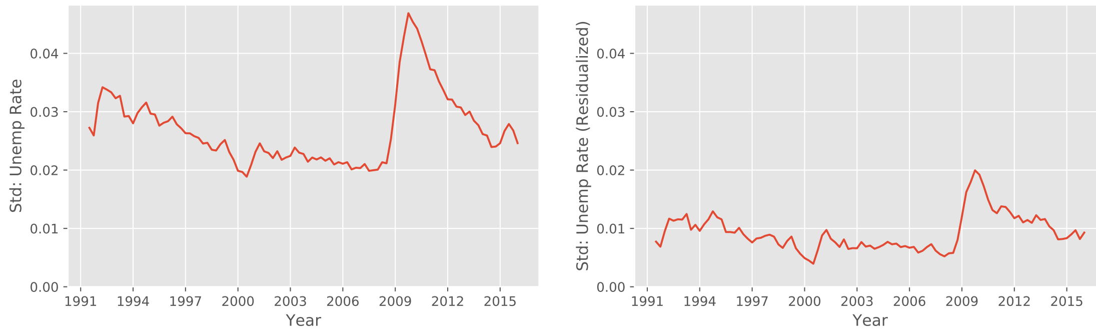
In this paper, I suggest a microfoundation for mismatch across industries that stems from an asymmetric impact of recessions on occupations. I document empirical evidence for the direct effects of this mechanism in the cross section. The general equilibrium effects of mismatch cannot be estimated directly. To do this, I build a general equilibrium model that is consistent with the empirical evidence and use it to study the macroeconomic implications of mismatch. The model will find little potential for mismatch to explain aggregate business cycle fluctuations. We will see how a particular general equilibrium mechanism will explain the apparent tension between the microeconomic evidence and the macroeconomic outcomes.

[1] I will use industry and sector interchangeably.

[2] In Appendix B, I perform a machine learning exercise that shows that both an individual's occupation and their industry are among the most important predictors of their unemployment status.

[3] This differential impact of the recession by occupation could potentially be explained by the industries that employ workers in these occupations: construction-related occupations have larger unemployment responses because the construction industry faced a large downturn during the recession. The right-hand panel shows that this is not the case: I residualize the individual-level unemployment status with individual demographics and full interactions of industry, state and year. Yet, after controlling for all these factors, occupations still display heterogenous unemployment dynamics during the Great Recession.

Figure 1: Dispersion of occupation-level unemployment rates during the Great Recession



Standard deviations of occupation-level unemployment rates. Left: occupation-specific unemployment rates. Right: occupation-specific unemployment rates, where I partial out individual demographics, and all combinations of industry, state and year fixed effects. Computation explained in Appendix A.

To this end, I distinguish between occupations that are "specialized" and used by very few industries – for example electricians – and those that are "broad" and employed in many different industries, for example engineers. I then postulate that, on average, workers face on average higher frictions when changing occupations, than when changing industries. This may be due to occupation-specific human capital (Kambourov and Manovskii, 2009a) or occupational licensing (Blair and Chung, 2018). If this was true, workers in broader occupations should be able to adjust to sectoral shocks more easily. Consequently, they are better insured against industry-specific shocks and less at the risk of being mismatched across industries. Consider the case of the construction sector in the Great Recession: unemployed electricians have limited employment perspectives outside of construction if they remain in their occupation. They face the difficult choice of either waiting for construction to recover, or changing occupations altogether. On the other hand, workers in broader occupations, for example engineers, can be employed in other sectors without changing occupations. They therefore have an easier time adjusting to a shift in sectoral demand. This is what I call the direct effect of broadness: the possibility of reducing the impact of sectoral shocks by relocating to less severely affected sectors. However, when workers move to these better-faring sectors, they increase the labor supplied in these sectors. Each sector operates at decreasing returns to scale in labor, and thereby these relocations negatively affect other workers in the destination sector. In the previous example, engineers respond to the Great Recession by moving to the IT sector. There, they increase competition for engineers that are already in the IT sector, and thereby reduce their job-finding rates and wages. I refer to this general equilibrium effect as the "relocation externality". This paper consists of two parts: I first use data from the Great Recession to measure the direct effect, and then build a general equilibrium model to gauge the importance of the relocation externality.

In the empirical part of the paper, I operationalize my concept of broadness by constructing a measure of the broadness of each occupation by using the dispersion of its workers across industries. I then estimate the strength of the direct effect during the Great Recession. Similar to Autor, Dorn, and Hanson (2013), I use geographical variation in industry composition to isolate the effect of broadness from other occupation-specific effects. In the 2008 recession, a bust in housing markets spilled over to the construction industry (Charles, Hurst, and Notowidigdo, 2018) and led to the unemployment of 20% of its workers. This large inflow of unemployed workers makes it a prime target for studying the heterogeneous employment perspectives of workers of varying broadness. I study the aftermath of workers that became unemployed in this sector and find that the job-finding rates of broader occupations were up to 38% higher than those of specialists. I also show that the broadness of the unemployed was much lower during the Great Recession than in previous recessions, suggesting that the degree of mismatch was higher in that recession. This is largely due to the large share of unemployed construction workers that are mostly specialized in the construction sector and have limited employment opportunities outside of that sector.

I then propose a microfoundation of mismatch unemployment that builds directly on specialized and broad occupations. Every occupation is a Lucas and Prescott (1974) type island with a Diamond-Mortensen-Pissarides (DMP) style frictional labor market. I use the abstraction of one-worker firms that are typical in the DMP environment. Consequently, each firm is associated with its worker's occupation, and produces occupation-specific output. In the model, firms in specialized occupations sell to a single sector, while firms in broad occupations sell their output to a continuum of sectors. This production network between occupations and industries is key in the propagation of sectoral shocks to individual workers. In the model, shocks to sectors that employ more workers in specialized occupations generate more mismatch as defined by Şahin et al. (2014). The model suggests that the average broadness of the unemployed workers can be used to estimate the extent of mismatch present in the economy, and I use this metric as a complement to the model-generated mismatch measure that Şahin et al. (2014) propose.

Recall that I estimated a larger degree of mismatch during the Great Recession than in previous recessions. Taken at face value, the empirical results on the direct effect would suggest that this high degree of mismatch during the Great Recession can explain a large share of the strong and persistent unemployment response during that recession. I use my model to study the relevance of mismatch in generating fluctuations in the unemployment rate. The model allows me to generate recessions with varying degrees of mismatch: "broad recessions" that predominantly affect sectors that employ broad occupations lead to less mismatch than "specialized recessions" that predominantly affect sectors that employ broad occupations.

In the model, specialized recessions affect workers in the specialized occupations a lot, since they cannot easily adjust to the change in sectoral demand. Their only remedy is to change occupation. Their job-finding rates are severely affected, and so a significant number of specialized workers leave the occupation in response to the recession. In the symmetric case of broad recessions, workers in broad occupations are affected much less, since they can shift to better-faring sectors. However, in my numerical analysis, the relocation externality is strong: for every job saved by the direct effect, approximately one job is lost due to this externality.

Ultimately, specialized recessions affect a small number of workers a lot, while broad recessions affect many more workers but to a lesser extent, since they spread throughout the broad occupations. As broad workers are individually less affected by the shock to their occupation, there is much less occupational mobility in response to the broad recession. The overall effects on the aggregate unemployment rate are roughly similar in both types of recessions. That is, recessions that generate more mismatch do not generate larger unemployment fluctuations *per se*.

The model is targeted towards occupations and industries, but can essentially be relabeled to match other dimensions of mismatch. It allows us to learn the following broader point about mismatch that is not specific to occupations and industries: regardless of whether one thinks of labor markets as being defined by occupations, geographical regions, or types of boundaries, shocks that generate more mismatch across these labor markets do not inherently lead to more total unemployment.

Literature Gathmann and Schönberg (2010) use task-based human capital to categorize occupations as specialized if they share few tasks with other occupations. My notion of specialization is with respect to the distribution of industries that employ those occupations. While similar, they have different implications: Gathmann et al. (2010) focus on occupational mobility, while I analyze mobility within occupations and across industries. Both papers are related to a larger body of literature on the portability of human capital. Becker (1962) studies firm-specific versus general human capital. Neal (1995) and Shaw (1984) focus on occupation and industry-specific human capital. Kambourov and Manovskii (2009b) first demonstrated that more human capital is occupation-specific than industry-specific – a necessary condition for the theoretical argument in this paper. Sullivan (2010) confirms these findings, but emphasizes occupation-level heterogeneity. These results have since been corroborated by Zangelidis (2008) using UK data, and Lagoa and Suleman (2016) using Portuguese administrative data.

Conceptually, the transferability of human capital relates to the structure of labor markets: within which boundaries are the unemployed searching for jobs? While Nimczik (2017) estimates labor markets non-parametrically, human-capital-based approaches provide testable theoretical foundations. Using the task-based approach, Macaluso (2017) finds that unemployed workers whose skills are less transferable to other locally demanded occupations were more prone to mismatch unemployment during the Great Recession. By providing a theoretical foundation for measuring mismatch unemployment, her approach is similar to mine. Our papers mainly differ in what dimension of portability of human capital we relate to mismatch unemployment during the Great Recession. Relatedly, Gottfries and Stadin (2016) suggest that mismatch is a more important determinant of unemployment than imperfect information. A complementary story to human-capital-based mismatch is geographical mismatch: Yagan (2016) shows that the convergence of geographical labor markets hit by an asymmetric shock is slow, suggesting that geographical mismatch contributes to employment responses.

Instead of looking at cross-sectional heterogeneity in mismatch unemployment during the Great Recession, one might compare total mismatch unemployment during the Great Recession with that of other recessions. A key contribution here is Şahin et al. (2014) who compute a mismatch index for each period by estimating the variance of market tightness across labor markets. Unlike the human-capital-based papers, they do not argue for any particular dimension of mismatch. Instead, they demonstrate that across occupations, industries, and geographies, variances in labor market tightness during the Great Recession did not significantly exceed those in other recessions. I show that even if the degree of mismatch was higher during the Great Recession, it cannot be thought of as the causal factor of the large unemployment response in that recession: the extent of mismatch that a shock generates does not significantly affect the overall impact of that shock on the unemployment rate. Herz and Van Rens (2011) and Barnichon and Figura (2015) perform related longitudinal decompositions of mismatch unemployment.

Conceptually, my empirical variation stems from geographic heterogeneity in industry exposure, similar to Autor et al. (2013) and Helm (2019). Here, the variation in industry exposure is not used as a shift-share instrument (Card, 1992), it is the variable of interest itself: broader occupations are less exposed to shocks due to the nature of their industry exposure. As in the aforementioned papers, the spatial variation in broadness then comes from the heterogeneous geographical presence of industries across labor markets. While they focus on homogeneous industry exposure of all individuals in geographical labor markets, I compute a differential exposure for each occupation. Since this exposure varies by occupation even within state and industry, I can flexibly control for industry-by-state fixed effects and do not need to impose a Bartik (1991)-type structure.

On the theoretical side, I integrate multiple labor markets as in Lucas et al. (1974) into the canonical DMP framework of the frictional labor market. In a similar fashion, Shimer (2007) and Kambourov et al. (2009a) model mismatch as caused by frictional mobility across frictionless labor markets. Shimer and Alvarez (2011) develop a tractable version of this framework in which relocation costs time and hence raises unemployment. Carrillo-Tudela and Visschers (2014) nest the directed search of occupations with random search within each occupation. In their framework, occupations all produce a homogeneous good. I contribute to this literature in three ways. First, my model can generate recessions that vary in the degree of mismatch that they cause. Thereby, I can study whether recessions that generate more mismatch lead to more total unemployment *per se*. Second, I contribute to this literature by integrating the notion of industries into the occupational framework in a tractable way. Third, each occupation produces a diversified good: there are decreasing returns to scale in each occupation. This implies that the thresholds at which individuals enter and leave occupations are no longer a function of productivity only, but a two-dimensional hyperplane. I suggest a solution method for this environment. In Pilossoph (2012) and Chodorow-Reich and Wieland (2019), taste shocks in the relocation choice yield gross mobility that exceeds net mobility. In their simulations, they reduce the number of labor markets to two. Instead, my methodology allows me to keep track of the entire distribution.

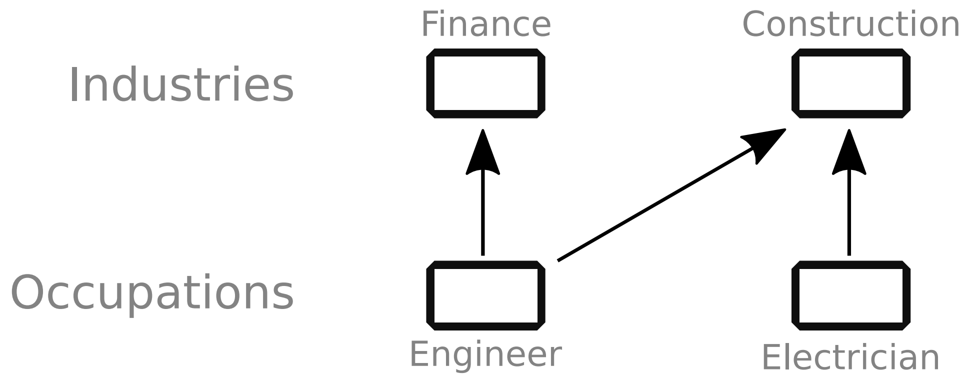
In section 2, I describe the concept of broad and specialized occupations and relate it to unemployment risk and mismatch unemployment. I then propose and describe an empirical measure of occupational broadness in section 3. I use that metric in section 4 to empirically estimate the impact of broadness on job-finding rates. In section 5, I propose a general equilibrium model that studies broadness more rigorously. Finally, I use the model to study recessions of varying degree of mismatch in section 6. Section 7 concludes.

2 Broad and specialized occupations

In this section, I introduce the notion of specialized occupations and relate it to unemployment risk and the notion of mismatch unemployment. I will use simplistic assumptions for the sake of exposition. We will later use both an empirical framework and a general equilibrium model to formalize and measure the effects of occupational broadness more rigorously.

Conceptually, firms are grouped into industries depending on what type of output they produce. I argue that firms with a similar output will use similar production functions and conclude that firms in the same industry will use inputs in similar proportion. I focus on a firm's labor input and its composition in terms of occupations. Occupations categorize workers into groups by the tasks that they typically provide in production: workers who perform similar tasks will be assigned the same

Figure 2: Stylized occupation-industry network



Here, engineers are employable in more industries than electricians, which makes them broader.

occupation.

I illustrate my concept of broadness by the example of engineers and electricians. Engineers are used by firms in many different industries. Electricians are employed in much fewer industries, mainly by firms in the construction industry. This stylized occupation-industry matrix is displayed in Figure 2. I define the broadness of an occupation by the degree to which the demand for its typically performed tasks is spread across many industries. The exemplary engineers would be broader than electricians.

Broadness is a function of the input-output network of industries and occupations, and hence an equilibrium outcome. In the face of price and wage changes, firms may choose to adjust their production functions and change the input composition of occupations. As the occupation-industry network changes, tasks will become more or less industry-specific, and the occupation-level broadness will change.

2.1 Broadness and unemployment risk in the cross section and the aggregate

I defined broadness as a metric of the production network, and not in relation to unemployment risk. However, broadness may have implications for unemployment risk. I demonstrate this using again the stylized case of engineers and electricians.[4] For simplicity, assume that workers are completely stuck in their occupation, but free to move across industries. Now, imagine that the productivity of the firms in the construction sector falls so much that firms in that sector are no longer hiring, and many workers are laid off. Since both sectors use engineers in their production function, the unemployed

[4] I provide a simple static model in Appendix C that formalizes the argument brought forward here.

engineers can search for jobs in the finance sector. In contrast, the unemployed electricians have no such outside option, and have to wait for the construction sector to recover. The reason that electricians are more affected by the recession in the construction sector is that they cannot respond that easily to industry-level changes in labor demand.

The relocation externality Workers in the broad occupation use the other industry that their occupation is employable at to insure themselves against industry-specific shocks. In the previous example, engineers move from the construction sector to the finance sector and begin to compete with engineers who were already employed in that sector. The increased competition likely decreases earnings or employment rates in the destination sector. I refer to this as the *relocation externality*: workers do not consider the impact of their relocation on workers that are already active in that submarket. We will study this situation more rigorously in the general equilibrium model in section 5.3. The calibration of my model implies that the reallocation externality is a strong channel that visibly affects aggregate outcomes. Translated to this simple example, a shock in the construction sector would lead to approximately the same number of unemployed workers in both the broad and the specialized occupation. Some workers in the broad occupation reduce their unemployment risk by moving to the finance sector, but the strength of the externality implies that this relocation does not reduce total unemployment in that occupation. Instead, the unemployment risk is lower for each individual engineer, but spread equally across a larger set of engineers that are active in both industries.

Caveats For the sake of exposition, I laid out the main mechanisms involving broadness under simplistic assumptions. For example, I assumed that workers are stuck in their occupations, but can change industries flexibly. This will not hold in reality. For occupational broadness to matter, it is sufficient that the adjustment costs across occupations are, on average, higher than across industries. Why would this be the case? First, Kambourov et al. (2009a) have spawned a large body of literature that demonstrates that more human capital is specific to occupations than to industries. Giving up human capital (and changing occupation) is costly to workers. Therefore, this suggests that workers are less willing to change occupations than to change industries. Second, occupational licensing impedes worker reallocation across occupations. No such licensing is specific to industries. The general equilibrium model in section 5.3 will generalize the argument in this section. It will, for example, allow for the presence of occupational mobility, decreasing returns to scale in each labor market, and substitutability of the industry-level output.

2.2 Broadness and mismatch

The notions of "mismatch" and "mismatch unemployment" have been used in various studies to describe situations in which the matching of workers to jobs is non-optimal. I borrow the concept of mismatch unemployment as it is used by Şahin et al. (2014). Let us reconsider the previous case of an economy that is segmented into different occupations and industries. The reallocation of workers and jobs across submarkets is costly, and the equilibrium distribution of unemployed workers and vacancies across these submarkets is subject to these frictions. Şahin et al. (2014) use the notion of mismatch unemployment to measure how much of unemployment in the economy is due to these frictions that prevent reallocation across submarkets. They consider the hypothetical case of a social planner that can reallocate workers across labor markets without cost. We denote the total hires in the competitive equilibrium and in the planner's solution as h_t and h_t^*. Şahin et al. (2014) then propose to measure mismatch as $\mathcal{M}_t$:

$$\mathcal{M}_t = 1 - \frac{h_t}{h_t^*}.$$

Mismatch unemployment then refers to the excess unemployment in the competitive equilibrium relative to the planner's solution.

Clearly, the planner is not facing the same constraints as the market participants, and so this concept of mismatch is not normative. Instead, it has an accounting character, and can be used to explain how much of the aggregate unemployment can be attributed to the specific distribution of workers across submarkets.

We have argued that workers in broad occupations can relocate across industries more easily. This reduces their risk of being mismatched across industries. Consequently, shocks to industries that predominantly employ specialized occupations should lead to more mismatch than shocks to industries that predominantly employ broad occupations. That is, the increased unemployment risk that stems from being employed in a specialized occupation stems from the risk of being mismatched across industries.

The general equilibrium model will confirm that shocks to industries that predominantly employ specialized workers lead to more mismatch. In the model, recessions with a higher unemployment rate among workers from specialized occupations are also recessions with more mismatch unemployment. Therefore, we can use the average broadness of the unemployed as an indicator of the extent of mismatch unemployment present in the economy. This will only capture mismatch along the industry dimension. Yet, one advantage of this approach is that it is not very data intensive: the empirical measure suggested by Şahin et al. (2014) requires both the unemployment rate and the vacancy rate in each submarket. The broadness of the unemployed only relies on data on the unemployed, which is widely available in the United States and many other countries. We will show that the broadness of the unemployed was much lower during the Great Recession than in the previous recessions, suggesting that the extent of mismatch unemployment along the industry dimension was particularly high during the 2008 recession.

3 Measuring occupational broadness

In this section, we will develop a measure of occupational broadness that we can use later to measure the relationship between broadness and unemployment risk.

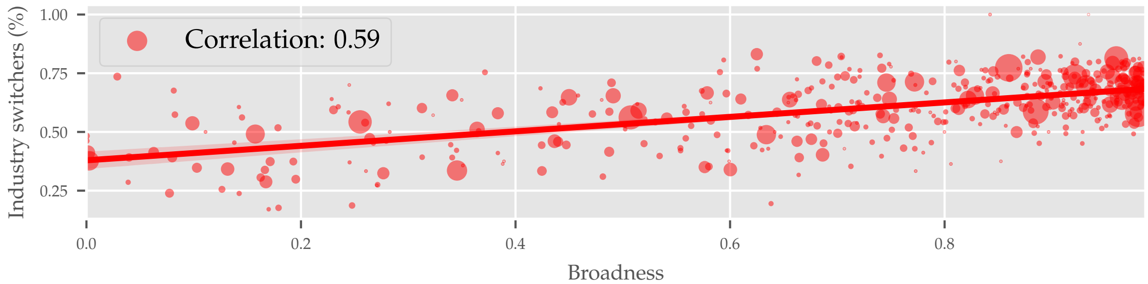
Conceptually, broadness refers to how well-spread the usage of an occupation is across the production processes of many different industries. Empirically, I compute for each occupation o its share of employment $s_{o,i}$ in each industry i. Its broadness is then measured as one minus its Herfindahl index of concentration across these shares, as shown in (1). We have that $m_o \in [0,1]$ and increases in an occupation's level of broadness.

$$\begin{aligned} s_{o,i} &= \frac{E_{o,i}}{\sum_j E_{o,j}} \\ m_o &= 1 - \sum_i s_{o,i}^2 \end{aligned} \tag{1}$$

This measure of broadness is ad hoc and not suggested by any particular model. It has several attributes that make it attractive. First, it is well-known: much research around trade or competition involves the Herfindahl index, and researchers are likely to be familiar with its properties. Second, it is stable: any metric of broadness is necessarily computed at the occupation-level, and a function of industries. At highest reasonable aggregation, this already leads to around 900 occupation-by-industry bins. Additional splicing of the data by time or geography, or finer categories of occupations and industries would mean that many occupation-industry bins would face few observations.

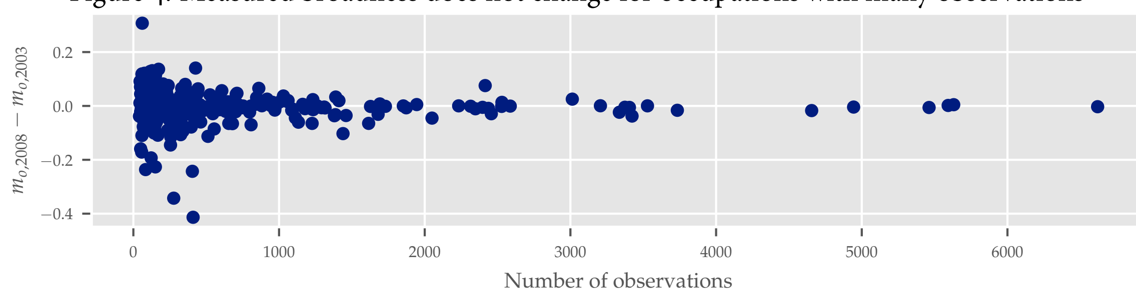
Mobility-based alternative The proposed theory is based on workers' ability to respond to industrial shocks by changing industry. The currently suggested measure only looks at the distribution of workers across industries and ignores actual mobility. One concern is that workers in an occupation may be distributed across many industries, but be completely immobile across them. A high measure of broadness for such an occupation would suggest that workers are well insured against

Figure 3: Share of industry switchers higher in broader occupations



For each occupation, I compute the share of workers that change industry when they change employer. I correlate that against the broadness of the occupation, measured using all years in the sample. The size of each dot is proportional to the number of observations in that occupation.

Figure 4: Measured broadness does not change for occupations with many observations



For each occupation, the difference in measured broadness between 2008 *and* 2003 *is plotted against the* minimum *number of observations for that occupation in either year.*

industry-specific shocks, while in reality they would not be. To address this concern, I measure the share of job switchers that also change industry. Figure 3 shows that this share correlates highly with the broadness of the occupation.

An alternative approach would be a mobility-based measure of broadness. I compute and estimate such a measure in Appendix D. This measure is much more data demanding and cannot be used for the empirical exercise. However, it correlates reasonably well with the baseline measure suggested here. I conclude that isolated industries among which workers move do not significantly bias the metric. In any case, any remaining "falsely measured broadness", that is, broadness in the metric that does not correspond to actual insurance against industry-specific shocks, will bias downwards the estimates of the importance of broadness in the following section.

For the remainder of this section, I will describe the morphology of broadness. First, Figure 4 plots changes in occupation-specific broadness across time against the number of observations used

Figure 5: Three exemplary occupations across the support of broadness

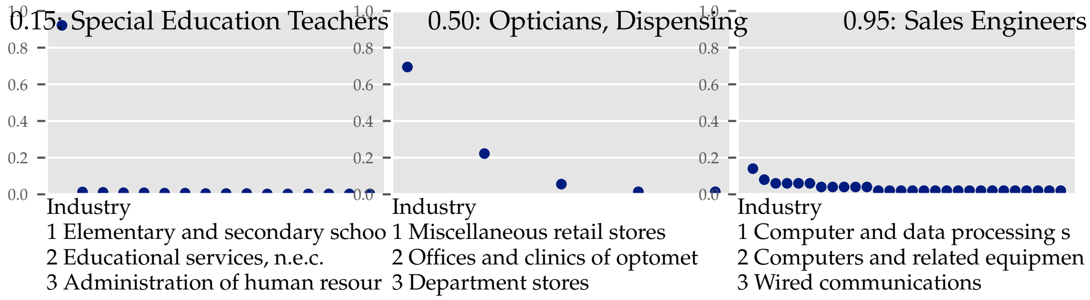
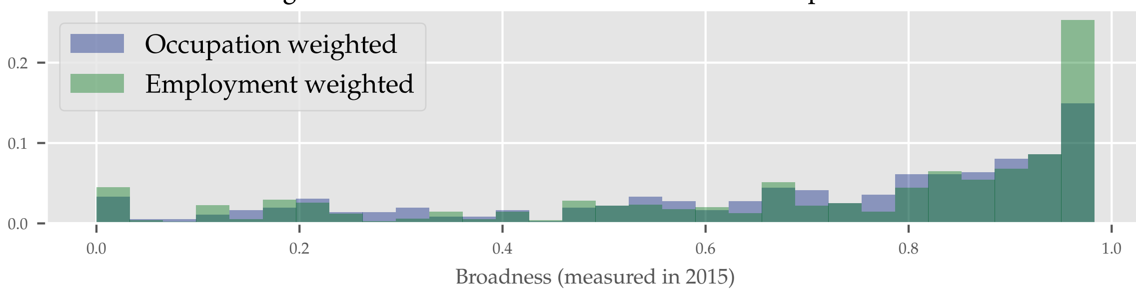


Figure 6: Distribution of broadness across occupations



to compute broadness.

The difference is centered around zero and is less dispersed for occupations with more observations, indicating that differences in broadness can largely be attributed to measurement error and less to actual structural change. This is in line with the argument that firms cannot quickly change their production functions and hence do not respond to short-run fluctuations in the composition of labor supply and the distribution of wages (Sorkin, 2015). I conclude that short-term changes in measured broadness stem from measurement error more than actual changes in the underlying production network. Therefore, unless otherwise indicated, I will use several years of data to compute a more precise estimate of broadness.

To provide some intuition for different employment structures that are hidden behind the one-dimensional measure of broadness, Figure 5 plots the cross-sectional distribution of employment for teachers, opticians, and sales engineers. Note that like most specialized occupations, teachers have most of their employment in a single industry. Opticians mostly work in retail and clinics. Most occupations with broadness around 0.5 have two major industries that they are employed in. As is the case for most very broad occupations, sales engineers work in a large variety of industries. The largest employing industry of sales engineers only contributes to 18% of their employment.

I plot the distribution of broadness across occupations in Figure 6. Broadness has full support: under the chosen metric, some occupations are measured as very broad, while others are very specialized. There are, however, more broad than specialized occupations in the US economy. The employment-weighted distribution looks similar, except for a much larger share of workers at the upper end.

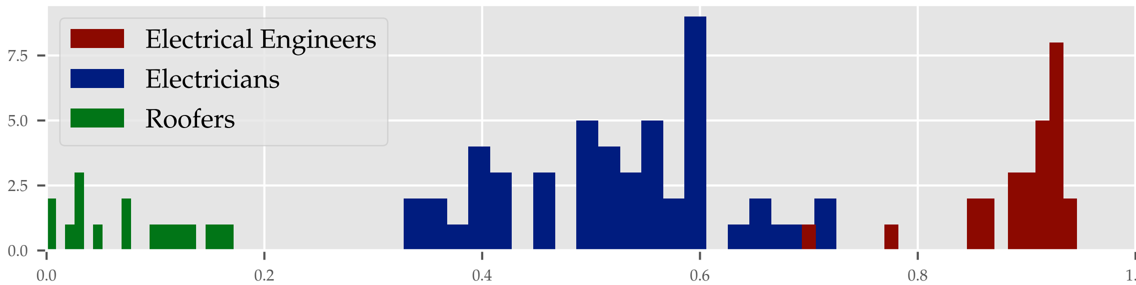
4 Measuring the direct effect of broadness on unemployment risk

Having developed a measure of broadness, I will now devise an empirical strategy to identify the relationship between broadness and the change in unemployment rates during the Great Recession. I discussed earlier that there will be two competing effects from being in a broader occupation. The direct effect of broadness allows you to relocate to less severely affected industries and improve your likelihood of finding a job. The indirect effect of broadness is that other workers in your occupation will be doing the same. If you are in a less severely affected industry and a broader occupation, you might face increased competition from workers that are seeking jobs in your industry. We referred to this indirect effect as the *relocation externality*.

In this section, we will compare individuals that were all previously employed in the construction sector, and show that those in broader occupations had 30% higher job-finding rates than their peers in more specialized occupations. The unemployment rates in the construction sector increased significantly during the Great Recession, and I will argue that it was one of the most severely hit sectors. Hence, it is likely that workers in the construction sector mostly benefited from the direct effect, and were less affected by the relocation externality. We will see that workers in broader occupations experienced a 30% higher job-finding rates rate. Since the construction sector was most severely affected in that recession, it is likely that the strong measured correlation between broadness and job-finding rates captures – at least partly – the direct effect of broadness. I will conclude this section by discussing measuring of the relocation externality. I will argue that it is infeasible to do this in a convincing way in this setup. The general equilibrium model that we introduce in the next section allows us to study broadness in a rigorous way. We will use that model to get a better impression of the strength of the relocation externality.

In what follows, I want to relate occupation-level broadness to occupation-level job-finding rates or unemployment rates. Many characteristics vary across occupations, and subsuming all of these differences into occupation-level broadness will lead to biased estimates. To isolate the effect of broadness from other occupation-specific characteristics, I use geographic variation in industry networks. As different industries are present in different US states, occupations will be differentiably

Figure 7: Geographical heterogeneity of broadness



Geographical variation of broadness for three different occupations. Broadness measured for detailed occupation categories, using data from 2002 *to* 2006*.*

broad across US states. This allows me to compute broadness $m_{o,z}$ for each occupation o and state z, as in (2).

$$s_{o,i,z} = \frac{E_{o,i,z}}{\sum_i E_{o,i,z}}$$
$$m_{o,z} = 1 - \sum_i s_{o,i,z}^2 \qquad (2)$$

I use data from the Current Population Survey (CPS). To reduce the noise, I will use data from 2002 to 2006 to compute $m_{o,z}$: I use data prior to the Great Recession to prevent spurious correlations as employment effects might affect both the measured broadness and the unemployment response. There was a minor change in the coding of occupations in the CPS in 2002, which is why I do not use data prior to that year.

Figure 7 displays $m_{o,z}$ for three selected occupations in the construction sector. Cross-occupation heterogeneity in broadness is much larger than within-occupation heterogeneity of broadness across states. Yet, within-occupation heterogeneity still appears large enough to potentially cause detectable differences in job-finding rates.

In this section, we will test whether the unemployed in broader occupations had higher job-finding rates during the Great Recession.[5] As elaborated previously, I will use occupation-by-state-level broadness to difference out occupation-fixed effects.

Here, I focus on unemployed workers that were previously employed in the construction sector.

[5] Unemployment rates may be more interesting in the aggregate than job-finding rates, but are the result of many equilibrium forces. I study the relationship between broadness and unemployment rates for the same sample in Appendix F.

Two-thirds of these unemployed workers had been employed in construction-related occupations that under two-digit representation aggregate into a single major occupation. Therefore, I am using the detailed occupational categories of which there are 303 in my sample. However, as these occupations are unevenly represented, most of the power will come from about 30 occupations with more than 500 observations.

The setup is then as follows: fix any particular month, and focus on all unemployed individuals whose last employment was in the construction sector. Figure 7 displays the distribution of broadness across states for three typical occupations of the construction sector. I compute the probability of being employed in the subsequent month for all of these occupations. Is it true that individuals from the same occupation that are in a state where their occupation is broader have a higher job-finding rate? As before, this setup allows the introduction of state-level fixed effects to control for the possibility that occupations are systematically broader in states that were less strongly hit by the Great Recession. In theory, this single-month setup should be enough for identification. As I have small samples in each period and many fixed effects to control for, I pool data from 2008 and 2009 to estimate these effects. For this purpose, I create one fixed effect for each state and month. The regression I estimate is given by (3): I relate the job-finding rate of each individual j in occupation o, state z and month t to their occupation-by-state broadness, individual demographics X_j, occupation-fixed effects Θ_o and state-by-month fixed effects $\Lambda_{z,t}$. X_j contains three education groups, a squared term in age, three race groups, and gender.

$$f_{j,o,z,t} = \alpha m_{o,z} + B_1 X_j + \Lambda_{z,t} + \Theta_o + \epsilon_{j,o,z,t} \tag{3}$$

Table 1 shows the results. Columns (1)–(2) build the regression by adding controls and column (3) shows the main specification. The average monthly job-finding rate in that period for that sample amounted to 0.18. A one-standard-deviation higher broadness corresponds to an increase in monthly job-finding rates of 0.06, or 30%. Column (3) is only significant at the 10% level, but this lack of precision can be attributed to the large number of controls, and differential job-finding rates by gender. To make this point, in column (4) I focus on the subset of males: when reducing the sample to males, the results become more precise.

Selection While I try to address several common selection issues with the controls in the final specification, one is particular to this type of setup. The ability of an unemployed worker to find a job is expected to correlate with market tightness: it is reasonable to believe that finding a job is

Table 1: Job-finding rates are higher for construction workers in broader occupations

Dependent variable: monthly probability of being hired

	(1)	(2)	(3)	(4)
Broadness	0.0724^{**}	0.0794^{***}	0.0600^{*}	0.0714^{**}
	(0.0293)	(0.0253)	(0.0353)	(0.0347)
Occ FE	Yes	Yes	Yes	Yes
State x Month FE	No	No	Yes	Yes
Indiv Demographics	No	Yes	Yes	Yes
Only male	No	No	No	Yes
Observations	7865	7864	7756	7173

Data from CPS. Sample: unemployed workers in the construction sector in 2008 *and* 2009. *Broadness standardized and computed using data before recession. Standard errors in parentheses. SE two-way clustered at the state and occupation level.* *** *significant at* 0.01, ** *at* 0.05, * *at* 0.10.

easier in labor markets with a lower unemployment rate. Therefore, a randomly drawn unemployed worker from a low-unemployment labor market is expected to have less ability to find a job than a randomly drawn unemployed worker from a high-unemployment labor market. Broadness acts similarly: being unemployed in a market with higher broadness signals less ability to find a job than being unemployed in a market with lower broadness. Therefore, I expect that randomly drawn unemployed workers from a broader occupation are, on average, less able to find a job than those drawn from a less broad occupation. This selection bias will be weaker in labor markets with a larger inflow of the unemployed. I thus try to address this issue by focussing on the construction sector. Note that any remaining bias will downward-bias the empirical estimate for α, since we will instead assign some of the lower job-finding rates caused by an unobserved lower ability to the higher broadness of the occupation.

4.1 Measuring the strength of the relocation externality

So far, we focused on the construction sector, which was one of the most severely hit sectors during the Great Recession. Naturally, most workers will leave rather then enter this sector. Consequently, the net effect of being in a broader occupation is positive, since workers in this sector benefit from the direct effect and are less affected by the relocation externality. To measure the relocation externality, one would have to study all the sectors that fared better in that recession, since broader workers would use those sectors as destinations for their relocation. By construction, sectors that fare better have lower unemployment rates, and so there will be fewer observations to estimate job-finding rates in those sectors. Furthermore, convincing evidence would have to rank sectors in terms of their desirability, and show that workers in broader occupations and in more desirable sectors suffer more from the relocation externality. Not all occupations are employable in all sectors, and so the ranking of sectors would have to be occupation-specific. Finally, in order to use the geographical variation of occupational broadness that I have introduced in this section, one would have to also compute these rankings at the US state level. The CPS is designed to be representative at the US state level only, and so all these additional intricacies render a convincing empirical approach in this environment infeasible.

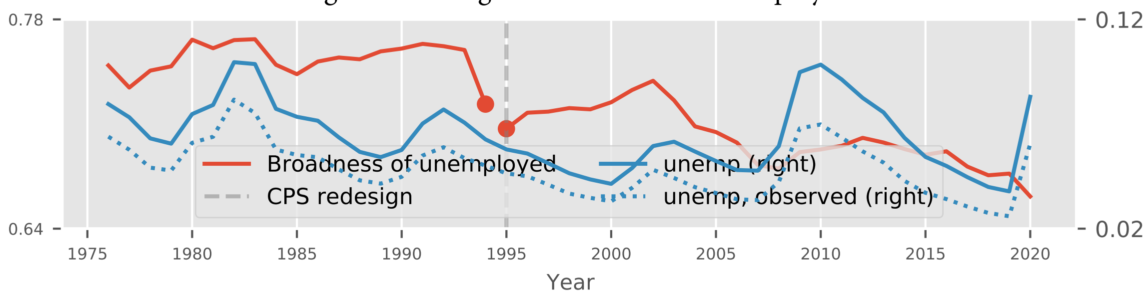
5 Macroeconomic model

We have documented that the broadness of an occupation strongly mitigates the extent to which shocks to its industries lead to mismatch. During the Great Recession, individuals in broader occupations experienced higher job-finding rates and lower unemployment rates than those in more specialized occupations. This suggests that individuals in specialized occupations face a higher risk of being mismatched. The number of such individuals is larger in recessions that affect more specialized occupations. Industry-specific shocks affect workers employed in those occupations. To the extent that different industries employ occupations of varying broadness, shocks to different industries will vary in the degree to which they affect specialized occupations, and thereby cause mismatch unemployment.

A large body of literature discussed the extent to which mismatch unemployment was relevant in explaining the large unemployment response during the Great Recession. We now show that, indeed, the type of industries and occupations affected during the Great Recession suggests a high relevance of mismatch unemployment.

Figure 8 displays the average broadness of the unemployed over time. Two features are remarkable. First, average broadness appears to be counter-cyclical: the correlation between the unemployment rate and the broadness of the unemployed is 0.37. To understand this, note that increases in unemployment at the onset of recessions typically coincide with a large increase in separations. It appears that these separations are such that the pool of unemployed workers becomes broader during the initial phase of a recession. As shown in the empirical section, broader unemployed workers have more jobs to sample from and thereby they have a higher job-finding rate, which makes them leave the pool of unemployed workers faster than workers in more specialized occupations. This is consistent with the countercyclical pattern of average broadness displayed.

Figure 8: Average broadness of the unemployed



Unemployment rates against the degree of broadness of the unemployed (correlation: 0.37*). Broadness is measured using a running index for every year. Observed unemployment refers to the unemployment rates among the subset of workers for whom we can measure broadness using their occupation of previous employment. The share of unemployed workers for whom we cannot do that increases during the Great Recession, which is mostly caused by the increase in unemployment in workers that had not been employed before. I refer to Appendix G for more information on the computation and robustness checks.*

The second feature is the decreasing trend in average broadness of unemployed workers over time. It appears that the unemployed have become more specialized over the past 30 years. A long-term comparison of occupations and industries is difficult and, therefore, this should only been taken as suggestive – in particular because of the structural break caused by the redesign of the CPS in 1994. However, it appears that the unemployed in the Great Recession were also more specialized than those unemployed during the preceding 2002 recession.

Şahin et al. (2014) empirically estimate that mismatch did not cause more unemployment during the Great Recession than it did during the 2002 recession. This appears puzzling: the recession in the IT sector affected broad occupations of managers and programming and led to almost no response in unemployment. Compare that to the Great Recession: the high share of specialized unemployed workers and large unemployment response suggests a causal link between the degree of broadness among the unemployed and aggregate unemployment fluctuations. It is difficult to devise a clean empirical strategy for comparing two recessions. Therefore, I build a model to test the relationship between mismatch and aggregate unemployment fluctuations. This model will confirm the findings by Şahin et al. (2014). By providing a microfoundation of mismatch, we can shed light on the missing link that brings together the large impact of mismatch in the cross-section, and its seeming absence in the aggregate.

The model needs to feature occupations that differ in their level of broadness. Therefore, it will feature both industries and occupations with a non-symmetric production network. Unemployment will be caused by frictional labor markets in each occupation. Occupational mobility gives the unemployed the option of leaving and establishes a lower bound to the risk that one may face in any given occupation. It is therefore an important substitute to broadness and will be included in the model. First, I will develop the model's stationary environment. Then, I will shed light on the question of aggregate unemployment volatility by subjecting the model to unexpected productivity shocks that differentially affect occupations by their broadness.

The discrete-time model consists of three layers of building blocks.

At the micro level, there is a continuum of islands as in Lucas et al. (1974). Each island is host to a Diamond-Mortensen-Pissarides (DMP) type frictional labor market with unemployed workers, vacancies and one-worker firms. Each island will be considered an occupation. Mobility across islands is frictional: the unemployed can change islands only after incurring a fixed cost that captures the loss of occupation-specific human capital and red tape. Additionally, the employed and the unemployed exit the labor force at the exogenous rate ζ. New workers enter the labor force at the same rate, decide which occupation to enter first, and begin their careers as the unemployed. One-worker firms in each occupation produce a differentiated intermediate good that is sold to industries.

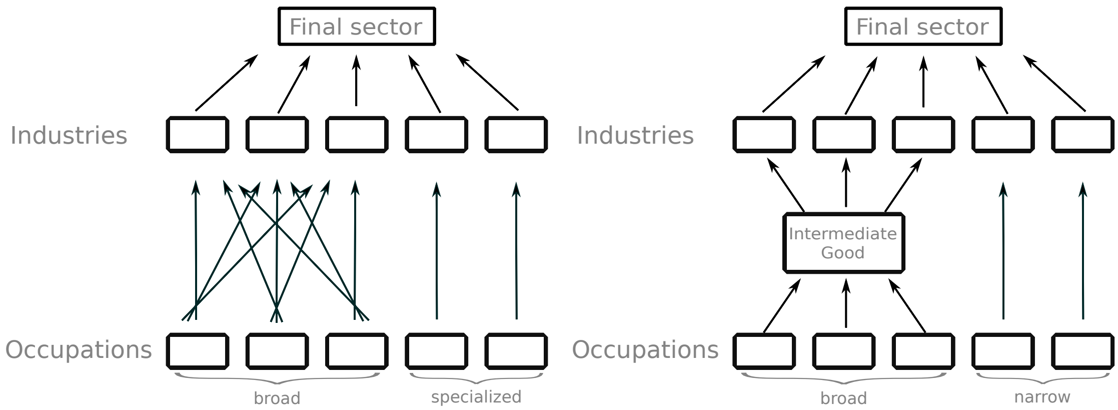
At the meso-level, a continuum of islands buy the occupation-specific inputs, face idiosyncratic and persistent productivity shocks and produce differentiated industry-specific goods. I assume a production network between occupations and industries that is not symmetric: occupations differ in the demand structure for their produced services.

The model features two types of occupations. A measure γ of occupations is labeled "broad": they provide a service that is employed by a large number of industries. A measure $1 - \gamma$ of occupations is labeled "specialists" and provides a service that is only used by a single industry. This input-output network is illustrated in Figure (9). Because of their distinct demand structure, broad and specialist occupations are differentially affected by these shocks.

In the aggregate, the final good is produced by aggregating the output from the continuum of industries. The model is stationary: individual industries and occupations are volatile, but we focus our attention on steady states where aggregate variables such as total output and average unemployment will remain constant over time.

I will now describe these building blocks in more detail.

Figure 9: The input-output structure between occupations and industries



The production network of the economy. Notice that the two versions of this network are isomorphic, as Section 5.3 shows.

5.1 Final sector

There is a unit measure of industries, each of which produces intermediate output $y(i)$. The final sector produces aggregate output Y by integrating the output from the industries with elasticity θ. The environment is dynamic. For ease of exposition, I ignore time indices until they are necessary.

$$Y = \left[\int_{[0,1]} y(i)^{\frac{\theta-1}{\theta}} di \right]^{\frac{\theta}{\theta-1}} \tag{4}$$

$$p(i) = \left(\frac{Y}{y(i)} \right)^{\frac{1}{\theta}} \tag{5}$$

5.2 Specialized industries

Each industry i features a competitive equilibrium in which firms produce the intermediate output $y(i)$ at zero profit. Each specialist industry i is linked to a unique specialist occupation with the same index. Firms in the linked occupation i provide intermediate output $z(i)$ which is used by firms in industry i in the production of $y(i)$. This is illustrated by (6), where $A(i)$ is the industry-specific idiosyncratic productivity shock. Notice that the industry-level problem is static. Denote the industry-specific and occupation-specific prices as $p(i)$ and $p_z(i)$. Perfect competition implies that industry-specific prices are computed as input prices divided by productivity (7)

$$y(i) = A(i)z(i) \tag{6}$$

$$p(i) = \frac{p_z(i)}{A(i)} \tag{7}$$

5.3 Broad industries

Firms in each broad industry i employ a CRS production function with elasticity of substitution θ_b. They use labor services from occupations indexed $o \in [0, \gamma]$.

$$y(i) = A(i)x(i)$$

$$x(i) \equiv \left[A_x \int_{[0,\gamma]} z(i,o)^{\frac{\theta_b - 1}{\theta_b}} do\right]^{\frac{\theta_b}{\theta_b - 1}}$$

where, as before, $A(i)$ denotes industry-specific productivity. A_x is a constant productivity parameter, and $z(i,o)$ denotes how much input of occupation o firms in industry i are using. Firms in broad industries also face perfect competition. The firms' problem is to optimize their input composition for a given vector of prices and a given level of output (8).

$$\min_{\{z(i,o)\}_o} \int_{[0,\gamma]} p_z(o)z(i,o)do \tag{8}$$

$$\text{s.t. } y(i) = A(i)\left[\int_{[0,\gamma]} z(i,o)^{\frac{\theta_b - 1}{\theta_b}} do\right]^{\frac{\theta_b}{\theta_b - 1}}$$

The appendix shows that optimal input composition is given by (9), where P_x is the price index associated with producing $x(i)$. The optimal input composition is identical across industries, as they only differ in their productivities. This difference in productivities only affects their level of output, but not the composition of $x(i)$.

$$\frac{z(i,o)}{x(i)} = \left(\frac{P_x}{p_z(o)}\right)^{\theta_b} \qquad , \forall i, o \tag{9}$$

$$P_x = \left[A_x \int_{[0,\gamma]} p_z(o)^{1-\theta_b}\right]^{\frac{1}{1-\theta_b}}$$

We use this result to solve for the equilibrium in the broad sectors as follows: we define x to be the total intermediate good available, produced using all occupation-level services as input:

$$x \equiv \left[A_x \int_{[0,\gamma]} z(o)^{\frac{\theta_b - 1}{\theta_b}} do \right]^{\frac{\theta_b}{\theta_b - 1}}$$
$$x = \int_{[0,\gamma]} x(i) di \tag{10}$$

The question remains as to how x is distributed across industries. The appendix answers this question by using feasibility (10) and a rewritten firm's problem to compute equilibrium $x(i)$ shares (11). For each industry, its share of intermediate inputs relates to its idiosyncratic productivity $A(i)$, an average productivity-index across broad industries A_b, as well as the elasticity of substitution across industries θ, as shown in (11).

$$\frac{x(i)}{x} = \left(\frac{A(i)}{A_b} \right)^{\theta - 1} \tag{11}$$
$$A_b = \left[\int_{[0,\gamma]} A(i)^{\theta - 1} di \right]^{\frac{1}{\theta - 1}}$$

Finally, the appendix shows how one can use this result, together with prices implied by perfect competition (12), to compute P_x in closed-form as in (13).

$$p(i) = \frac{P_x}{A(i) A_x} \tag{12}$$
$$P_x = A_x A_b \left(\frac{Y}{A_b x} \right)^{\frac{1}{\theta}} \tag{13}$$

To summarize the broad sector, I define the following partial equilibrium:

Definition 1. *A* Static Broad Industry Partial Equilibrium *is, for a given*

- *aggregate output Y, and*
- *distribution of inputs $\{z(o)\}_{o \in [0,\gamma]}$*

a collection of

- *masses* $\{x, \{x(i)\}_{i\in[0,\gamma]}\}$, *and*
- *prices* $\{p_z(o)\}_{o\in[0,\gamma]}$

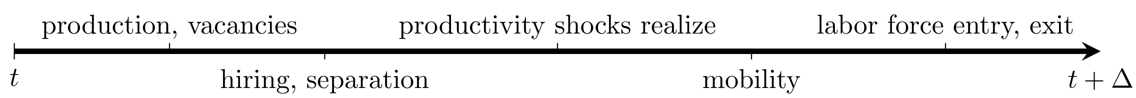
such that:

1. *Industry choice:* $z(i,o)/x(i)$ *is optimal given prices* $\{p_z(o)\}_o, P_x$, $\forall i$ (9)
2. *Industry choice: intermediate output consistent with zero profits,* $\forall i$ (12)
3. *Feasibility: the* $x(i)$ *add up to* x (10)

5.4 Occupations

A DMP-style frictional labor market exists in each occupation. The timing is as in Figure 10. First, production occurs, followed by separations and hiring. Then, industry-specific productivity shocks materialize. The unemployed then have the option of changing occupations. Finally, a share ζ of workers exits the labor force, and is replaced by a new cohort.

Figure 10: Timing of events within each period

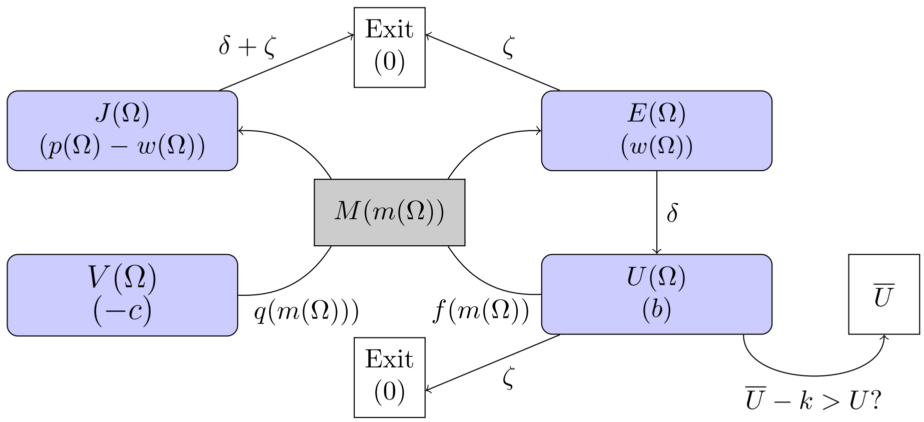


The main innovation compared to the canonical DMP setup is labor market mobility after the realization of productivity shocks. Here, productivity shocks are not realized at the start of the period. This is slightly unconventional but simplifies the notation when defining labor market adjustment: the definition of a period start will not affect any outcomes in the model.

Figure 11 summarizes the dynamics within all occupations, both broad and specialized. As the figure suggests, the fundamental structure of all occupations is the same. Broad and specialized occupations differ in their price function $p(\Omega)$, as they face a different demand structure. The relevant state variable Ω differs across broad and specialized occupations – we will discuss these differences in detail.

The purple boxes in the schematic diagram are standard in the DMP environment: posting a vacancy implies a flow cost of c, and the value function of vacancies is denoted as V. The unemployed's value functions are denoted as U, they receive b in each period. The market tightness is denoted as $m = v/u$. The unemployed and the vacancies match according to $M(m(\Omega))$. The resulting one-worker firms produce output at value $p(\Omega)$, of which the workers receive wage $w(\Omega)$. The value

Figure 11: Dynamics within each occupation



functions of firms and workers are denoted as J and E. Matches separate at rate δ. When that happens, workers become unemployed and the firms simply exit.

The white boxes in that schematic diagram are non-standard. In each period, the unemployed have the option of incurring fixed cost k and changing their occupation. I assume that relocation is directed and workers have perfect information: if they decide to leave, workers will relocate to the occupation that delivers the highest attainable utility $\overline{U}$. We take $\overline{U}$ as given here, but will endogenize it later on. k summarizes loss of human capital and other barriers to occupational mobility.

The second innovation is exogenous labor force exit. I assume labor force exit for a technical reason: in its absence, multiple steady states may exist. At rate $\zeta > 0$, the employed and the unemployed exit the labor force. Firms connected to exiting workers also exit the market.

Next, I provide a more technical summary of the model. Note that the state vector Ω, all value functions and policy functions differ across broad and specialized occupations and require subscript $j \in \{b, s\}$. I now drop this subscript for clarity, but will add it when required.

Denote the value of staying in an occupation as $U^{\text{stay}}(\Omega)$. As they have to pay a fixed cost k, we can define the value before the leaving stage as

$$U(\Omega) = \max\{U^{\text{stay}}(\Omega), \overline{U} - k\}.$$

In each period, the unemployed either find a job at rate $f(m(\Omega))$, or stay unemployed and are allowed to change occupations again. Both employed and unemployed workers exit the labor force at the exogenous rate ζ with the terminal value 0. This implies that the effective discount rate ρ is a sum of both impatience and the exit rate: $\rho = \tilde{\rho} + \zeta$.

$$U^{\text{stay}}(\Omega) = b\Delta + e^{-\rho\Delta}\left[\left(1 - e^{-f(m(\Omega))\Delta}\right)\mathbb{E}[E(\Omega')] + e^{-f(\Omega')\Delta}\mathbb{E}[U(\Omega)]\right] \tag{14}$$

Vacancies match at rate $q(m)$. The remaining value functions can be written as

$$E(\Omega) = w(\Omega)\Delta + e^{-(\tilde{\rho}+\zeta)\Delta}\mathbb{E}\left[e^{-\delta\Delta}\mathbb{E}[E(\Omega')] + \left(1 - e^{-\delta\Delta}\right)\mathbb{E}[U(\Omega')]\right] \tag{15}$$

$$J(\Omega) = [p_s(\Omega) - w(\Omega)]\Delta + e^{-(\tilde{\rho}+\zeta+\delta)\Delta}\mathbb{E}[J(\Omega')] \tag{16}$$

$$V(\Omega) = -c\Delta + \left(1 - e^{-q(m(\Omega))\Delta}\right)e^{-\tilde{\rho}\Delta}\mathbb{E}[J(\Omega')] \tag{17}$$

In equilibrium, market tightness is governed by free entry, (18), and wages are determined by Nash bargaining with workers' bargaining power β, (19).

$$V(\Omega) = 0 \tag{18}$$

$$\beta J(\Omega) = (1 - \beta)\left(E(\Omega) - U(\Omega)\right) \tag{19}$$

Connecting occupations and industries Firms in broad and specialized occupations differ in the set of industries they provide their input for. This implies different demand structures and pricing functions for their output. This model is structured with simplifying the computation of these pricing functions in mind: we will now derive analytical solutions for the pricing functions of both occupation types. The logic will be the same: industry-level prices are given by the final sector Constant Elasticity of Substitution (CES) aggregator, given industry-level output. Industry-level output is a function of occupation-level output. Since all firms produce one unit of output, it is sufficient to know occupation-level employment to compute occupation-level output.

For specialized occupations, this amounts to using (5), industry-level technology (6), and free-entry, (7), to compute p_s (20). p_s is a composite of a, and a bracketed term. The bracketed term computes the price of industry-level output, combining total occupation-level input $(1 - u)\ell$ and industry-level productivity a. The outer a translates occupation-level output into industry-level output and ensures that occupation-level firms gain all the revenues from selling multiple units whenever their connected industry is more productive.

This pricing function p_s determines the state vector: u and ℓ together yield the number of one-worker firms. For each specialized occupation, the productivity of the connected industry a is relevant for computing industry-level output and prices, and hence appears in the state vector. Aggregate output Y is constant, and hence does not characterize the state space. That is, the specialist occupation's state vector can be written as $\Omega_s = \{a, u, \ell\}$.

$$p_s(a, u, \ell) = a\left(\frac{Y}{a(1-u)\ell}\right)^{\frac{1}{\theta}} \tag{20}$$

$$p_b(u, \ell) = \left(\frac{x}{(1-u)\ell}\right)^{\frac{1}{\theta_b}} \cdot P_x \tag{21}$$

We apply a similar logic for the price of output from broad occupations, p_b. Using the appropriate equations from the industry side together with feasibility, we obtain p_b (21). This price is composed of two products: the first bracketed term denotes the relative importance of any particular occupation in producing x. The second term P_x denotes the value of each unit of output x. Broad occupations are perfectly insured against industry shocks since they can sell to any industry $i \in [0, \gamma]$. This is why no productivity-related variable a is required to compute p_b: the relevant state vector for broad occupations is $\Omega_b = \{u, \ell\}$.

Laws of motion It remains to describe the transitions for Ω_b and Ω_s. I will denote by $g_{x;j}$ the law of motion for dimension $x \in \{a, u, \ell\}$ and occupation type $j \in \{b, s\}$. We begin with specialized occupations. For now, we will take the law of motion for the labor force $g_{l;s}(a', a, u, \ell)$ as given. Productivity a follows an AR(1) process, and the law of motion for the unemployment rate has to be corrected for changes due to migration:

$$g_{u;s}(a, u, \ell, \ell') = 1 - e^{-\zeta\Delta}(1 - \tilde{u}(a, u, \ell))\frac{\ell}{\ell'} \tag{22}$$

$$\tilde{u}(a, u, \ell) = (1 - e^{-\delta\Delta})(1 - u) + e^{-f(m(a,u,\ell))\Delta}u$$

where $\tilde{u}(\Omega)$ denotes the unemployment rate post separations and matching, but prior to relocation. Note that without relocation ($\zeta = 0$ and $\ell' = \ell$), we recover $g_{u;s} = \tilde{u}$.

Laws of motion for broad occupations are similar. The main noticeable difference is the lack of a as a state variable.

$$\tilde{u}_b(u,\ell) = (1-e^{-\delta\Delta})(1-u) + e^{-f(m_b(u,\ell))\Delta}u$$
$$g_{u;b}(u,\ell,\ell') = 1 - e^{-\zeta\Delta}(1-\tilde{u}_b(u,\ell))\frac{\ell}{\ell'} \tag{23}$$

We can summarize each type of occupation by defining a partial equilibrium.

Definition 2. *A* Stationary Recursive Specialist Occupation Partial Equilibrium *takes as given*

- *A price function* $p_s(\Omega_s)$
- *A law of motion for labor* $g_{\ell;s}(\Omega_s)$
- *A leaving utility* $\overline{U}$

and contains

- *A set of value functions* $\{J_s(\Omega_s), E_s(\Omega_s), U_s^{stay}(\Omega_s), U_s(\Omega_s)\}$,
- *Wages* $w_s(\Omega_s)$
- *Law of motion for u* $\{g_{u;s}(\Omega_s, \ell')\}$,
- *Market tightness* $\{m_s(\Omega_s)\}$

such that

1. *Given* $\{g_{u;s}, w\}, \overline{U}, Y$*:* $\{J_s, E_s, U_s^{stay}, U_s\}$ *satisfy* (14)-(16)
2. *Given* $\{J_s, E_s, U_s^{stay}\}$*: wages satisfy Nash bargaining* (19)
3. *Given* $\{J_s\}$*: m satisfies free-entry* (18)
4. *Law of motion* $g_{u;s}$ *is consistent with* $\{m\}$ (23)

Definition 3. *A* Recursive Broad Occupation Partial Equilibrium *is, taken as given*

- *A price function* $p_b(\Omega_b)$
- *A law of motion for labor* $g_{\ell;b}(\Omega_b)$
- *A leaving utility* $\overline{U}$

and contains

- *A set of value functions* $\{J_b(\Omega_b), E_b(\Omega_b), U_b^{stay}(\Omega_b), U_b(\Omega)\}$,
- *Wages* $w_b(\Omega_b)$
- *Law of motion for u* $\{g_{u;b}(\Omega_b, \ell')\}$,
- *Market tightness* $\{m_b(\Omega_b)\}$

such that

1. *Given* $\{g_{u;b}, w\}, \overline{U}, Y$*:* $\{J_b, E_b, U_b^{stay}, U_b\}$ *satisfy* (14)-(16)
2. *Given* $\{J_b, E_b, U_b^{stay}\}$*: wages satisfy Nash bargaining* (19)
3. *Given* $\{J_b\}$*:* m *satisfies free-entry* (18)
4. *Law of motion* $g_{u;s}$ *is consistent with* $\{m\}$ (24)

5.5 Mobility

So far, labor force flows across occupations have been taken as exogenous. Here I describe the labor force flows that will be consistent with individual-level decisions.

The unemployed can incur a movement cost k and move to any occupation of their liking. We presume that *if they move*, they will go to the occupation that will deliver the highest expected utility to an unemployed worker. This highest utility in each sector is denoted as U_b and U_s.

$$\overline{U}_b = \max_{(u,\ell):g_b(u,\ell)>0} U_b(u,\ell)$$
$$\overline{U}_s = \max_{(a,u,\ell):g_s(a,u,\ell)>0} U_s(a,u,\ell)$$

where g_b and g_s denote the density of broad occupations over the (u,ℓ) space, and specialist occupations over the (a,u,ℓ) space.

As mentioned before, the mobility cost is independent of the type (broad/specialist) of the originating and the destination occupation. Therefore, the relevant variable for the optimization problem is the best attainable utility of any of those, denoted $\overline{U}$. The present discounted value of moving net of the migration cost k will be denoted $\underline{U}$.

$$\overline{U} = \max\{\bar{U}_b, \bar{U}_s\}$$
$$\underline{U} = \overline{U} - k$$

It is optimal for the unemployed to leave whenever their next period's value $U_b(\Omega_b')$ or $U_s(\Omega_s')$ is below $\underline{U}$. All unemployed workers have this option, and will use it whenever their utility $U_b(u,\ell)$ or $U_s(a,u,\ell)$ is less than $\underline{U}$. In what follows, I will describe the law of motion for the labor force in the broad occupations (24).

To understand mobility, denote by $U'(g_\ell)$ the next period's utility as a function of mobility at the end of this period. There are four cases to distinguish. In case (i) $U'(0) \in (\underline{U}, \overline{U})$. If without mobility, next period's utility is strictly between the boundaries, there is no incentive for workers to leave. Moreover, as the occupation does not belong to the set of "best occupations for the unemployed to enter", no worker will enter. In case (ii) $U'(0) \geq \overline{U}$: next period's utility would be at or above $\overline{U}$. In equilibrium, $\overline{U}$ has to be the highest attainable utility value: we will observe positive mobility into the occupation. However, positive mobility is only an equilibrium outcome if $U'(g_\ell) \geq \overline{U}$. Thus, we know that mobility will be such that $U'(g_\ell) = \overline{U}$. Next, we have to deal with $U'(0) \leq \underline{U}$. Whenever that is the case, unemployed workers will leave the occupation. The measure of workers that are leaving is such that either (iii) all unemployed workers have left, but next period's utility remains below the threshold, or (iv) that utility has moved to the threshold $\underline{U}$ – whatever requires fewer relocations. The law of motion for the specialist occupations' labor force (25) follows the same spirit.

$$
g_{\ell;b}(u,\ell) = \begin{cases} e^{-\zeta\Delta}\ell & \text{if } U_b(g_{u;b}(u,\ell,e^{-\zeta\Delta}\ell), e^{-\zeta\Delta}\ell) \in (\underline{U}, \overline{U}) \\ x : U_b(g_{u;b}(u,\ell,\ell' = x), x) = \overline{U} & \text{if } U_b(g_{u;b}(u,\ell,e^{-\zeta\Delta}\ell), e^{-\zeta\Delta}\ell) \geq \overline{U} \\ (1 - \tilde{u}_b(u,\ell))e^{-\zeta\Delta}\ell & \text{if } U_b(g_{u;b}(u,\ell,e^{-\zeta\Delta}\ell), e^{-\zeta\Delta}\ell) < \underline{U} \\ x : U_b(g_{u;b}(u,\ell,\ell' = x), x) = \underline{U} & \text{otherwise} \end{cases} \tag{24}
$$

$$
g_{\ell;s}(a',a,u,\ell) = \begin{cases} e^{-\zeta\Delta}\ell & U(a', g_u(a,u,\ell,e^{-\zeta\Delta}\ell), e^{-\zeta\Delta}\ell) \in (\underline{\mathrm{U}}, \bar{U}) \\ x : U(a', g_u(a,u,\ell,\ell' = x), \ell' = x) = \bar{U} & U(a', g_u(a,u,e^{-\zeta\Delta}\ell, e^{-\zeta\Delta}\ell), \ell) \geq \bar{U} \\ (1 - \tilde{u}(a,u,\ell))e^{-\zeta\Delta}\ell & U(a', 0, e^{-\zeta\Delta}(1 - \tilde{u}(a,u,\ell))\ell) \leq \underline{\mathrm{U}} \\ x : U(a', g_u(a,u,\ell,\ell' = x), \ell' = x) = \underline{\mathrm{U}} & \text{else if } U(a', g_u(a,u,e^{-\zeta\Delta}\ell),, e^{-\zeta\Delta}\ell) \leq \underline{\mathrm{U}} \end{cases} \tag{25}
$$

5.6 General equilibrium

So far, we have described the building blocks of the model in isolation. To close the model, two margins need to be addressed. First, Y is being taken as exogenous by all agents in the economy, but must be consistent with industry-level output. Second, the amount of inputs used by industries $\int z(i,o)di$ has to be consistent with the employment level of each occupation o. Third, the distribution and flows of labor across occupations have to be consistent with the (constant) aggregate labor force.

5.7 Connection between industries and occupations

Industries are lined up on the unit line. Industries $i > \gamma$ are specialist industries. Each industry has a productivity state $A(i)$. It is linked to a specialist occupation with state $(\tilde{a}, \tilde{u}, \tilde{\ell})$, where $\tilde{a} = A(i)$, and $(\tilde{u}, \tilde{\ell})$ are drawn from the stationary distribution $G_s(\tilde{a}, u, \ell)$:

$$A(i) \sim \log\text{Normal}(\text{s.t. stationary AR (1)}) \qquad \forall i \in [0,1] \tag{26}$$

$$(u(i), \ell(i)) \sim G_s(a, u, \ell | a = a(i)) \qquad \forall i \in (\gamma, 1] \tag{27}$$

Industries $i \leq \gamma$ are broad industries. They have productivity states $A(i)$, but no $(\tilde{u}, \tilde{\ell})$ state, since they are not linked to any particular occupation.

We have the following feasibility constraint:

$$z(o) = (1 - u(o))\ell(o) \qquad , \forall o \in [0,1] \tag{28}$$

Prices for broad and narrow occupations come from the demand structure of the corresponding industries:

$$p_b(u, \ell) = \left(\frac{x}{\ell(1-u)}\right)^{\frac{1}{\theta_b}} P_x \tag{29}$$

$$p_s(a, u, \ell) = a\left(\frac{Y}{a(1-u)\ell}\right)^{\frac{1}{\theta}} \tag{30}$$

Feasibility in terms of labor is stated as follows:

$$
\begin{aligned}
L &= \gamma \int_{\mathcal{U}\times\mathcal{L}} \ell dG_b(u,\ell) + (1-\gamma)\int_{\mathcal{A}\times\mathcal{U}\times\mathcal{L}} \ell dG_s(a,u,\ell) \\
L &= L_b + (1-\gamma)\int_{\mathcal{A}\times\mathcal{U}\times\mathcal{L}} \ell dG_s(a,u,\ell) \qquad (31)
\end{aligned}
$$

where L is a parameter.

Definition 4. *A* General Equilibrium *is a collection of*

1. *Aggregate output* Y
2. *Specialist industry states* $\{A(i), u(i), \ell(i)\}_{i\in(\gamma,1]}$
3. *Broad industry states* $\{A(i)\}_{i\in[0,\gamma]}$
4. *Occupation-level distributions* $\{G_b(u,\ell), G_s(a,u,\ell)\}$
5. *Occupation-level output* $\{z(o)\}_{o\in[0,\gamma]}$
6. *Leaving threshold* $\underline{U}$
7. *Laws of motion for labor* $\{g_{\ell;s}(a,a',u,\ell), g_{\ell;b}(u,\ell)\}$
8. *Prices of occupation-specific output* $\{p_s(a,u,\ell), p_b(u,\ell)\}$
9. *All previous variables (value-functions, masses, prices...)*

such that

1. Y *is consistent with industry output* (4)
2. $z(i)$ *is consistent with occupation-level output* (28)
3. *Specialist industry states are consistent with specialist occupation distribution* (27)
4. $\underline{U}$ *is consistent with* G_b, G_s
5. *Prices are consistent with industry-level demand and feasibility* (29)-(30)
6. *Laws of motion for labor are consistent with* $\{\underline{U}, \overline{U}\}$ (24)-(25)
7. $\{G_b, G_s\}$ *are consistent with the productivity process and* $\{g_{\ell;s}, g_{\ell;b}, g_{u;s}, g_{u;b}\}$
8. $\forall i \in (\gamma,1]$*: given* $\{A(i), z(i)\}$*:* $\{p(i)\}$ *solves specialist industry prices* (7)
9. $\forall i \in (\gamma,1]$*: given* $\{p_s(a,u,\ell), g_{\ell;s}, \underline{U}\}$*:* $\{J_s, E_s, U_s, w, g_{u;s}, m_s\}$ *solve* Stationary Recursive Specialist Occupation PE
10. $\forall i \in [0,\gamma]$*: given* $\{Y, \{z(o)\}_{i\in[0,\gamma]}$*:* $\{x, x(i), p_z\}$ *solve* Broad Industry PE
11. *Given* $\{L_b, p_b(u,\ell), \underline{U}, \overline{U}\}$*:* $\{J_b, E_b, U_b, m, u, g_{u;b}\}$ *solve* Recursive Broad Occupation PE
12. *Feasibility w.r.t* L (31)

Table 2: Parameters of the model

Parameter	Value	Description	Source
General			
ρ	0.001	Discount rate	
Δ	0.333	Length of period	
Industries			
σ	0.050	Productivity std	
ρ_A	0.800	Productivity autocorr	
θ	4.500	Elasticity, Final sector	
Network			
A_x	4.346	Productivity (x)	Labor force distribution
$\underline{\gamma}$	0.500	Measure of broad occupations	Illustration
$\overline{\theta}$	0.500	Elasticity, broad industries	High complementarity
Occupations			
A	1.355	Matching productivity	Literature
α	0.510	Matching elasticity	Literature
c	0.128	Vacancy posting cost	Average unemployment rate
b	0.955	Home production	HM (2008)
β	0.052	Bargaining Power: Worker	HM (2008)
δ	0.100	Monthly separation rate	Shimer (2005)
ζ	0.006	Labor force entry/exit	Average working years
k	0.103	Moving cost	

All rates in quarterly units.

5.8 Parameter selection

The general strategy behind parameter selection is to make the potential impact of broadness as large as possible, so as to give this exercise the spirit of a benchmark. For other parameters, I will either select values that expose the mechanism more clearly or are in line with the literature.

The unit of time is a quarter. To prevent issues from time aggregation, the period length is a month. Here, I trade off precision and computational complexity.

In this paper, I study differential responses between specialist and broad occupations. In the data, broad occupations and industries differ in other dimensions that have little to do with this mechanism. For the sake of exposing this particular mechanism, I do not recalibrate broad occupations and industries to different productivity processes or labor market structures. The discount rate appears small, but it adds up with the labor force exit rate to an effective annual discount rate of 0.03.

Industries I assume that volatility and persistence of industry-specific productivity processes are of similar magnitude to those typically measured for aggregate productivity. Higher values here increase the insurance provided by broadness. I normalize the average broad and specialist innovations to be zero. Industry-specific goods are substitutes, which implies that a positive productivity shock at the industry level yields higher equilibrium employment in linked occupations. By choosing high values for σ and θ, I increase the role of broadness: large productivity shocks and highly substitutable industry-level outputs will imply that labor demand is highly elastic with respect to productivity shocks. In this type of environment, the difference in volatility of unemployment between broad and specialized occupations will be higher.

Network I have empirically measured the average broadness of the economy to be 0.68. However, to more clearly expose underlying mechanisms, I will set $\gamma = 0.5$, as this will ease the comparison between shocks to broad and specialized industries. The main results from the aggregate exercises are independent of γ, and I will emphasize whenever that is not the case. The labor-force weighted average broadness of the economy is similar to the average occupation-level broadness, and therefore I calibrate A_x to yield an average labor force share of γ in broad occupations. There is little evidence on the within-sector substitutability of different occupations. Finally, $\overline{\theta}$ has been understudied in the empirical literature. Here, all broad occupations are identical, and therefore aggregate fluctuations will not induce any substitution across occupations. Hence, $\overline{\theta}$ only plays a role in relative productivity between broad and specialized occupations, something that is already calibrated using A_x. In any case, I have used the rise and fall of construction-specific demand together with relative weak outside options for blue-collar workers in the construction sector to estimate an elasticity of substitution around 0.05 between blue-collar and white-collar workers in the construction sector. Recognizing that the chosen split and sector are at the lower end of the distribution for $\overline{\theta}$, I choose $\overline{\theta} = 0.5$. As emphasized before, this particular parameter does not affect the results.

Occupations Shimer (2007) makes the point that perfectly competitive local labor markets can display an aggregate behavior similar to the typically calibrated matching function. That is, there is no bijection between aggregate labor flows and required local labor market matching functions. Moreover, vacancy data is quite noisy and a precise estimation of matching parameters at the occupation level appears infeasible. Therefore, there is no clear and robust empirical guidance to set up labor-market-level matching parameters. α is set to a median value in the domain between 0 and 1, in line with Pissarides and Petrongolo (2001). As explained in Shimer (2005), the level of market tightness m is meaningless. The productivity of the matching function A controls this level and therefore I simply set A to the value in Shimer (2005). I calibrate c to match an average unemployment rate of $u = 0.05$.

There are several ways of creating high unemployment fluctuations in this environment. One can select a wage process that is more persistent than what is implied by Nash bargaining, force productivity to be very volatile, or calibrate the firm's share of the surplus to be small and volatile. For ease of implementation, I here choose to do the latter and follow Hagedorn and Manovskii (2008) in calibrating home production and bargaining power. While this does affect the absolute responses of unemployment rates to a productivity shock, *relative* unemployment rates across occupations will not be affected.

Finally, k will govern the rate at which workers respond to shocks by changing occupations. Unfortunately, there is no causal evidence of the link between occupation-specific shocks and exit rates. Moreover, even the unconditional rate at which the unemployed change occupations is not well documented. This is because occupation data is measured with noise. Since occupation changes are measured as differences in individual-specific occupation tags, measurement error attributes to an upward bias in estimated occupational transition rates. The CPS introduced dependent coding in 1995 to address this issue. However, unemployed agents' occupation tags are still measured without dependent coding. I summarize this issue in Appendix E and argue that, in practice, observed occupational mobility is not a good target for k. To calibrate k, I simulate an economy in which mobility is impossible. I observe the fluctuations in the unemployed's value function, and compute the corresponding 20th and 80th percentiles. k is set to match the difference in these percentile values. Notice that the resulting k is small: the costs of changing occupations are around one-tenth of a worker's average quarterly wage. I will emphasize results that depend on the resulting calibration for k.

5.9 Steady state

This model nests directed search across occupations with random search within each occupation. As other models with directed search, a steady state always exists. Moreover, each occupation has decreasing returns to scale. This would not be sufficient to ensure uniqueness of the steady state. I assume a strictly positive exogenous labor force exit rate, $\zeta > 0$. This anchors the utility from broad occupations relative to the utility of specialized occupations and ensures that the steady state is unique.

Table 3 summarizes some aggregate statistics of the steady state. By virtue of the calibration, the labor force is equally spread across broad and specialized occupations. The average unemployment

Table 3: Key statistics of the steady state

Moment	Description	Value	
		Specialized	Broad
Industries			
y	Sectoral output	0.390	0.390
$\mathcal{P}$	Price index	1.219	1.219
Occupations			
$\mathbf{E}[v]$	Average vacancies	0.308	0.290
$\mathbf{E}[u]$	Average unemployment	0.052	0.051
$\mathbf{std}[u]$	Std. of unemployment across occupations	0.012	0.000
$\mathbf{E}[w]$	Average wages	0.997	0.996
L	Total labor force	0.500	0.498

rates are also similar in both parts of the economy. There is, however, a difference in the dispersion of the unemployment rates: all broad occupations are identical, and their unemployment rate is the same. The specialized occupations however depend on the productivity of the industry that they are individually connected to, and so there are differences in their unemployment rates. Yet, the total output produced by broad and specialized industries is roughly equal.

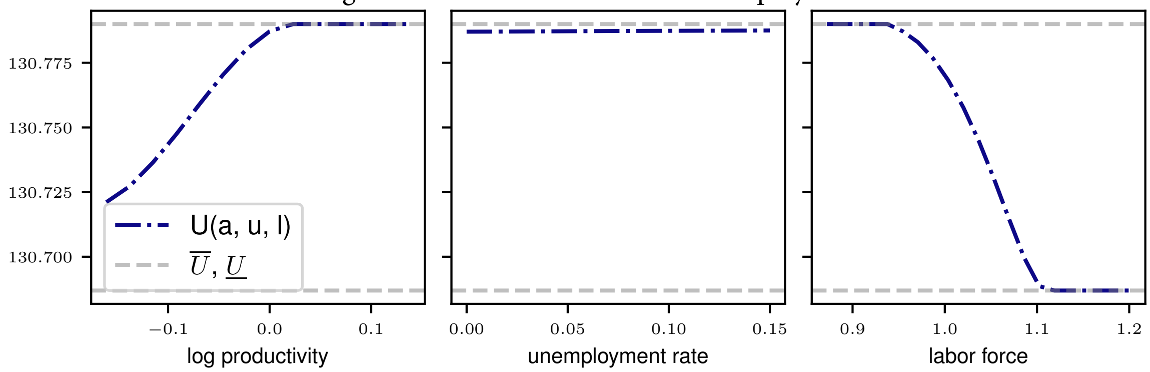
It is useful to analyze the steady state to gain some familiarity with the environment before moving on to the question that this model was designed to address.

Mobility We begin our steady state analysis by analyzing the behavior of individuals within a single given occupation. Figure 12 plots the value functions for unemployed workers in specialized occupations over the three state variables. All three state variables impact the value of occupation-level firms. As the unemployed expect to eventually become employed, a change in the value of firms will be reflected in wage changes, and thereby affect the value of the unemployed.

When the productivity of an occupation rises, the connected industry produces more output, which lowers the price of the industry-specific good, and with it the price of the occupation-specific intermediate good. However, each firm in each industry is also able to produce more, which overcomes the price effect and implies that the occupation-specific output yields a higher price when productivity increases.

When the labor force increases, the measure of occupation-specific firms increases and the evaluation of occupation-specific goods decreases, thus reducing the price of the occupation-level good and with it expected future wages.

Figure 12: Value function of the unemployed



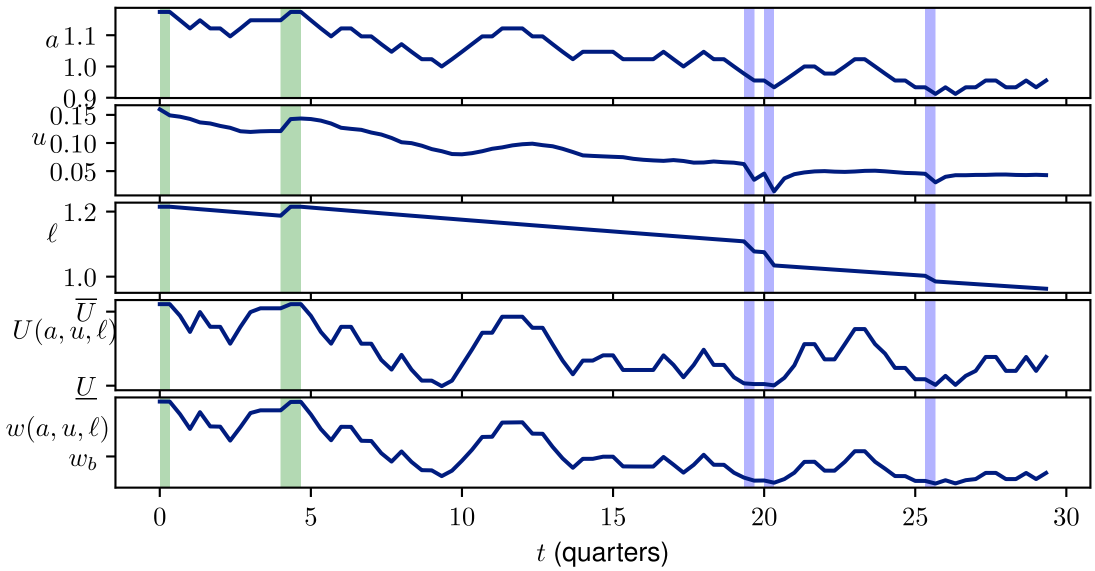
The value functions of unemployed workers in specialized occupations. Each panel displays the value function across one dimension, holding the value at the other dimensions fixed.

The less intuitive dimension is the unemployment rate: a higher unemployment rate slightly increases the value of the unemployed. This is because we are holding all other dimensions constant. In this type of model, free entry pins down a rate of market tightness: a higher unemployment rate will, ceteris paribus, simply mean a higher vacancy rate, and does not affect the job-finding rate. In addition, a higher unemployment rate implies that a smaller share of workers are employed, which leads to a higher price of the occupation-level good.

We conclude that individuals typically move towards occupations that have high productivity and a low labor force, and leave those with a high labor force and low productivity. We can see this more clearly when looking at the path of an occupation over time. Figure 13 plots the dynamics of a specialized simulated occupation. The first three panels display the evolution of the state vector $\Omega_s = \{a, u, \ell\}$. a is exogenously drawn from the industry's productivity sequence, while u and ℓ are equilibrium outcomes. The fourth panel displays $U(\Omega_s)$, which is in equilibrium bound between $\underline{U}$ and $\overline{U}$. Episodes where U_s is at its entry and exit values are highlighted in green and purple. Whenever a positive productivity shock would push U_s above $\overline{U}$, ℓ increases to prevent that from happening. Notice that these migrants start unemployed, and we can see a spike in u at those periods. Labor markets are calibrated to capture the fluidity of the US labor markets. In good times, these additional unemployed workers find a job very quickly, and the spikes in u vanish quickly: mobility does not contribute largely to measured unemployment fluctuations.

Whenever the occupation is not among the set of "best" occupations – $U(a, u, \ell) < \overline{U}$, we have no mobility into that occupation. Exogenous labor force exit slowly reduces the labor force in that occupation. I highlight in purple episodes where directed mobility out of that occupation is taking

Figure 13: The dynamics of a simulated specialized occupation



Dynamics of a simulated specialized occupation. The first three panels show the evolution of the state vector $\{a, u, \ell\}$*, and the fourth panel depicts the evolution of the value function.*

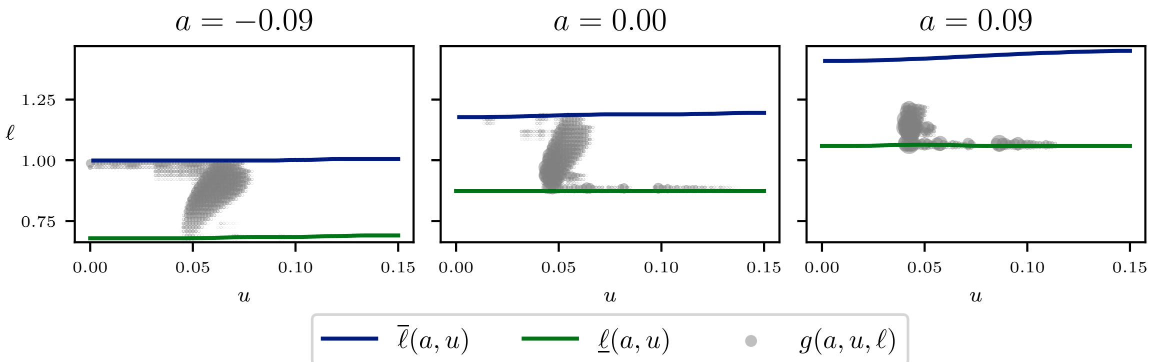
place: the utility of the unemployed in that occupation has deteriorated sufficiently to induce some unemployed workers to leave the occupation. When unemployed individuals leave the occupation, we observe a sharp decline in both the labor force and the unemployment rate.

Wages and compensating differential Next, we analyze the wage formation in this model.

As the summary statistics in Table 3 indicate, average wages are equal in specialized and broad occupations: no wage premium is required to induce our risk-neutral agents into the more volatile specialized occupations. However, there are still some interesting wage dynamics going on in specialized occupations. The fifth panel in Figure 13 plots the evolution of wages w_s in the simulated occupation. Whenever there is mobility into the occupation, wages in the occupation are higher than average. Wages then revert back to average, and eventually are even lower than those in broad occupations. This is because relocation frictions prevent households from moving to broad occupations as soon as the wage rate in their current occupation is dominated by that of broad occupations. Eventually, when the state of the occupation deteriorates too much, individuals leave.

At the firm level, efficient contracts under one-sided commitment often imply that firms hire workers at a low wage rate, but promise them a steep wage profile. This reduces turnover as workers

Figure 14: Mobility



The distribution of specialized labor markets across productivity, unemployment rates and labor force, for four selected productivity states. Circle size is proportional to mass.

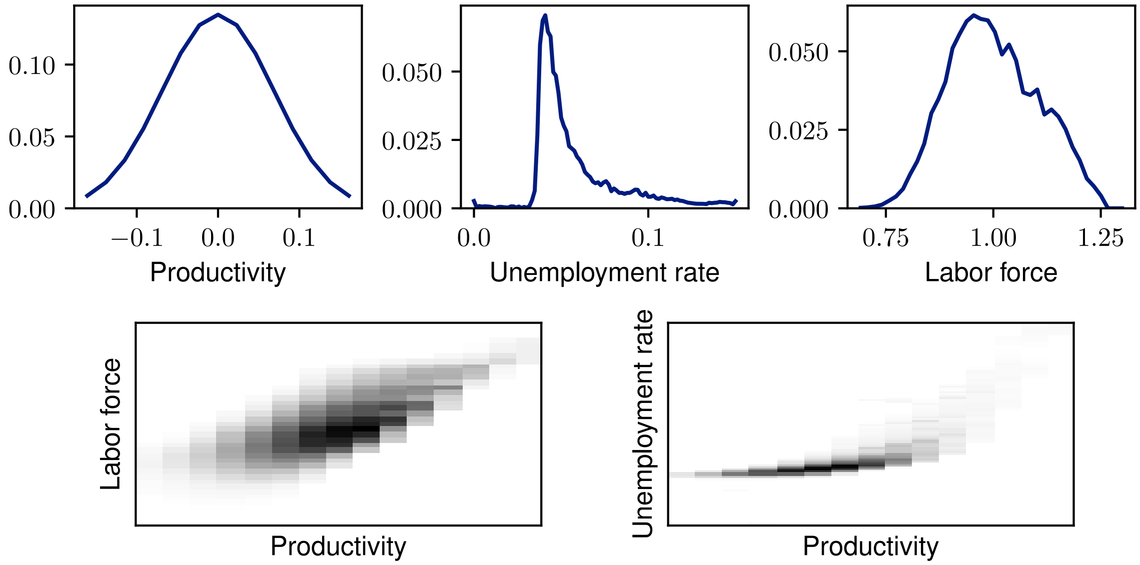
stay to receive the higher promised future wages. In this environment, workers are already "stuck" in their labor market. To be enticed to enter an occupation that is eventually deteriorating, workers receive a starting wage that is higher than that in broad occupations.

We conclude that in this particular framework with risk-neutral agents, workers need not be compensated for the additional riskiness of specialized occupations. However, they are being compensated for the expected deterioration of their labor market by receiving a higher wage when entering.

Stationary distribution Next, we analyze the stationary distribution that is implied by the dynamics of each occupation. Figure 14 displays the cross-sectional distribution of labor markets. The green and blue lines denote the lower and upper boundaries of the labor force for any given unemployment rate and productivity. Notice that these boundaries weakly increase in both productivity and unemployment rates, as the value functions also increase in a and u. Occupations move in this state space for four reasons. First, productivity shocks will shift occupations across these panels. Second, an occupation's (u, ℓ) adjusts if it finds itself outside of $(\underline{\ell}, \overline{\ell})$ at the new productivity state a'. Third, unemployment rates change whenever they are not equal to the stationary unemployment rate implied by the current job-finding rate. Fourth, an exogenous labor force exit will lead to the slow depreciation of labor until occupations are pushed towards $\underline{\ell}$.

Notice that occupations with the high productivity state tend to have a higher unemployment rate than occupations with the low productivity state. This becomes more clear in Figure 15, which plots the marginal and the joint distribution of occupations across the state space. The top panels in that figure show that distribution of occupations across log productivity and labor force are symmetric

Figure 15: Cross-sectional distributions



The distribution of specialized labor markets across productivity, unemployment rates and labor force. Top panels: partial distributions. Bottom panels: joint density of productivity with labor force and unemployment rate, respectively.

and single-peaked, while the distribution of occupations across unemployment rates is highly skewed: there is a small set of occupations with a very high unemployment rate.

This is because unemployment rates are not only a function of the job-finding rate, but also of mobility: occupations with high productivity states will receive a lot of occupation switchers, who start unemployed, thereby increasing their unemployment rate. On the other hand, the unemployed leave low productivity occupations, decreasing their unemployment rate. The bottom-right panel of that figure displays the joint distribution of unemployment rates and productivity: in this model, highly productive occupations are those that have large unemployment, caused by workers that enter the occupation. These workers however quickly find employment, and the high unemployment rate does not persist in these productive occupations. The bottom-left panel of Figure 15 plots the joint distribution of occupations over productivity and labor force. In line with the previous explanation, productivity and labor force are positively correlated.

6 Aggregate shock

Having set up the machinery, we can now turn to the effects of aggregate shocks. Before turning to the main results, I will summarize two additional experiments that I perform in the appendix, to help us understand the model better.

In the first exercise, I study a recession in which all industries are affected. Our intuition tells us that broadness does not provide insurance against shocks that are perfectly correlated across industries, and we would expect both types of occupations to fare similarly in such a recession. Appendix I.1 shows that this is not the case: broad occupations are actually hit worse by aggregate shocks. I study this phenomenon in detail in the appendix. In short, the aggregate productivity shock interacts with the industry-specific productivity process. A negative productivity shock reduces the dispersion of effective productivities across industries. All value functions are concave in productivity and hence benefit from the relative compression. This effect is not present in broad occupations, which explains these qualitative findings.

Second, I study a recession in which both broad and specialized industries are affected in Appendix I.2. Qualitatively, this targets a period like the Great Recession, in which industries with occupations of varying broadness were affected. In this exercise, I compare the response of job-finding rates and unemployment rates across broad and specialized occupations, and can qualitatively reproduce the empirical findings: in the same recession, broader occupations' job-finding rates and unemployment rates were less responsive than those of specialized occupations.

The main goal, however, is to compare the impact of recessions that generate differential degrees of mismatch depending on what industries are directly affected by the aggregate shock. We will see that the intuition from the cross-sectional results in the empirical section is misleading when estimating aggregate effects of mismatch: recessions in more specialized occupations do *not* lead to significantly larger or more persistent unemployment responses.

$$
\begin{aligned}
A(i,t) &= \begin{cases} A(t) + \tilde{A}(i,t) & \text{if } i \in \mathcal{I} \\ \tilde{A}(i,t) & \text{else} \end{cases} \qquad (32) \\
\tilde{A}(i,t) &= \phi A(i,t-1) + \epsilon_t \\
A(t) &= \begin{cases} \mu & \text{if } t \leq T \\ 0 & \text{else} \end{cases}
\end{aligned}
$$

Equation (32) describes the productivity process. A common aggregate component $A(t)$ will affect the productivity of a subset of industries that belong to the set $\mathcal{I}$. For those industries, their effective productivity sequence is the product of their idiosyncratic productivity $\tilde{A}(i,t)$ and $A(t)$. The remaining industries are not affected by the aggregate component. This aggregate component has the constant value μ, and switches back to zero after T quarters. In the following illustrative simulation, I set T to 12 quarters. The productivity shock has size $\mu = -0.05$, and the size of $\mathcal{I}$ is $|\mathcal{I}| = 0.2$: 20% of industries are affected by each recession.

This recession is unexpected by the agents. As soon as the initial shock hits, all agents have perfect foresight about the remaining evolution of the process. Zero-probability aggregate shocks of this type are often referred to as "MIT shocks".[6]

This experiment is comparing recessions that are affecting either broad or specialized occupations. These recessions are identical in all but the type of industries that are affected. In one recession, the 20% of industries that are affected all have $i < \gamma$: only industries employing broad occupations are directly affected, and I refer to that recession as a "broad recession". The other recession draws 20% of industries among those with $i > \gamma$, and I call that recession a "specialized recession".

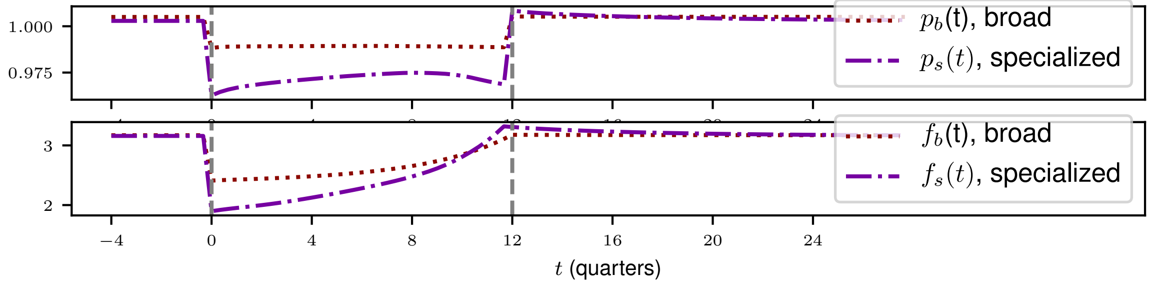
In what follows, we will study these two recessions in the following order. First, we analyze the *direct effect* and study to what extent workers in broader occupations can adjust to shifts in industry demand. Then, we focus on the *relocation externality*, and analyze the general equilibrium effects from workers' adjustments to shifts in sectoral demand. Another general equilibrium effect is the *workers' decisions to change occupations*, which we study subsequently. We then look at the overall effect of all of these channels on the *aggregate unemployment rate*. Finally, in section 6.5, we will study the *evolution of mismatch* in both recessions through the lens of the model introduced by Şahin et al. (2014).

6.1 The direct effect

The top panel in Figure 16 compares the evolution of the prices of the directly affected occupations across both recessions. The orange dots display the evolution of the price of the output of broad occupations. Not all specialized occupations are directly affected by the specialized recession: the purple dashed line displays the output prices of specialized occupations that are directly affected by the specialized recession. As established earlier, workers in broader occupations are insured against industry-specific recessions as they can sell their good to unaffected sectors. This insurance manifests

[6] Studying the economy's deterministic response to shocks that are ex-ante unexpected is useful to understand its response to recurring aggregate shocks, see Boppart, Krusell, and Mitman (2018)

Figure 16: Cross-sectional responses



I plot the evolution of the prices of the occupations that are directly affected by the recession. Orange dots are broad occupations in the broad recession. Purple lines are directly affected *specialized occupations in the specialized recession. The grey dashed lines denote the beginning and the end of the recessions. Top: output prices of firms in the respective occupations. Bottom: job-finding rates in the respective occupations.*

itself in lower sensitivity of the price of the occupation-level good to the respective aggregate shock. The bottom panel plots the evolution of job-finding rates for the affected occupations in the respective recessions, directly tracking the evolution of the prices.

This evolution establishes the implications of the direct effect in the model and qualitatively tracks what we measured in the empirical section.

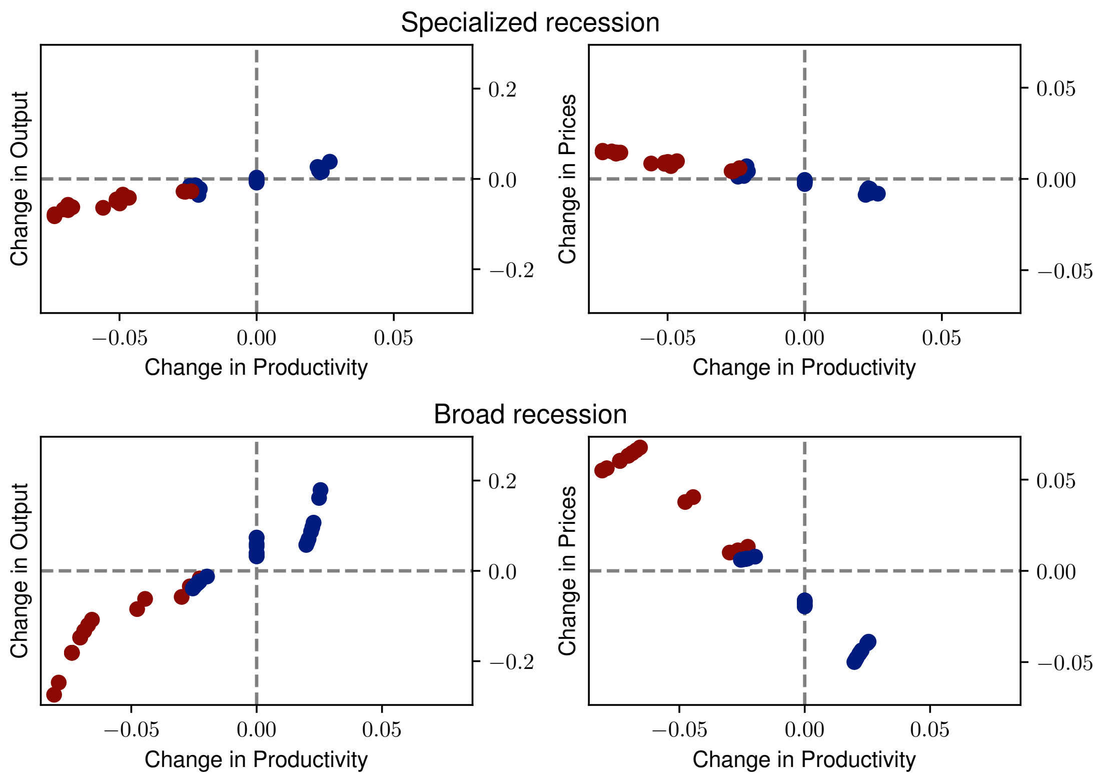
6.2 The relocation externality

Next, we identify the implications of the relocation externality in the model.

I simulate a number of occupations and industries to visualize the relocation externality. Figure 17 displays the impact of the recessions for the simulated industries. The top panels illustrate that all industries naturally face changes in productivity in each period. Industries that are affected by the aggregate shock are highlighted in red: these industries face, on average, a larger drop in productivity. In the model, industries that are less productive produce less. The top-right panel shows the general equilibrium effect: in the model, the price of output increases in the scarcity of the output. Therefore, the price of output of industries that are affected by the productivity shock increases. Yet, this is only a second-order effect: the revenue of firms in sectors that are affected by the productivity shock decreases. The two bottom panels depict the same evolution in prices and output for the broad industries in the broad recession.

Note that all changes for the non-shocked industries in the top panel are centered around zero, while the same is not true for the bottom panel. Firms in broad occupations sell to non-affected broad industries in the broad recession, thereby increasing the average output of those sectors and

Figure 17: Changes in output and prices for shocked and non-shocked industries in each recession



Each dot represents the immediate impact of a recession for a simulated industry. In the two top panels, I display the impact of the specialized recession on specialized industries. In the bottom panels, I display the impact of the broad recession on broad industries. Industries that are affected by the aggregate shock are colored in red. The top-left panel scatter-plots the immediate changes in productivity against immediate changes in output at the onset of the specialized recession for specialized industries. The top-right panel scatter-plots changes in prices against changes in productivity for the same industries. The two bottom panels display the same characteristics for the broad industries in the broad recession.

reducing the average price. These are the direct effects of the relocation externality. This also can be seen in the fact that the fluctuations in output and prices are much larger in the bottom panels than in the top panels. Naturally, the relocation of broad occupations towards unaffected broad industries means that the relative change in output between affected and non-affected broad industries is higher than that between affected and non-affected specialized industries since no such relocation can take place in the latter case.

Next, we study how the relocation externality plays out at the occupation-level. Figure 18 depicts the changes in revenue for each industry, and the changes in output prices of each occupation for both recessions. In both panels, we can see that 20% of industries are highlighted in red and are affected by the productivity shock. In the top panel, we can see that the direct effect of this productivity shock is isolated to the specialized occupations that are suppliers to the affected industries. In the bottom panel, we can see, however, that workers in all broad occupations are affected by the shock. The revenue losses from affected broad industries are offset partially by revenue gains from unaffected broad industries. Yet, the overall effect is non-zero and equivalent to the direct effect of the recession: through the relocation externality, the direct effect of the recession is spread equally across all broad workers. While affecting each individual worker much less, a broad recession affects a much larger share of workers.

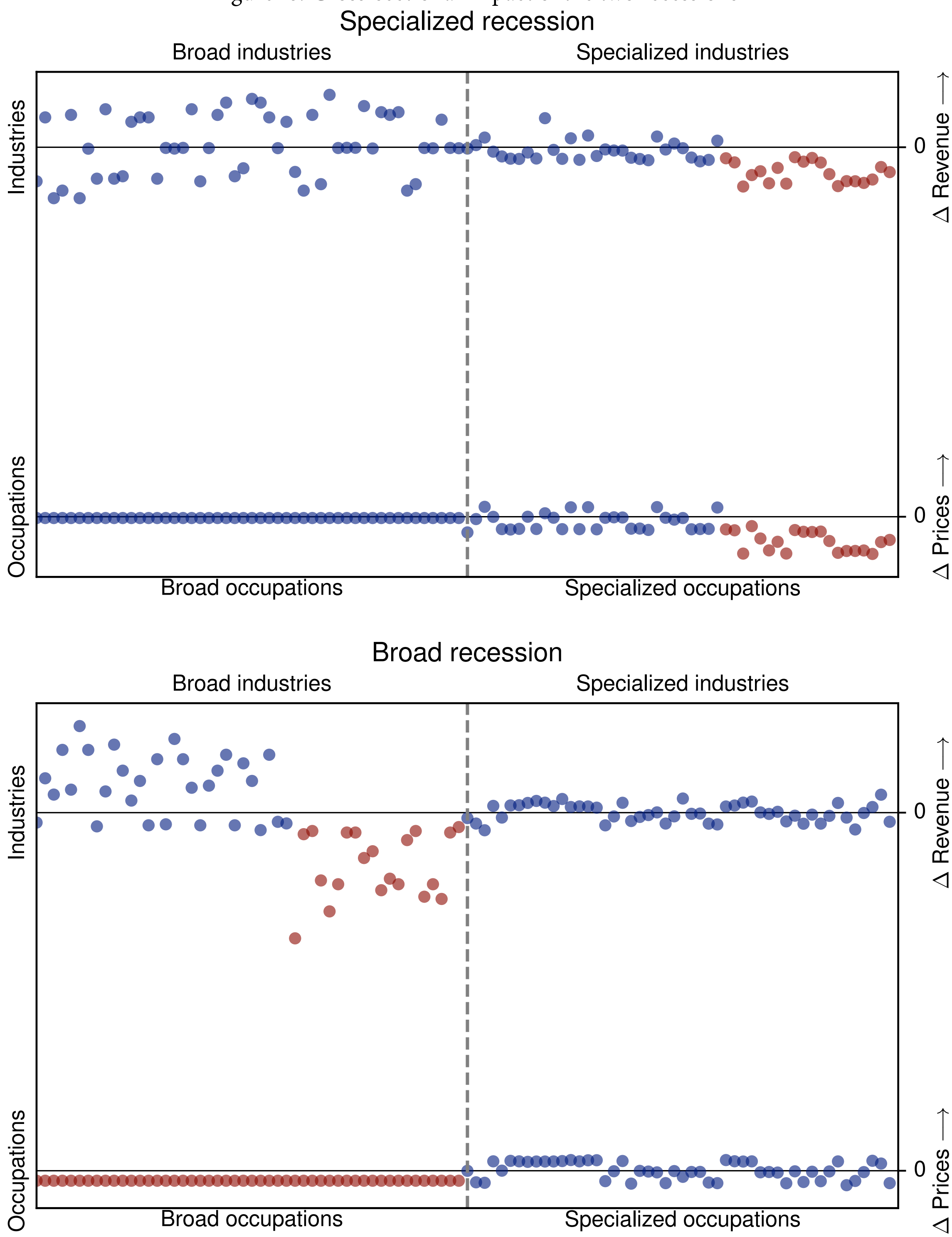
In the real world, this important general equilibrium effect is more intuitive: engineers in construction are insured against construction-sector shocks as they can move to other unaffected industries. However, by moving to other industries, they will affect workers that were previously already active in those industries. Broadness insures individuals against industry-specific shocks, but the occupation as a whole has to take a hit.

6.3 Labor force mobility

As we just argued, each individual broad worker is affected much less in the broad recession than specialized workers in the specialized recession. We now study how this translates into occupational mobility. Figure 19 displays the relative size of the labor force in broad and specialized occupations over both recessions. When facing their respective aggregate shock, a larger share of affected specialized workers leaves their occupation as compared to affected broad workers. This is because specialized workers are individually affected much stronger than their broad counterparts, and so a larger share of specialized workers is willing to incur the fixed cost of moving occupations.

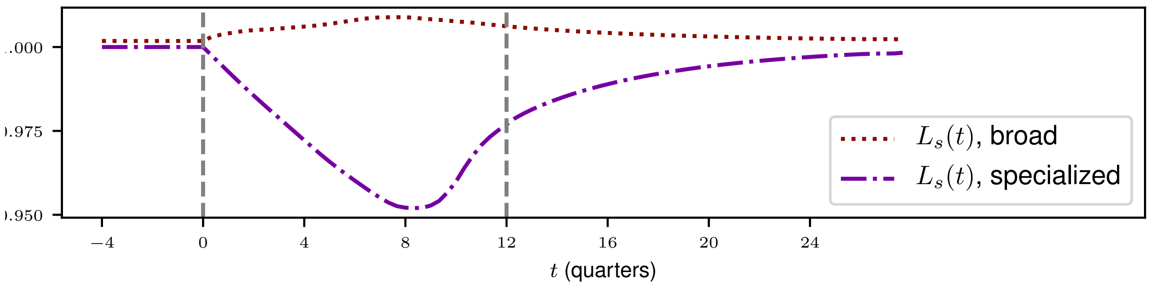
Workers are forward-looking, and so the return towards the steady state distribution of the labor force begins before the impact of the recession has ceded. These changes in the labor force are

Figure 18: Cross-sectional impact of the two recessions



Each dot represents a single industry or the associated occupation. The top panel displays the impact of the specialized recession, and the bottom panel displays the impact of the broad recession. For each occupation and industry, I plot the change in price and revenue, respectively, at the onset of each recession. Occupations and industries directly affected by the MIT shock are colored in red.

Figure 19: Occupational mobility



I plot the evolution of the labor force in the occupations that are directly affected by the recession. Orange dots denote broad occupations in the broad recession. Purple lines denote directly affected *specialized occupations in the specialized recession.*

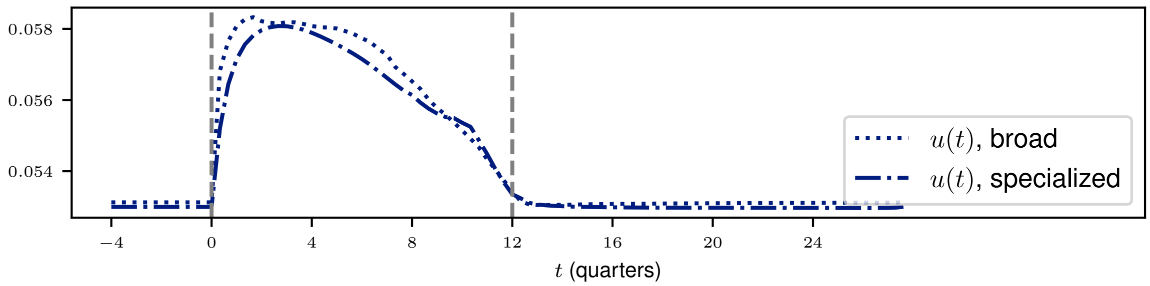
quite persistent: it takes approximately three years for the labor force to return to the steady state distributions. The length of this persistence is roughly as long as the duration of the productivity shock.

6.4 The aggregate unemployment rate

The response of the aggregate unemployment rate is a composite of all these effects: the strength of the direct effect, the size of the labor force that each shock affects, the relocation externality and the occupational mobility. Figure 20 compares the aggregate unemployment responses of the whole economy in both types of recessions. The evolution of the aggregate unemployment rate is roughly similar in both recessions. That is to say, the relocation externality mostly cancels out the direct effect in the average: a shock to specialized occupations affects few workers a lot, while a shock to broad occupations affects many workers a little bit. However, the exact model specifications and the built-in nonlinearities may change which recession qualitatively leads to a larger unemployment rate response.

In Appendix H, I show that this model-generated hypothesis is not rejected by the data: when repeating my empirical analysis from the Great Recession and extending the analysis to *all sectors*, the average correlation between broadness and job-finding rates is not significantly different from zero. There are many caveats to such an empirical approach and further study of this subject is required. Yet, it at least suggests that the direct effect and the relocation externality are, on average, of roughly equal size.

Figure 20: Aggregate unemployment response



6.5 Mismatch unemployment in both recessions

We have so far speculated that specialized recessions generate more mismatch. In this section, we will confirm this hypothesis and study how mismatch unemployment evolves in each recession.

Figure 21 visualizes two empirical measures of mismatch. In the top panel, I plot $u_b(t)$, the broadness of the unemployed. This is the model analog to Figure 8. As expected, the recession that predominantly affects broad occupations increases the share of broad workers in the pool of unemployed. The inverse occurs in the recession that predominantly affects specialized workers. Here, the pattern is not as smooth as with the broad recession: there is a downward spike in the broadness of the unemployed in quarter 10, two quarters before the end of the aggregate shock. This is because workers relocate back to the specialized occupations at the end of the recession. In the model, workers are indexed by their current, not their previous, occupation. Therefore, unlike in the data, the relocation of broad workers to the specialized occupations will first lead to a decrease in $u_b(t)$. Then, as these workers find jobs, $u_b(t)$ recovers.

The bottom panel of Figure 21 displays a measure of mismatch following Şahin et al. (2014). As described in section 2, it relates to the solution of a planner that can relocate workers across labor markets without cost. In this context, it implies that the fixed cost of occupational mobility is set to $k = 0$. The planner's problem is detailed in Appendix J. The mismatch index is then computed as

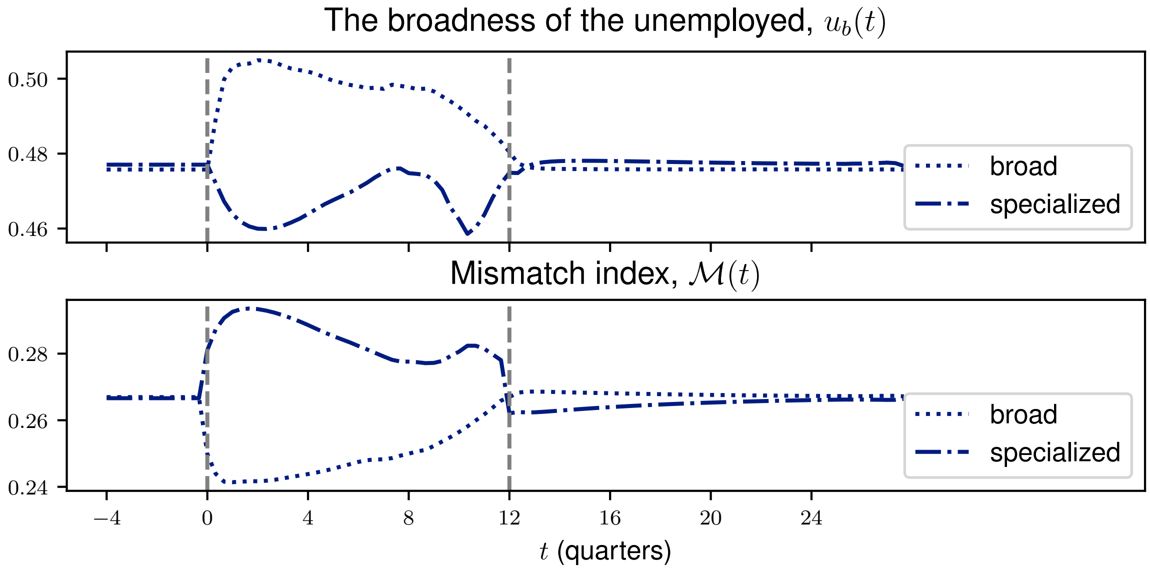
$$\mathcal{M}(t) = 1 - \frac{h(t)}{h^*(t)},$$

where $h(t)$ and $h^*(t)$ are hiring in the market's solution and the planner's solution, respectively.

To solve the planner's problem in the context of this model, I follow Şahin et al. (2014) in assuming that all shocks to an industry's productivity are permanent. This simplification is necessary but renders the analysis difficult: the planner assumes that the specialized or broad recession in each sector is permanent. This additionally reduces the planner's hiring at the onset of the recession, $h^*(0)$. The impact of this simplification is so strong that mismatch actually decreases at the onset of the specialized recession. Therefore, this approach is not suitable to analyze the development of mismatch over time. Instead, we can compare both recessions within each point in time. When doing so, the strong level effect stemming from our simplification that starts at $t = 0$ should roughly cancel out. We measure more mismatch in the specialized than in the broad recession. This is in line with our prior expectation: shocks to broad recessions generate less mismatch as broad workers can adjust to sectoral productivity shocks more easily.

Moreover, this suggests that we can use $u_b(t)$ as a mismatch index as well. The disadvantage of doing so is that $u_b(t)$ only correlates with mismatch across industries, and not for example occupations or regions. Yet, it comes with a clear advantage: the computation of $\mathcal{M}(t)$ is data intensive both in the data and in the model. For example, data on vacancies is usually less abundant, and so the computation of occupation-industry specific vacancies can become challenging. The broadness of the unemployed $u_b(t)$ therefore is a useful complementary measure of mismatch as it does not require any data on vacancies.

Figure 21: Two measures of mismatch



7 Conclusion

Understanding the determinants of unemployment is key to providing solid policy advice. This paper connects the phenomenon of mismatch unemployment to two key outcomes: heterogeneous unemployment risk in the cross section, and unemployment fluctuations in the aggregate.

We have shown in a general equilibrium model that workers in broader occupations are better insured against industry-specific shocks. This insurance partially protects workers that are in negatively affected industries. Yet, when they use the broadness of their occupation to move to better-faring industries, they affect workers in the same occupation in their destination sector. This relocation externality turns out to be very strong in the model: for roughly every job saved due to the broadness of the occupation, another job is lost due to the relocation externality: on average, workers in broad and specialized occupations face similar unemployment rates in response to sectoral shocks.

Thus, recessions that generate more mismatch and more mismatch unemployment do not lead to larger unemployment responses *per se*. We have used the model to argue that the broadness of the unemployed can be used as an empirical measure of mismatch across the industry dimension. According to this metric, mismatch increased during the Great Recession. Yet, due to the strong relocation externality, the model suggests that the large unemployment response of that recession cannot be explained by the increased mismatch at that time.

Empirical evidence from that recession is in line with the mechanism and the strength of the relocation externality: workers in broader occupations in the severely-affected construction sector benefited from the broadness of their occupation. Yet, broad occupations do not *on average* fare better in that recession.

This paper is one of the first to microfound the mechanisms underlying mismatch unemployment, and the results complement the findings in Şahin et al. (2014). They find that mismatch unemployment did not significantly increase during the Great Recession, and cannot explain the large increase in unemployment in that recession. I show that recessions that cause more mismatch do not lead to larger unemployment responses. Mismatch can only account for a larger share in the unemployment response if it coincides with other factors that lead to a larger unemployment response.

My novel mismatch measure, the broadness of the unemployed, indicated that the degree of mismatch was higher during the Great Recession than in previous recessions. The model is geared towards the analysis of the concept of occupational broadness, and was not designed to quantitatively match the Great Recession. Therefore, it cannot be used to confirm whether the increase in mismatch during that recession was, as Şahin et al. (2014) find, quantitatively insignificant. The solution methods used to solve the model render such a quantitative analysis difficult.

This paper emphasizes the importance of occupational and sectoral mobility to understand mismatch unemployment. I hope that it motivates further empirical work on measuring the relocation externality directly, and theoretical work on further incorporating the underlying mechanism into quantitative modeling.

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A Occupation-level unemployment during Great Recession

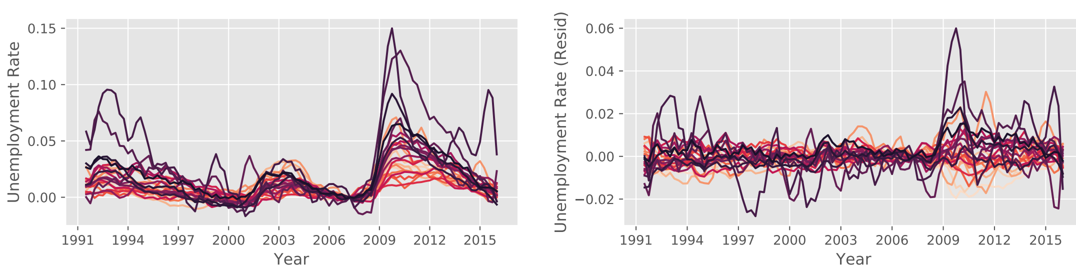
In the introduction, Figure 1 displays the standard deviation of occupation-level unemployment rates.

I compute that by changing the data as little as possible: I take raw individual-level data from the CPS and assign each individual into one of the 26 major occupation groups. I compute average unemployment rates for each occupation and quarter. When I partial out other effects, I control for three education groups, three race groups, and all industry-by-state-by-year groups before computing occupation-quarter specific unemployment rates.

Then, to control for seasonal variation and other noise in the data, I apply a Savitzky-Golay filter with a third-order polynomial and a window length of 7 quarters, where the small window length is chosen in order to pick up only short-term variation and not changes at business-cycle frequency. As other filters, the Savitzky-Golay filter does poorly at the boundaries, therefore I drop the first quarter of data.

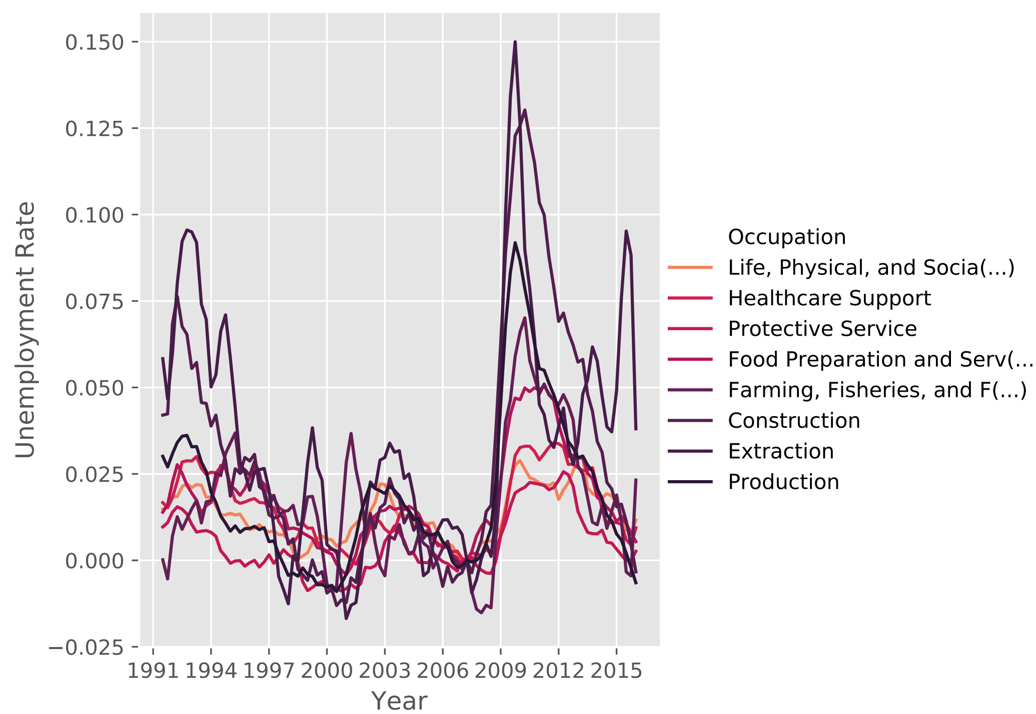
The resulting unemployment rates are displayed in Figure A.1. To give a feeling of which occupations are affected most and least, I display the unemployment rates for the least and most affected occupations in Figure A.2.

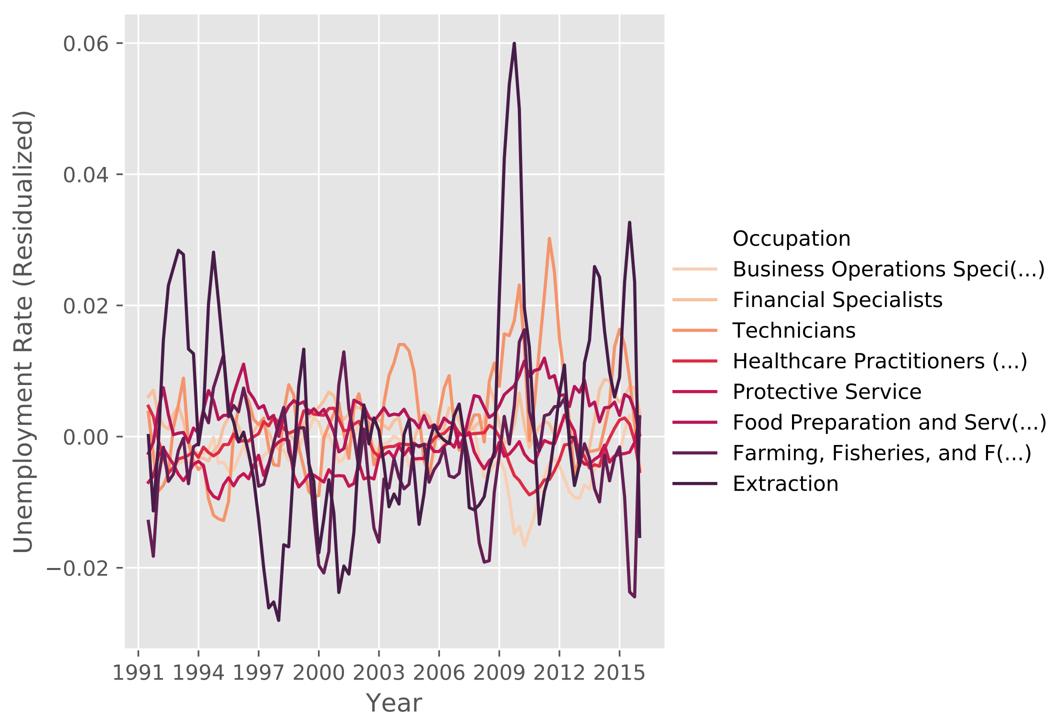
Figure A.1: Occupation-level unemployment rates during Great Recession



Standard deviations of occupation-level unemployment rates. Left: occupation-specific unemployment rates. Right: occupation-specific unemployment rates, where I partial out individual demographics, and all combinations of industry, state and year fixed effects. All unemployment rates fit through a Savitzky-Golay filter and normalized in 2007. Data: CPS.

Figure A.2: Occupation-level unemployment rates for subset of occupations





B Classification

In the introduction, I summarize findings from a machine learning exercise where individual-level unemployment status is predicted using occupation, industry, year, month, county, metropolitan area, age, sex, education, and race. Random forest is used to predict individual-level outcomes for each individual non parametrically. To attribute outcomes to predictors, I follow Lundberg and Lee (2018) by implementing Shapley Additive Explanations.

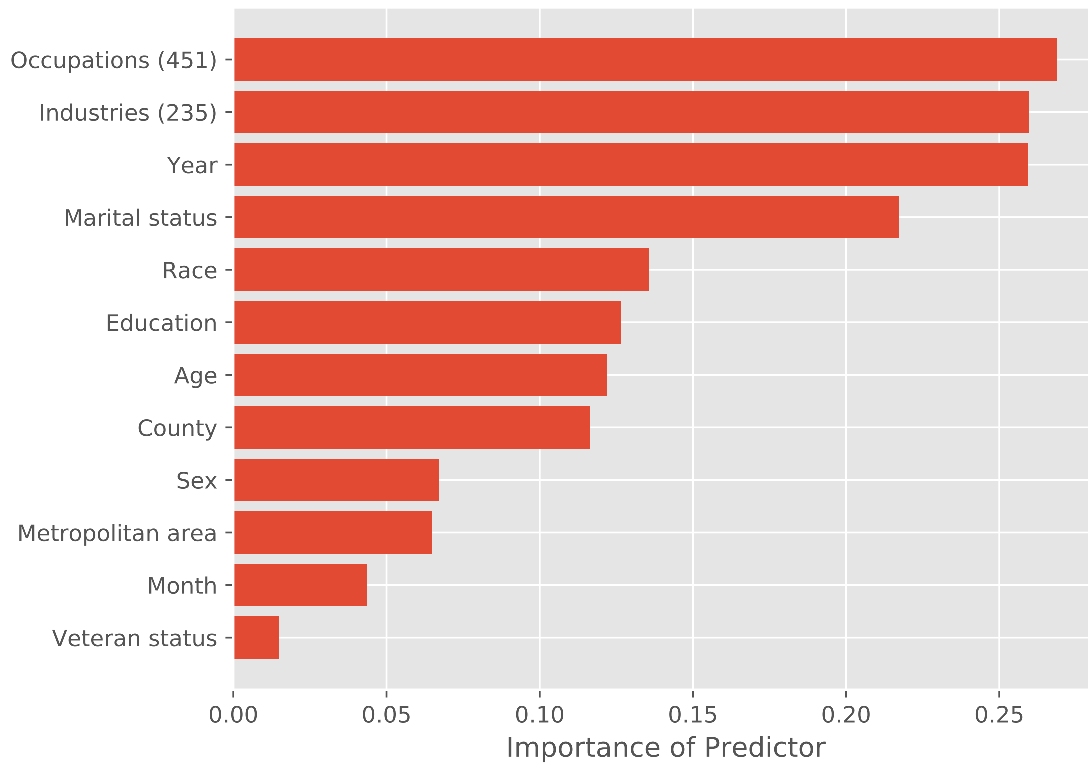
Shapley values constitute a solution concept in game theory: they uniquely distribute a surplus to a coalition of players. Shapley values are the unique distribution that satisfies the following four important characteristics for a given player set: they distribute the total surplus ("efficiency"), attribute the same outcomes for equivalently important players ("symmetry"), preserve linearity, and attribute 0 to a null player.

Lundberg and Lee (2018) apply Shapley values to describing the relevance of "features" (independent variables) in predicting an outcome. The parallel to the game theoretical setup is clear: the surplus generated is the predicted value, and the players are the features.

One can think about the Shapley value as each player's average marginal contribution to the surplus in a random ordering. This is exactly the way one can compute Shapley Additive Explanations, *irrespective of the prediction method*.

Figure B.3 plots average absolute Shapley Additive Explanations across all observations for each independent variable.

Figure B.3: Occupations are an important predictor of individual-level unemployment status



The predictors of unemployment status ranked by importance. Data: CPS. Years: 2000-2010.

C Broadness and mismatch

The strong assumptions put forward here will be relaxed in the quantitative model.

Assume that both electricians and engineers (indexed by e and m) are employable by the construction sector but that engineers also are employable in finance. The construction sector has with equal probability either a low or high number of hires $h_c \in \{x, 2x\}$ from each occupation, while finance hires $h_f = x$ in each state of the world. Consider a two-period setup where in period 1 agents have to choose between the two occupations, and in period 2 random hiring is realized. Given labor force ℓ_o and hires h_o, an occupation's job-finding probability f in a frictionless environment is h_o/ℓ_o, when we ensure $h_o < \ell_o\,, o \in \{e, m\}$. Assume that all unemployed workers receive benefits b, and workers get a fixed wage $w > b$.

The general form of preferences for each occupation o is

$$U_o = \mathbf{E}[f(\ell_o, h_o)w + (1 - f(\ell_o, h_o))b]$$

which for both occupations boils down to

$$\begin{aligned} U_e &= b + \frac{1}{2}\left[\left(\frac{x}{\ell_e}\right) + \left(\frac{2x}{\ell_e}\right)\right](w - b) \\ U_m &= b + \frac{1}{2}\left[\left(\frac{2x}{\ell_m}\right) + \left(\frac{3x}{\ell_m}\right)\right](w - b) \end{aligned}$$

Indifference in period one requires the expected utility to be the same, which here simplifies to equal average job-finding rates.

$$\begin{aligned} U_e = U_m \Rightarrow \mathbf{E}[f(\ell_e, h_c)] &= \mathbf{E}[f(\ell_m, h_c + h_f)] \\ \Rightarrow \ell_e &= \frac{3}{5}\ell_m \end{aligned}$$

Notice that there will be more engineers than electricians to make up for the fact that there are more jobs for engineers than for electricians. Next, we compute the variance of job-finding rates for both occupations, denoting by $\overline{f}$ the common average job-finding rate.

$$\text{Var}\left[f(\ell_e, h_c)\right] = \mathbf{E}\left[\frac{1}{2}\left(\frac{x}{\frac{3}{5}\ell_m}\right) + \frac{1}{2}\left(\frac{2x}{\frac{3}{5}\ell_m}\right)\right] - \overline{f}^2$$
$$\text{Var}\left[f(\ell_m, h_c + h_f)\right] = \mathbf{E}\left[\frac{1}{2}\left(\frac{2x}{\ell_m}\right) + \frac{1}{2}\left(\frac{3x}{\ell_m}\right)\right] - \overline{f}^2$$

Using these expressions, we can show that the volatility of job-finding rates is strictly higher for electricians.

$$\text{Var}\left[f(\ell_e, h_c)\right] - \text{Var}\left[f(\ell_m, h_c + h_f)\right] = \frac{1}{2}(25 - 13)\left(\frac{x}{\ell_m}\right)^2 > 0$$

In this example, an equal average job-finding rate ensures that the occupation with more volatile hires also has a more volatile job-finding rate. Here, the fraction of unemployed workers is equal to those that did not find a job, $u = 1 - f$. Therefore, broader occupations both have less volatile job-finding rates and less volatile unemployment rates. This is because they are at lower risk of being mismatched: broad occupations are employable in more sectors and therefore are insured against volatile labor demand in any of their industries. Workers in the specialized occupation might find themselves in a situation where only few of total hires occur in their occupation: they are mismatched and therefore at higher unemployment risk.

Caveats Here, separation rates were fixed. The result extends to volatile separation rates that are not positively correlated with hires. These are typically negatively correlated, and the resulting relationship between broadness and mismatch is even stronger.

In the example, one of the industries had constant hires. One can extend the previous framework to show that in the insurance value of broadness is weaker when hires are positively correlated. The insurance value is completely lost when hires are perfectly positively correlated. Empirically, that appears not to be true.

Several general equilibrium mechanisms potentially dampen these effects. First, individuals might adjust their occupation after the shock has been realized. The degree to which this happens depends on the costs of changing occupations, among other the opportunity cost of not using their occupation-specific human capital. As I show in Appendix E, a significant number of unemployed workers does not change their occupation – thereby dampening the expected effect from occupation switching. Second, individuals might not be willing to change their industry – e.g. if they have accumulated human capital in their previous industry. While Kambourov et al. (2009a) show that, on average, there is less human capital associated with industries than occupations, this need not be true for all occupation-industry pairs. Third, as workers in more specialized occupations are more dependent on firms in fewer industries, those firms might be able to bargain lower wages. This could lead to higher profits, and thereby more jobs in industries that hire from specialized occupations. Finally, the prices of industries that employ more specialized occupations might interact with the aforementioned profit response.

D Mobility-based measure of broadness

The measure of broadness suggested in the main text looks at the distribution of occupations across industries, without taking into account whether workers in those occupations are actually mobile across those industries. Here, I suggest an alternative measure that considers mobility. Since it is based on movers only, the estimated measure suffers from data limitations. I do not use it in the main analysis, but show that it correlates well with the baseline measure.

Fix a time period. To study movers across industries, I look at workers that switch employer. The number of such movers in the CPS is small, so the measure designed cannot be too demanding. I denote by $z_{o,i,i'}$ the number of workers in occupation o that switch from industry i to industry i'.

$$
\begin{aligned}
\tilde{s}_{o,i,j} &= \frac{z_{o,i,j}}{\sum_j z_{o,i,j}} \\
\tilde{m}_{o,i} &= 1 - \sum_j \tilde{s}_{o,i,j}^2 \\
\tilde{z}_{o,i} &= \frac{\sum_j z_{o,i,j}}{\sum_i \sum_j z_{o,i,j}} \\
m_o^{\text{mobility}} &= \sum_i \tilde{z}_{o,i} \tilde{m}_{o,i}
\end{aligned}
$$

Essentially, I compute a measure of broadness $\tilde{m}_{o,i}$ for each occupation-industry pair depending on the concentration of the movers from that occupation and industry to other industries. To generate my mobility-based measure of broadness, I compute a weighted average using $\tilde{z}_{o,i}$, the share of observations from the originating industry. It will be useful to also compute a placebo measure.

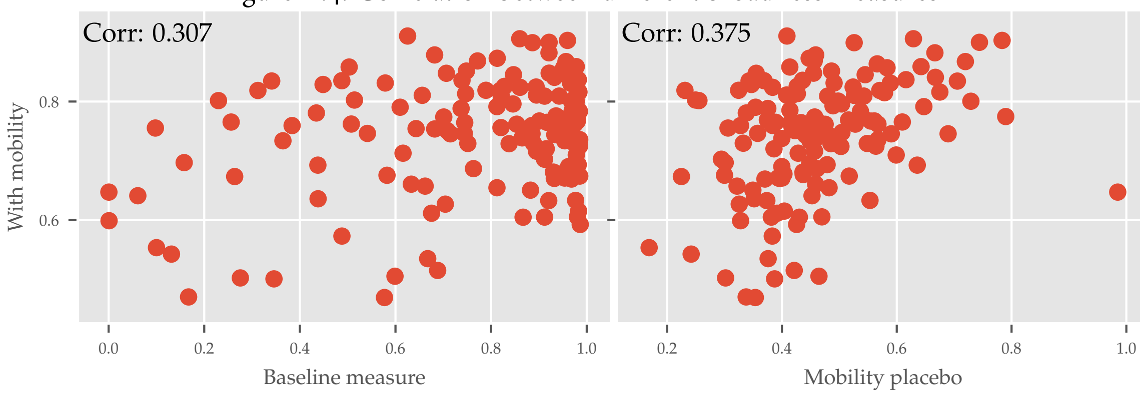
$$
\begin{aligned}
M_{o,i} &= \sum_{j \neq i} z_{o,j,i} \\
\hat{M}_{o,i} &= \sum_{j} z_{o,j,i} \\
\hat{s}_{o,i} &= \frac{\hat{M}_{o,i}}{\sum_j \hat{M}_{o,j}} \\
m_o^{\text{placebo}} &= 1 - \sum_i \hat{s}_{o,i}^2
\end{aligned}
$$

m_o^{placebo} computes the same measure of broadness as the baseline measure from the main text. However, it is computed over the set of movers only. It will be a useful indicator to judge the noisiness of measures based on mover data.

The mobility-based measure is much more data demanding: when aggregating over the 2002-2007 years and all US states, we can only compute it for 145 out of 450 occupations. For comparison: we can The actual empirical estimation relies on state-level heterogeneity, and there are not enough occupations for which we can compute the mover-based measure for multiple states. Therefore, I fall back on showing how well this mover-based measure correlates with the baseline measure and the new placebo measure. Figure D.4 shows the relevant scatter plots.

It correlates well with the placebo measure. If there was a substantial set of industries that are isolated from other industries, the mobility-based measure should not correlate well with the placebo measure. The high correlation of 0.37 suggests that we can ignore this issue. The lesser (but still positive) correlation of the mobility-based measure with the baseline measure then can to some extend be explained by the much higher noisiness of the estimate that has the higher data requirements. I conclude that the baseline measure does not suffer heavily from isolated industries that are add to the measure of broadness without actually providing insurance. Any such remaining bias will bias downwards the empirical estimates.

Figure D.4: Correlation between different broadness measures



Left: scatter-plot of m_o from main text against m_o^{mobility}. Right: scatter plot of m_o^{placebo} against m_o^{mobility}. Correlation between the placebo and the baseline measure: 0.61

E Measuring occupation and industry switching

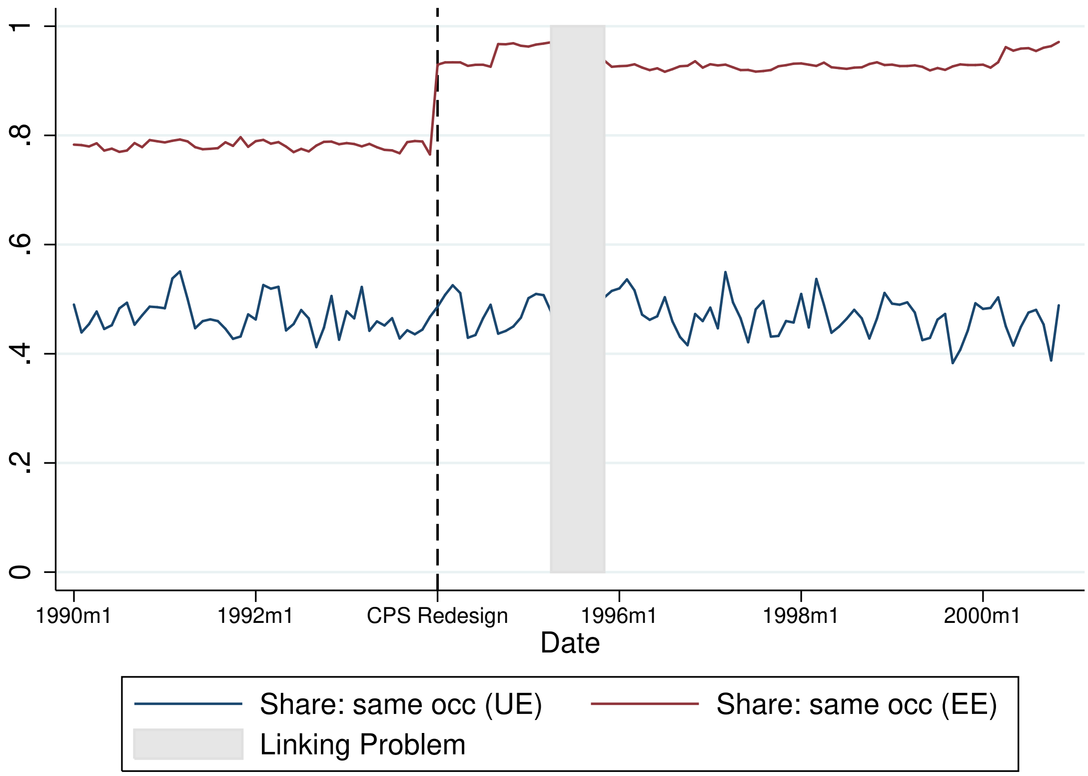
In the CPS, respondents are asked about their typically performed tasks. After the interview, these are coded into occupation groups. The reported tasks may change from interview to interview even if the individual is still in the same occupation. This may be the case when two occupations have a large set of coinciding tasks, and the interviewee reports a different subset of tasks in each interview[7].

As misreporting on either the first or the second interview is sufficient to miscode an occupational transition when none was happening, measurements of occupational transitions will be biased upwards in the data. While there is no translation from tasks present for industries, a similar upwards bias is a problem there as well.

In order to address this problem, the CPS introduced *dependent coding* in 1994. If an interviewee had reported an occupation in $t-1$, and is employed in t, they will not be asked to report their tasks. Instead, their previous occupation will be read to them, and they have to confirm whether their occupation is still the same or not. I compute for each individual transitions across either occupations or industries. For example, denote by $x_{i,t}$ the occupation of individual i in month t. $S_{x,i,t}$ measures whether an individual stayed in the same occupation between t and $t-1$.

[7] Another question is whether these similar tasks should be coded into different occupations, but out of the scope of this summary.

Figure E.5: Occupation stayers by employment status



Occupations are grouped into 26 larger time-consistent groups.

$$S_{x,i,t} = \begin{cases} 1 & \text{if } x_{i,t} = x_{i,t-1} \\ 0 & \text{else} \end{cases}$$

Denote by u the unemployment status of an individual. I compute the average probability of staying in the same occupation for employed-employed (EE) transitions and unemployed-employed transitions (UE) as

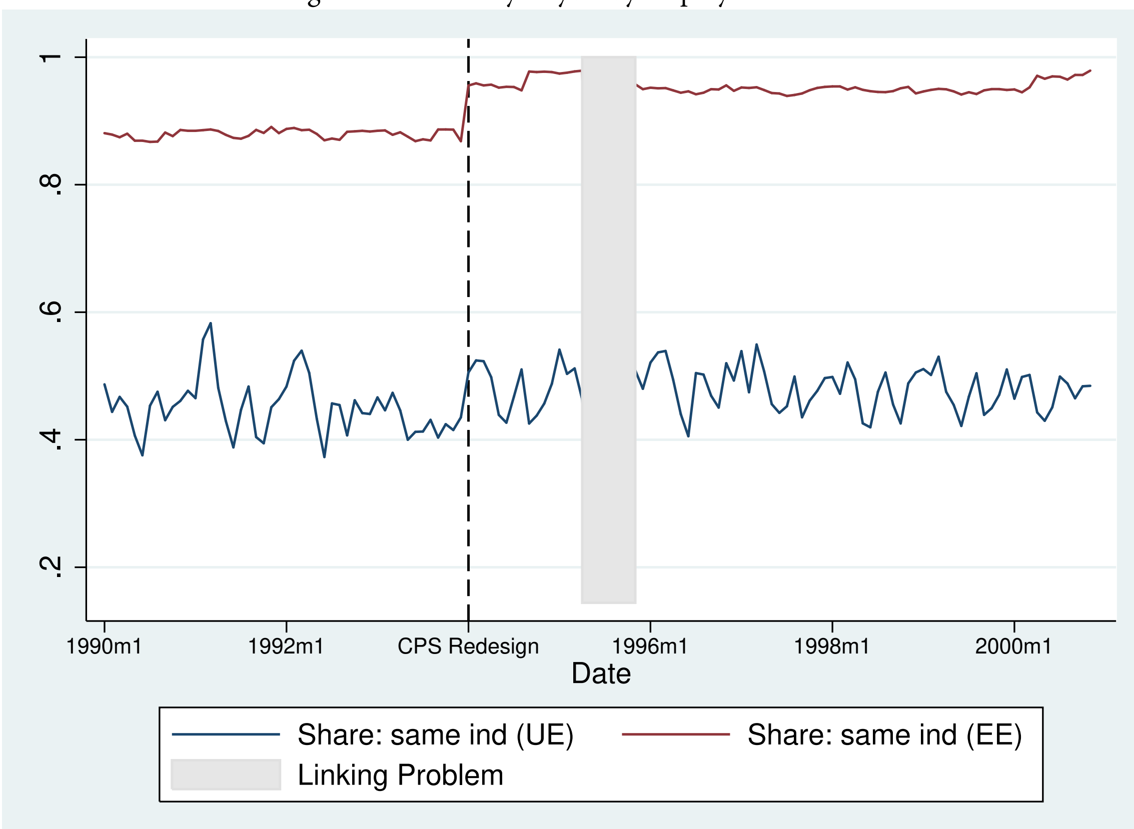
$$\begin{aligned} \overline{S}_{x,EE,t} &= \mathbf{E}\left[S_{x,i,t} | u_{i,t-1} = 0 \wedge u_{i,t} = 0\right] \\ \overline{S}_{x,UE,t} &= \mathbf{E}\left[S_{x,i,t} | u_{i,t-1} = 1 \wedge u_{i,t} = 0\right] \end{aligned}$$

Figure E.5 displays $\overline{S}_{x,u,t}$ and $S_{x,e,t}$ for the United States computed using the CPS, where t is measured in monthly frequency. Note that, on average, $\overline{S}_{x,e,t} > \overline{S}_{x,u,t}$. Additionally, the CPS redesign in 1994 introduced a sharp break in $\overline{S}_{x,e,t}$: dependent coding increased the share of identified occupation stayers. The same is not true for $\overline{S}_{x,u,t}$: as dependent coding was only introduced for the employed, estimated transitions for the unemployed are still very noisy.

In analogue, I can define x to instead hold industry status. Figure E.6 displays industry stayers for the same sample. The similar patterns are clear here: staying is more likely in EE than in UE transitions. Again, the CPS redesign increases the measured stayers for the employed, but not the unemployed.

This suggests that switchers are overestimated for the unemployed, both across industries and occupations. In the model, we want to calibrate k against the responsiveness of occupational transitions to occupation-specific productivity shocks among the unemployed. This leads to two problems: first, it is difficult to isolate productivity shocks and the likelihood of switching occupations in the face of selection issues. Second, even the *unconditional* likelihood of switching occupations is difficult to measure, given the suggested bias in occupation coding for the unemployed.

Figure E.6: Industry stayers by employment status



Industries are grouped into 29 larger time-consistent groups.

F Did broader occupations have a lower unemployment response during the Great Recession?

In section 4, we cleanly isolated the impact of broadness on job-finding rates for workers in the construction sector. In order to tie these estimates back to the motivating differential unemployment responses in the cross-section, I now aggregate the individual unemployment status to compute occupation-by-state unemployment rates. Then, I relate changes in unemployment rates to broadness. To reduce noise, I will aggregate occupations into 26 major groups, and use several years of data prior to the recession to compute $m_{o,z}$. My setup is schematized by Figure F.7. For each occupation and state, I regress the difference in unemployment rates between 2007 and 2010 against the occupation-state level of broadness. I choose 2007 and 2010 as the two years since they characterize the peak and trough of unemployment during that period. The regression setup is summarized by (F.1).

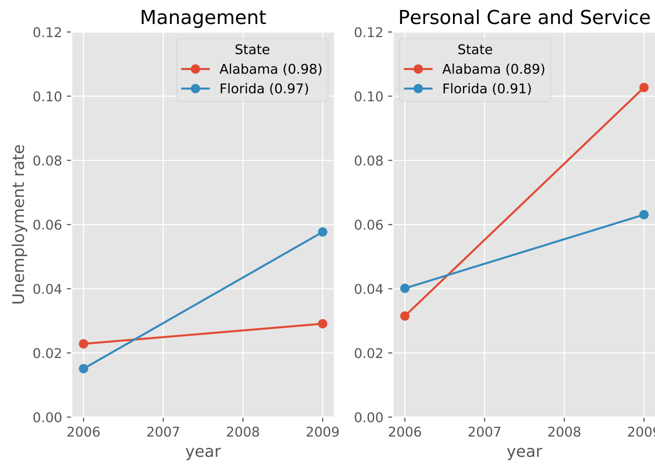
$$u_{o,z,2010} - u_{o,z,2007} = \alpha m_{o,z} + \Lambda_z + \Theta_o + \epsilon_{o,z} \tag{F.1}$$

Figure L.13 draws the regression line against all observations. Table 4 summarizes the empirical results after standardizing $m_{o,z}$. The baseline result is displayed in column (3): on average, one standard deviation increase in broadness is associated with a reduced *increase* in unemployment. To put this into perspective, the mean increase in occupation-state specific unemployment rates between 2007 and 2010 weighted by occupation-by-state cell sizes was 0.034 (unweighted: 0.04), implying that a one standard deviation change in broadness explains a third of the increase in unemployment during that period.

The coefficient of interest increases between columns (1) and (3). As occupations vary on other dimensions besides broadness and it is unclear how that correlates with broadness, I will not read too much into the results in column (1). The coefficient becomes stronger when controlling for state-fixed effects (3). This suggests that high-broadness states also tended to be affected more by the Great Recession, which biased the estimates in columns (2).

Finally, I control for two types of heterogeneities across occupation-by-state bins. One type is individual-level characteristics which control for demographics that are potentially associated with a lower reemployment rate. Another type is the industry of last employment, interacted with state. Industry-by-state fixed effects control for a differential exposure of industries to the recession, which is allowed to vary by state. I control for both heterogeneities by appyling the Frisch–Waugh–Lovell theorem: in each year, I partial out individual-level broadness and unemployment status for a quadratic

Figure F.7: The regression setup



Each panel illustrates the simple setup within occupation and across states. Occupation-state specific broadness in brackets. By putting together both panels I can difference out the state-specific effects.

term in age, three racial groups, three education groups, two sex groups, and 223 × 51 industry-by-state groups. Then, I compute cell means for each state, occupation and year, and compute the inter-year difference as before. The findings are summarized in column (4) in Table 4. The point estimates rise considerably, suggesting that one standard-deviation decrease in broadness contributed more than half of the rise in unemployment during that period.

Threat to identification All remaining variation after the residualization at the occupation-by-state dimension is captured by my measure. Any such variation that is unrelated to broadness will bias my estimates. For example, individuals' selection into riskier occupations might depend on their risk aversion. If the correlation between risk aversion and ability is not zero, individuals' ability will vary by occupation-by-state and influence unemployment changes that bias the the estimate for α.

Table 4: Broader occupations' unemployment rates are less responsive to recession

Dependent variable: difference in unemployment rates between 2007 and 2010

	(1)	(2)	(3)	(4)
Broadness	-0.00960	-0.0153	-0.0168**	-0.0273**
	(0.00912)	(0.00992)	(0.00769)	(0.0103)
Occ FE	No	Yes	Yes	Yes
State FE	No	No	Yes	Yes
Individual Demographics	No	No	No	Yes
Industry × State	No	No	No	Yes
N	1228	1228	1228	1228

Observations weighted by the number of observations used to compute cell averages. Broadness standardized and computed using data before recession. Standard errors in parentheses and two-way clustered at state and occupation level. *** *significant at* 0.01, ** *at* 0.05, * *at* 0.10.

G Broadness of the unemployed

In Figure 8, I plot the time series of average broadness of the unemployed. This is done as follows: I compute $m_{o,t}$ for each occupation, using a whole year to compute the shares $s_{i,o,t}$ and the corresponding broadness. I then essentially compute the average broadness of the unemployed $\overline{m}_t$ as

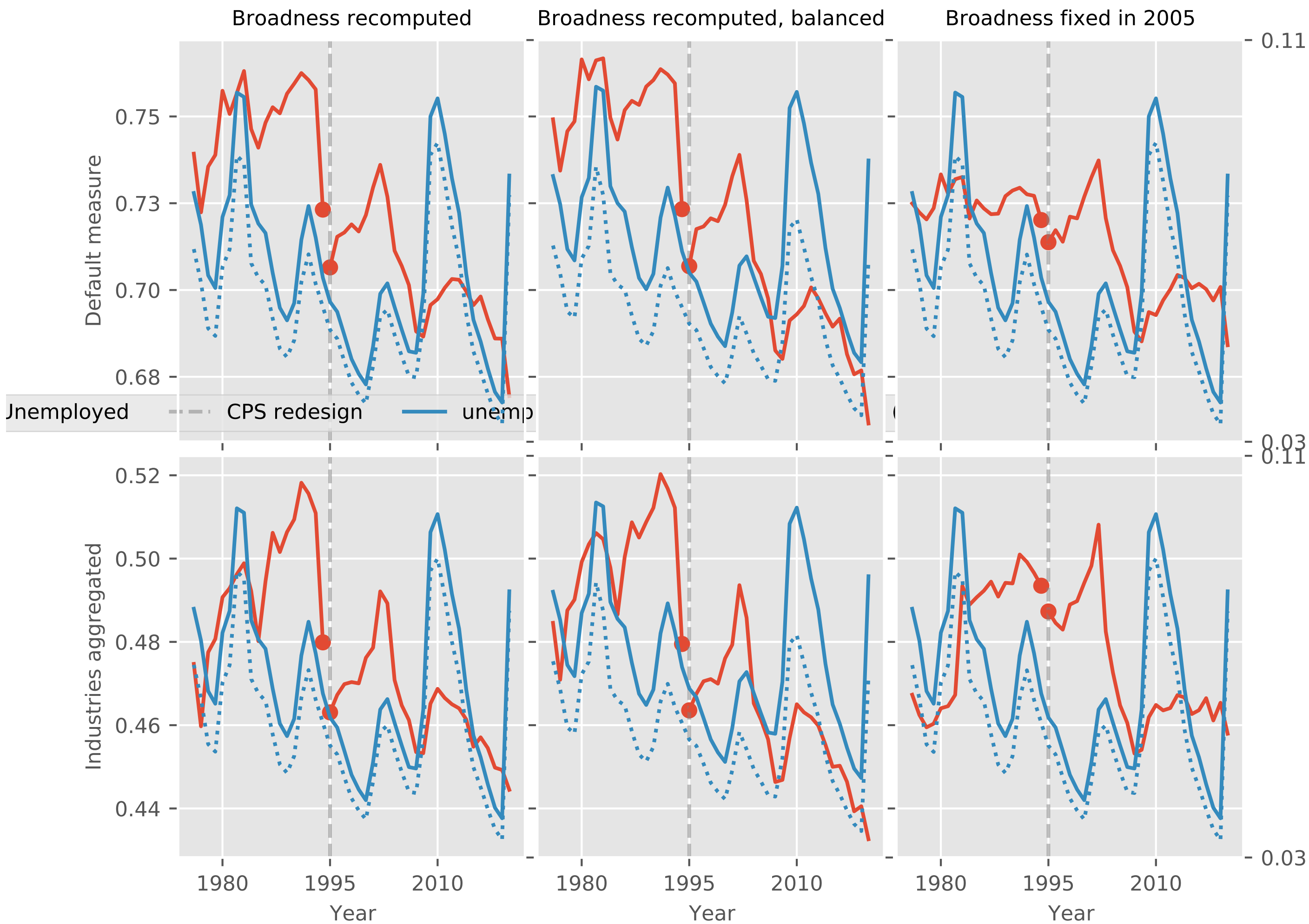
$$h_{o,t} = \frac{u_{o,t}}{\sum_o u_{o,t}}$$
$$\overline{m}_t = \sum_o h_{o,t} m_{o,t}$$

Note that $\overline{m}_t$ is not affected by the *level* of the unemployment rate, only the composition of the underlying occupations $h_{o,t}$, or the broadness of those occupations $m_{o,t}$. As I am computing these results for a long time horizon, I prefer recomputing $m_{o,t}$ every year over collapsing the data. The disadvantage of doing so is that the measure might be more noisy in each year, but it is more robust to changes in broadness over long time horizons, or changes in occupational coding.

Figure G.8 displays several robustness checks to that baseline computation. The top-left panel is identical to the figure in the main text. The top-right panel computes $m_{o,t}$ in 2005 and holds it constant. The second row computes both versions for aggregated industry groups.

The key take-away is that the long-term patterns are more sensible when $m_{o,t}$ is allowed to vary. Naturally, aggregating industries reduces average $m_{o,t}$, as the set of industries is reduced and hence the dispersion will be less. However, qualitatively, the cyclical and trend patterns are the same. In all four panels, the broadness of the unemployed was much lower during the Great Recession than in previous recessions.

Figure G.8: Broadness of the unemployed



First row: computed using the standard measure of broadness. Second row: industries are aggregated into 31 major groups. Left column: $m_{o,t}$ is recomputed every year. Center column: the same $m_{o,t}$, but only for occupations observed through the whole period. Right column: $m_{o,t}$ is computed in 2005 and held constant for the whole series.

H Empirically measuring the relocation externality

In the main text, I have argued that convincing evidence on the relocation externality would show that workers in more desirable sectors and more broad occupations suffer more from the relocation externality. This type of setup is infeasible in the environment that I study in the empirical part of the paper.

In the general equilibrium model, I find that the relocation externality is on average roughly as strong as the direct effect: the evolution of the aggregate unemployment rate is roughly equivalent in recessions that affect broad or specialized occupations. In this section, I show that I cannot reject the model-generated hypothesis that both effects are of equal magnitude.

To do this, I extend the previous analysis of studying the job-finding rates of unemployed workers during the Great Recession. Instead of focusing on unemployed workers from the construction sector only, I include unemployed workers from all sectors in my analysis. The setup is described by (H.2).

$$f_{j,i,o,z,t} = \alpha m_{o,z} + B_1 X_j + \Lambda_{z,t} + \Gamma_{i,t} + \Theta_o + \epsilon_{j,i,o,z,t} \tag{H.2}$$

Since I now study workers in all sectors of the economy, I add a series of industry-by-month fixed-effects relative to the previous specification in (3). Table 5 summarizes the findings. In short, the average effect of broadness on job-finding rates across all sectors is statistically indifferent from zero, and statistically much smaller than the effects that we found when studying the construction sector.

This is consistent with the previously discussed theory: being in a broader occupation helps workers in the severely affected industries more than the average worker. Moreover, it suggests that – on average – the relocation externality is as strong as the direct effect: the broadness of an occupation does not increase its job-finding rates *on average over all sectors*.

Table 5: Job-finding rates are *not* higher for individuals in broader occupations

Dependent variable: monthly probability of being hired				
	(1)	(2)	(3)	(4)
Broadness	0.00297	0.00827	0.00382	0.00182
	(0.0135)	(0.0148)	(0.0137)	(0.0158)
Occ FE	Yes	Yes	Yes	Yes
State x Month FE	No	No	Yes	Yes
Indiv Demographics	No	Yes	Yes	Yes
Industry x Month FE	No	No	Yes	Yes
Observations	50688	50688	49913	36825

Data from CPS. Sample: unemployed workers in 2008 *and* 2009 *from all sectors. Broadness standardized and computed using data before recession. Standard errors in parentheses. SE two-way clustered at the state and occupation level.* *** *significant at* 0.01, ** *at* 0.05, * *at* 0.10.

I Cross-sectional Experiments

In this section we will explain the differential responses by broadness in a general equilibrium framework. The partial equilibrium responses are straight-forward: a broader occupation is linked to more industries. Broader occupations mitigate shocks that are not perfectly correlated across these industries. In general equilibrium, there are two additional forces at play that will be the focus of this section.

We will focus on two shocks: first we will hit the economy with an indescriminate shock that affects all sectors equally. Then, we will shock a subset of the economy only.

I.1 Indescriminate shock

Here, we play through an experiment in which the productivity in each sector is reduced for a finite number of periods. I will now denote the industry-specific shock $A(i,t)$ as a sum of an industry-specific AR(1) process $\tilde{A}(i,t)$, and an aggregate component $A(t)$. For clarity of exposition, $A(t)$ will not dissolve geometrically. Instead, it will switch between any non-zero value during the periods of the experiment, $t \in \mathcal{T}$, and zero otherwise. The shock structure is summarized in (I.3).

$$
\begin{aligned}
A(i,t) &= A(t) + \tilde{A}(i,t) \\
\tilde{A}(i,t) &= \phi A(i,t-1) + \epsilon_t \\
A(t) &= \begin{cases} \mu & \text{if } t \in \mathcal{T} \\ 0 & \text{else} \end{cases}
\end{aligned}
\tag{I.3}
$$

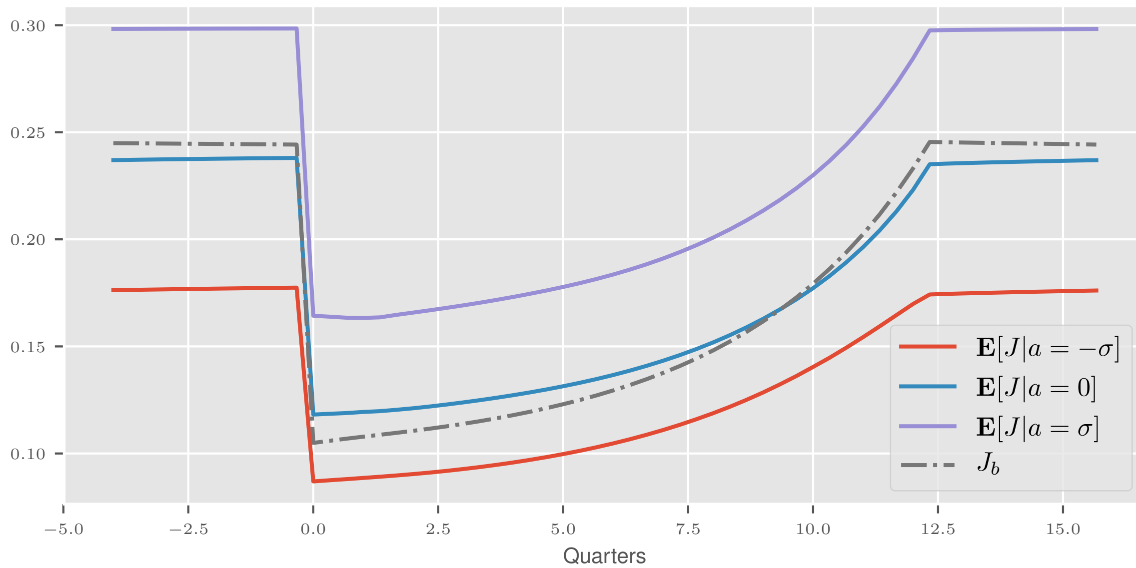
As it turns out, broad occupations fare *worse* than specialists throughout the episode. Figure I.9 displays the impact of the aggregate shock on firm values at the occupation level. As the aggregate productivity enters multiplicatively with idiosyncratic productivity, firms with a high idiosyncratic productivity are affected more by the aggregate shock. This leads to a compression of firm values during the aggregate shock. Firms in broad occupations face no idiosyncratic shocks as they are diversified across industries. Prior to the aggregate shock, broad firms had the same value as the median productivity specialist firms. However, their values drop more during the recession. This is because of the interaction of idiosyncratic shocks with aggregate shocks: specialist firms' upside from a positive shock dominates the downside from a negative shock. The riskiness of their output price has positive value, which is why broad firms (which lack this value) lose more on value during the recession than their specialist counterparts.

Figure I.10 separates the effects into the three main layers of the model. As all industries are affected, relative productivity changes are equal in both broad and specialist industries. The shock hits at time 0. Notice that unemployment is frictional, and production is timed to happen before adjustments through hirings and separations can happen: the initial output response in $Y(0)$ purely comes from the change in productivity. Labor market responses then result in a further reduction of output in subsequent periods.

As the second panel shows, output is roughly proportionally reduced in broad and specialist industries. The price-index of output from broad industries slightly increases during the experiment, while that of specialist industries slightly decreases. The increase of the broad price-index is required to keep up production of broad services, as broad firms are affected more by the aggregate shock.

The disadvantage of broad occupations is displayed among all margins of the labor market: their quarterly job-finding rate drops more than that of specialists, leading to a higher unemployment response. An exception is the first period, where the unemployment response of broad occupations is masked by a relocation to specialist occupations, as can be seen in the last panel. Finally, these differential responses in productivity also manifest in wages, where workers in broad occupations

Figure I.9: Interaction between aggregate and idiosyncratic shocks



Aggregate shock leads to a compression of firm values across idiosyncratic productivity shocks. The upside from an increase in productivity is now larger than the downside from a decrease in productivity: riskiness is valuable. Therefore, broad occupations are affected more by the aggregate shock.

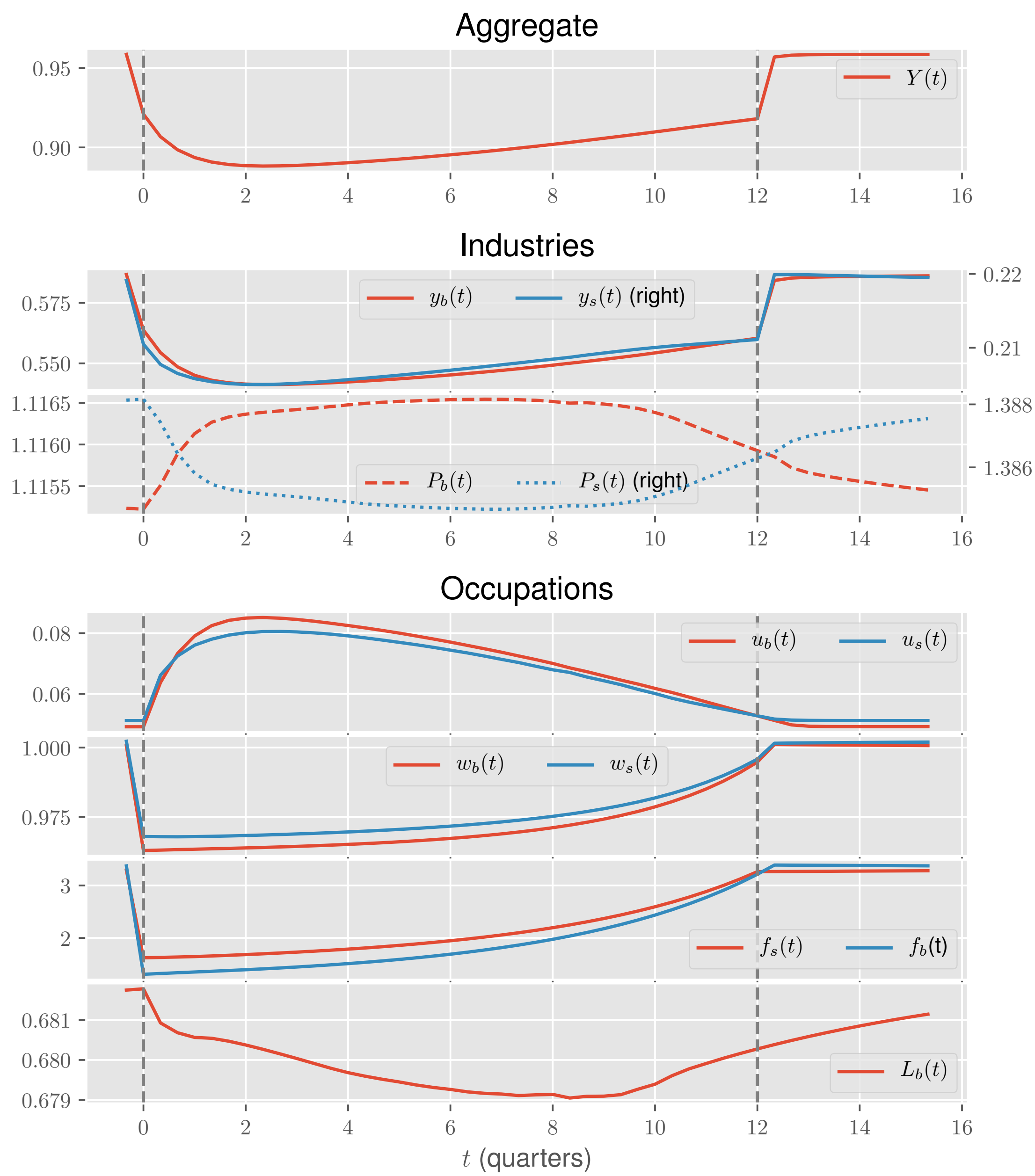
receive larger cuts than those in specialist occupations.

I.2 Lilien-type recession

Now we focus on an aggregate shock that does not affect all industries in the same manner. This type of productivity-shock could represent an oil-price shock that affects industries differentially by their dependency. Lilien (1982) conceptualizes the notion that shocks to a subset of sectors will still have aggregate effects, in particular due to the slow adjustment of labor across sectors. To distinguish from "true" aggregate shock that affect all industries indiscriminately, we will refer to these shocks as "Lilien-type" shocks.

I will denote the set of industries that are affected by the aggregate shock by $\mathcal{I}$. I adjust the previous shock structure as in (I.4).

Figure I.10: Response of the economy to an indiscriminate shock

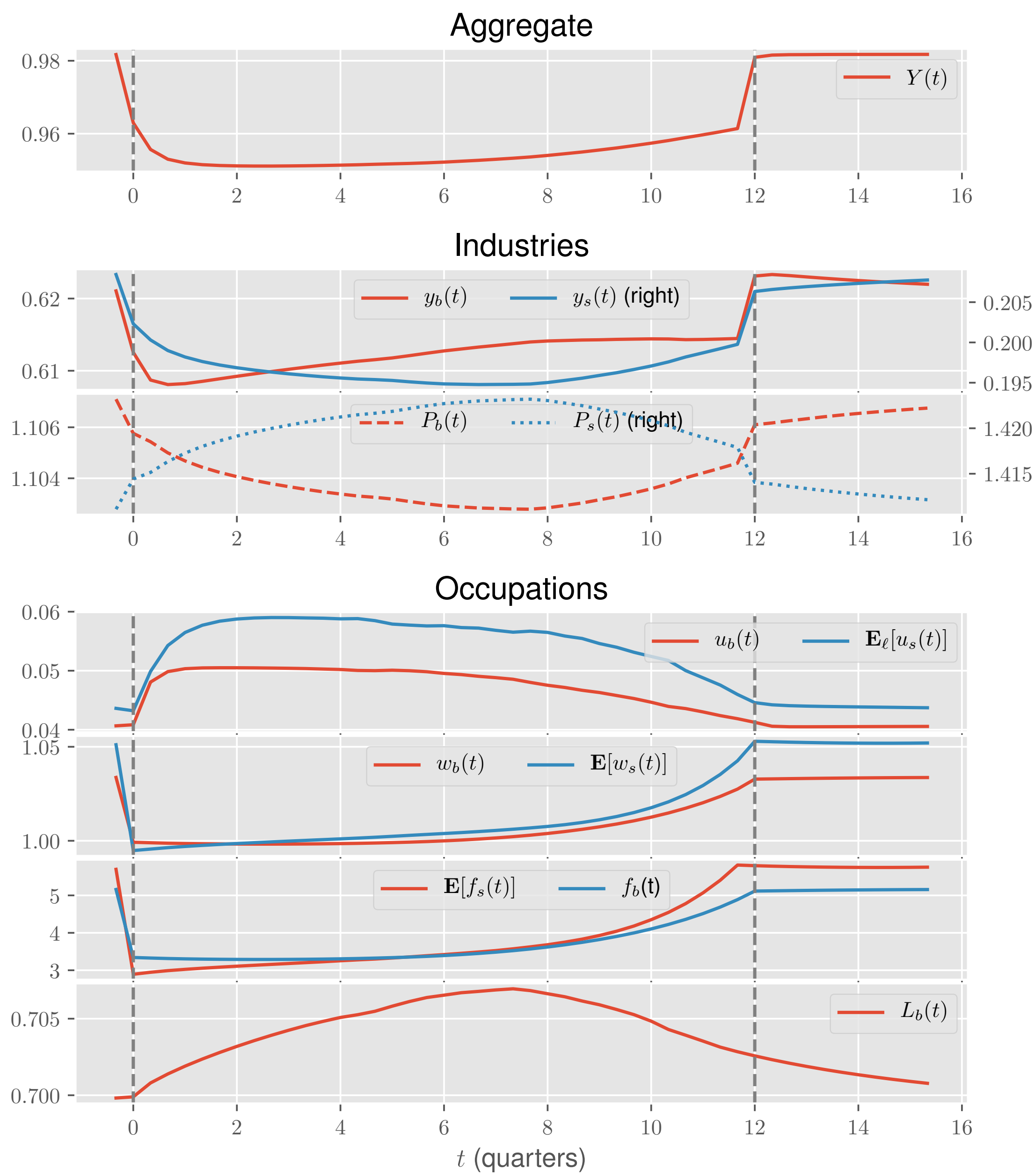


$$
\begin{aligned}
A(i,t) &= \begin{cases} A(t) + \tilde{A}(i,t) & \text{if } i \in \mathcal{I} \\ \tilde{A}(i,t) & \text{else} \end{cases} \\
\tilde{A}(i,t) &= \phi A(i,t-1) + \epsilon_t \\
A(t) &= \begin{cases} \mu & \text{if } t \in \mathcal{T} \\ 0 & \text{else} \end{cases}
\end{aligned}
\tag{I.4}
$$

$\mathcal{I}$ consists of an equal measure of (randomly drawn) broad and specialist industries. Figure I.11 summarizes the effects for level of aggregation.

As before, one can distinguish the instantaneous drop in productivity from the changes from employment by comparing the output response in period 0 against those in subsequent periods. In a recession where not all industries are hit, specialist occupations fare substantially worse than broad occupations: the change in unemployment is doubled, and the relative wage cuts are higher. All these effects coexist with a larger response in labor force adjustments: 7 quarters into the experiments, an additional .5% of the labor force have now relocated in broad occupations. This additional labor force has been successfully integrated in the broad occupations in such a way that unemployment rates and wages are still performing better in that part of the labor market.

Figure I.11: Response of the economy to a Lilien-type recession



J A measure of mismatch unemployment

We solve the problem of a planner that can move unemployed workers across labor markets free of cost. Following Şahin et al. (2014), we write this problem in recursive formulation as follows.

$$
\begin{aligned}
V(u,e,z,v) = \max_{u_i \geq 0} & \; Y + b\Big(1 - \sum_i (e_i + h_i)\Big) + \beta E[V(u', e'; z', v')] \\
\text{s.t.} \; \sum_i u_i \leq u & \qquad \text{(J.5)} \\
h_i = Am(u_i, v_i) & \qquad \text{(J.6)} \\
e_i' = \exp(-\delta)(e_i + h_i) & \qquad \text{(J.7)} \\
u' = \ell' - \sum_i e_i & \qquad \text{(J.8)} \\
Y = \sum_i \left(y_{i,t}^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}} & \qquad \text{(J.9)} \\
y_i = \begin{cases} A_i \left(\frac{A_i}{A_b}\right)^{\theta-1} x & \text{if } i < \gamma \\ y_i = A_i z_i & \text{if } i \geq \gamma \end{cases} & \qquad \text{(J.10)} \\
x = \left[A_x \int_{[0,\gamma]} z_o^{\frac{\theta_b - 1}{\theta_b}} \, do \right]^{\frac{\theta_b}{\theta_b - 1}} & \qquad \text{(J.11)}
\end{aligned}
$$

The planner maximizes the discounted sum of total output, which consists of output produced at work plus home production of the unemployed. (J.5) states that the unemployment in each labor market has to sum up to the total amount of unemployed workers in the economy. Equations (J.6-J.8) specify the law of motion for unemployment in line with the model described in this paper. Equations (J.9-J.11) define aggregate output consistently with the model developed in this paper.

To solve this system, I hereinafter assume that the industry-specific productivity shocks follow a Martingale process. This allows to solve for the planner's solution in closed-form. This simplification introduces the bias that the planner overestimates the impact of changes in productivity, both for changes in productivity in industries that are connected to broad and to specialized occupations. Under this assumption, Şahin et al. (2014, See Online Appendix A.2) show that the Planner's solution for the optimal unemployment rate equalizes weighted unemployment rates across each labor market.

In this environment, that entails to equalizing the surplus-weighted matching rate in each occupation:

$$\chi_i \mathbf{A} v_i^{1-\alpha} u_i^{1-\alpha}$$

, where χ_i denotes the present-discounted output net of home production in industry i, which varies across broad and specialized occupations:

$$\chi_i = \frac{\left(\sum_i y_i^{-\frac{1}{\theta}} Y^{\frac{1}{\theta}} A_i \left(\frac{A_i}{A_b} \right)^{\theta - 1} A_x x^{\frac{1}{\theta_b}} z_i^{-\frac{1}{\theta_b}} - b \right)}{1 - \beta(1 - \delta)} \quad , i < \gamma$$

$$\chi_i = \frac{\left(y_i^{-\frac{1}{\theta}} Y^{\frac{1}{\theta}} A_i - b \right)}{1 - \beta(1 - \delta)} \quad , i \geq \gamma.$$

The implied share of unemployed workers in each occupation is then given by

$$\frac{u_j}{u} = \frac{1}{\left(\chi_j \mathbf{A} v_i^{1-\alpha} \right)^{\frac{1}{\alpha - 1}} \sum_i \frac{1}{\left(\chi_j \mathbf{A} v_i^{1-\alpha} \right)^{\frac{1}{\alpha - 1}}}}.$$

Hereinafter we will use stars to indicate the planner's solution. The total amount of hiring in the competitive equilibrium and in the planner's solution are given by

$$h_t = \sum_o \mathbf{A} u_o^{\alpha} v_o^{1-\alpha}$$
$$h_t^* = \sum_o \mathbf{A} u_o^{*\alpha} v_o^{1-\alpha}.$$

Finally, we use these to compute the Mismatch index specified in Şahin et al. (2014) as

$$\mathcal{M}_t = 1 - \frac{h_t}{h_t^*}.$$

K Computational appendix

The computational scheme for the stationary environment is outlined as follows:

- Guess one value for Y
  - Guess one value for L_b

* Solve $U_b(u, \ell)$ given $L_b \Rightarrow \overline{U}$
    * Solve specialized occupations given $\overline{U}$
    * Compute stationary distribution L_s given $\overline{U}$
    * Is $L_s + L_b = 1$? Update L_b
  - $y_b + y_s = Y$? Update Y

In the remainder of this section, I will elaborate these steps.

K.1 Solving for U_b

We can write the broad occupations' problem as a scalar root-finding problem. Given L_b, we need to find equilibrium employment, and the implied prices. That is, we have the following three key relationships

$$\begin{aligned} J_b &= J_b(p_b) \\ p_b &= p_b(L_b(1-u_b)) \\ u_b &= u_b(J_b) \end{aligned}$$

where the first comes from the value functions, the second one from the CES pricing, and the last one from the free-entry condition and the matching function. We solve these for a given L_b as a function of p_b:

- Given p_b, compute J_b and u_b
- Given u_b, compute $\tilde{p}_b = p_b(L_b(1-u_b))$
- Given $p_b - \tilde{p}_b$, update p_b.

The broad occupations support a unique equilibrium for a given L_b. This can be seen from the last step, where we compute $p_b - \tilde{p}_b$. Notice that J_b increases in p_b. Hence, u_b decreases in p_b, and $\tilde{p}_b$ decreases in p_b. p_b increases in p_b and $\tilde{p}_b$ decreases in p_b, which implies that $p_b - \tilde{p}_b$ is strictly increasing in p_b, leaving us with a unique solution – if one exists. As the CES prices follow standard Inada conditions, existence is guaranteed, and hence we have a unique partial equilibrium in the broad occupations.

K.2 Solving for $\overline{U}$ given U_b

Notice that the law of motion implies that $U_b \in [\underline{U}, \overline{U}]$. In general, the equilibrium is indeterminate here. However, when we have a strictly positive labor force exit rate, the unique equilibrium is when $U_b = \overline{U}$.

Assume this is not the case: a steady state supports $U_b < \overline{U}$. In that case, no unemployed worker would choose to enter broad occupations. However, due to labor force exit, workers would exit those occupations. This implies that the labor force in the broad occupations is not constant, which is inconsistent with the notion of stationary as defined in the main text.

K.3 Solving for mobility given $\overline{U}$

We have $\underline{U} = \overline{U} - k$. What we have to solve for are $\underline{\ell}(a, u)$ and $\overline{\ell}(a, u)$, which are the rules for the labor force mobility. The general strategy is as follows:

1. Guess on values for $\underline{\ell}(a, u)$ and $\overline{\ell}(a, u)$
2. Compute $U_s(a, u, \ell)$ given mobility
3. Compute $U_s(a, u, \overline{\ell}(a, u))$ and $U_s(a, u, \underline{\ell}(a, u))$
4. If $U_s(a, u, \overline{\ell}(a, u)) - \underline{U} = 0$ and $U_s(a, u, \underline{\ell}(a, u)) - \overline{U} = 0$ stop, otherwise update $\underline{\ell}$, $\overline{\ell}$

The main computational problem in this environment is exactly how to do the 4th step here: there is no contraction mapping at play here, or no other obvious updating process. Also, every time we have to compute value functions in the 2nd step is very costly. Thus, a good method for updating $(\underline{\ell}, \overline{\ell})$ is crucial. The following methodology is stable, and I will argue why that is the case.

We have placed (a, u, ℓ) on a grid with n_A, n_U, n_L many grid points. The problem consists in finding $\underline{\ell}(a, u)$ and $\overline{\ell}(a, u)$, which is a root problem in $2 \times n_A \times n_U$ many equations and variables. A standard approach would be to use a quasi-newton method. There is no closed-form solution for the gradient, but one could precondition the guess for the gradient with economic intuition. In practice, this approach underperforms significantly relative to what I will suggest.

Denote

$$\overline{\epsilon}(a, u; \overline{\ell}, \underline{\ell}) = U_s(a, u, \underline{\ell}(a, u); \overline{\ell}, underline\ell) - \overline{U}$$

where I have emphasized that the value of the value function at (a, u, ℓ) is a function of both entire decision planes at all grid points. We know that

$$\frac{\partial \bar{\epsilon}(a,u;\bar{\ell},\underline{\ell})}{\partial \bar{\ell}(a,u)} < 0$$

since a higher "maximum amount of labor" will decrease utility U_s at all grid points. Due to discounting, this effect will be higher directly at (a,u) than at distinctly different (a',u'):

$$\frac{\partial \bar{\epsilon}(a,u;\bar{\ell},\underline{\ell})}{\partial \bar{\ell}(a,u)} < \frac{\partial \bar{\epsilon}(a',u';\bar{\ell},\underline{\ell})}{\partial \bar{\ell}(a,u)} < 0 \qquad (a,u) \neq (a',u')$$

Therefore, I use the following updating mechanism, for a given tolerance τ, and a fixed percentile $\in (0,100)$. I will stack $\mathbf{L} = [\bar{\ell},\underline{\ell}]$, which has dimensionality $(n_A, n_U, 2)$.

- Given $\mathbf{L}$, compute $\epsilon = [\underline{\epsilon},\bar{\epsilon}]$
- Pick out of the $2 \times n_A \times n_U$ residuals ϵ those, which have an absolute value above the percentile of absolute values, and above τ
- For those selected, if $\epsilon(a,u,i) > 0$ (with $i \in \{1,2\}$), decrease $L(a,u,i)$ otherwise decrease $L(a,u,i)$

The exact implementation requires a choice of update size. Here, I have done the following: I start with a relatively large update size. Once the absolute distance $|\epsilon|$ is not improving over several periods, I decrease the update size.

Unfortunately, it is not clear how strong to decrease the update size, and what to choose for . In my calibrations, I start with = 70 that implies updating many grid points simultaneously. As we get closer to the solution, I increase up to eventually 99. I have placed the solution $\mathbf{L}$ on a grid, that I start relatively wide. Increasing $\mathbf{L}(a,u,i)$ implies simply moving to the next higher grid point. To decrease the size of the update step, I multiply the number of grid points with a factor of 1.3.

K.4 Solving for specialized value functions

I solve value functions on a grid with (n_A, n_U, n_L) grid points for the three state variables (a,u,ℓ). I follow Acemoglu and Hawkins (2014) in translating the problem consisting of $\{J_s, U_s, E_e, w_s\}$ into a problem consisting of $\{J_s, U_s\}$.

The simplified problem then consists of value functions J, U, and a transition matrix T:

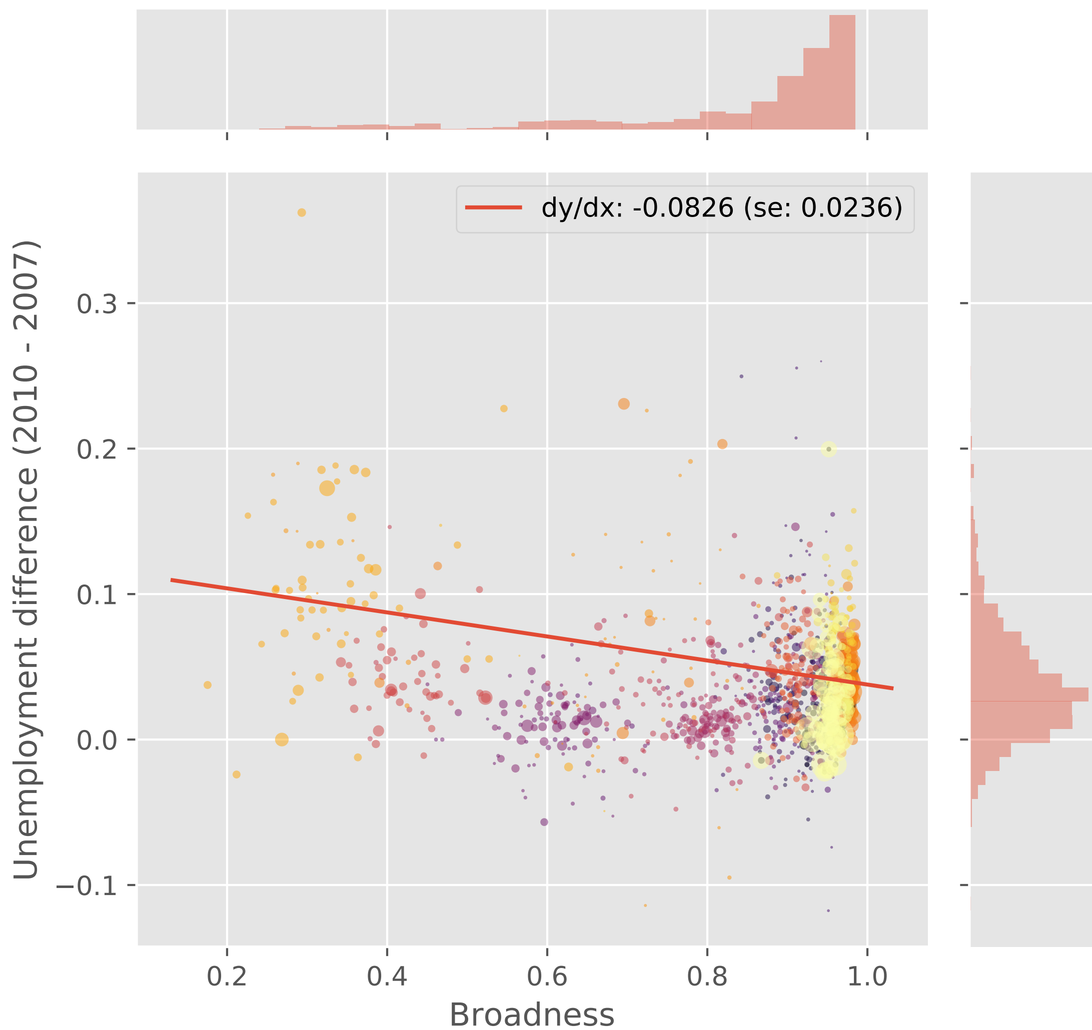
$$
\begin{aligned}
J &= J(f(m(J), T) \\
T &= T(f(m(J), \underline{\ell}, \overline{\ell}) \\
U &= U(J, f(m(J), T, \underline{U})
\end{aligned}
$$

The structure above makes it clear that I can solve (J, T) separately from U.

Building the transition matrix T is the most expensive part of the problem. This is because it is not vectorizable, as the transition rules implied by $(\underline{\ell}, \overline{\ell})$ do not permit a closed-form solution of transition matrix. As $J(a, u, \ell)$ only depends on $T(a, u, \ell)$ and not on any $T(\{a, u, \ell\}')$, this system can be relatively effectively be solved with quasi-Newtonian methods.

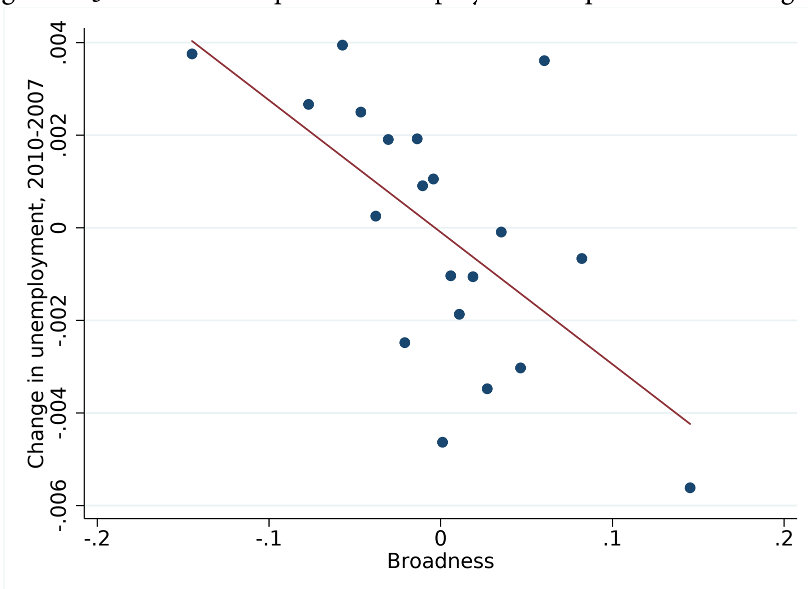
L Figures

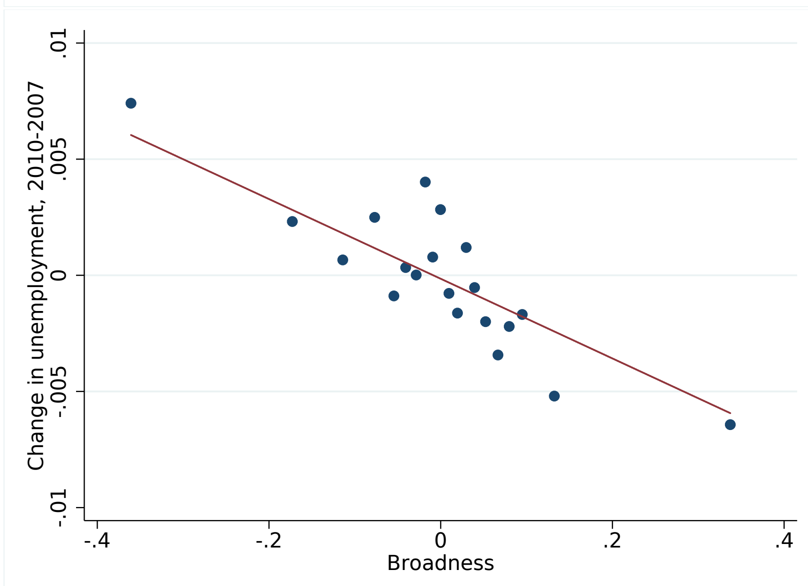
Figure L.12: Broader occupation's unemployment responses were mitigated



Each dot represents one occupation x state. Occupations aggregated to 26 major groups.
Points colored by occupation. Regression line controlling occupation and state-fixed effects.

Figure L.13: Broader occupation's unemployment responses were mitigated





Occupation-specific unemployment responses during the great recession as a function of their broadness. Top panel: only controlling for occupation and state-fixed effects, correponding to column (3) in table 4. Bottom panel: controlling for individual demographics, and state-year fixed effects – as in column (4).

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