

Darougheh, Saman

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Occupation-industry mismatch in the crosssection and the aggregate

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

Saman Darougheh
sdma@nationalbanken.dk
DANMARKS NATIONALBANK

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

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 cross-sectional 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

Macroeconomics, labor economics, unemployment, mismatch

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JEL classification

E24; J22; J24; J63; J64

The authors alone are responsible for any remaining errors.

Occupation-industry mismatch in the cross-section and the aggregate^{*}

Saman Darougheh[†]

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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 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. To explain the seeming contradiction between the impact of mismatch on individual unemployment risk and aggregate unemployment outcomes, I build a general equilibrium model that uses occupational broadness as a microfoundation of mismatch. The model uncovers an important general equilibrium channel that realigns the strong cross-sectional effects of mismatch with its missing aggregate impact. 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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[†]Danmarks Nationalbank. E-mail: s.darougheh@gmail.com.

1 Introduction

Between 2007 and 2009, the United States experienced one of the largest downturns in the post-war era. During that period, the US 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 is “mismatch unemployment” – the idea that job seekers may be of a different type than what firms are looking for.

There are many potential dimensions of mismatch, and they all require some friction that prevents job seekers from adjusting to the requirements of the vacancies. To see which dimensions are most important in explaining unemployment, I carry out an empirical investigation that lets the data speak without imposing any structural assumptions. I perform a machine learning exercise where the individual unemployment status is predicted out of sample using independent variables from the CPS. I find that an individual’s occupation and industry are among the most important predictors of their unemployment status.¹ This is in line with the notion of mismatch: human capital that is specific to occupations or industries might impede the unemployed from changing labor markets. If shocks affect occupations and industry asymmetrically, an individual’s current occupation and industry will be an important determinant of their unemployment risk.

It is a well-known hypothesis that industries are affected unequally by aggregate business cycles (Lilien, 1982), and that the Great Recession affected some industries more than others. As for occupations, the sharp increase in unemployment during the Great Recession was accompanied by a rise in the dispersion of occupation-specific unemployment rates, as displayed in Figure 1. For example, the unemployment rate of construction-related occupations increased by up to 12 percentage points, whereas it increased by less than 2 percentage points in many other occupations. 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 heterogeneous unemployment dynamics during the Great Recession.

It appears that mismatch is a potent explanation of unemployment risk in the cross-section. Yet, the seminal paper by Şahin et al. (2014) found that only a small part of the large increase in U.S.

¹For details on the empirical exercise see Appendix B.

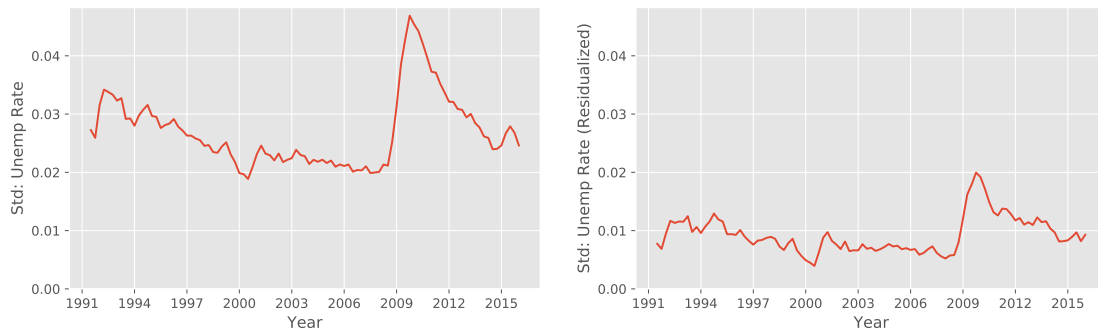
unemployment during Great Recession can be attributed to mismatch. How can we realign this seeming contradiction?

In this paper, I estimate cross-sectional and aggregate implications of mismatch. To this end, I distinguish between occupations that are specialized and used by very few industries, and those that are general and employed in many different industries. I will refer to less specialized occupations as “broader” occupations. Previous research has found that a larger share of human capital is occupation-specific than industry-specific (Kambourov and Manovskii, 2009a). This suggests that the unemployed are *ceteris paribus* less willing to change occupations than to change industries in order to find a new job. Since individuals in broader occupations have a larger set of industries from which to sample job offers, I argue that they are less dependent on any single industry and thereby better insured against mismatch unemployment caused industry-specific shocks. I first confirm empirically that broadness is an important determinant in cross-sectional unemployment risk. I then use a model to show that this cross-sectional relevance does not translate into a large aggregate impact of broadness: aggregate shocks that affect less broad occupations do not coincide with larger unemployment responses.

In the empirical part of the paper, I measure the broadness of each occupation using the dispersion of its workers across industries. I then estimate the extent to which occupation-specific broadness dampened the impact of the Great Recession’s cross-sectional unemployment risk using data from the CPS. Similar to Autor, Dorn, and Hanson (2013a), I use geographical variation in industry composition to isolate the effect of broadness from other occupation-specific effects. During the Great Recession, occupation-specific unemployment rates increased less for broader occupations. These effects are large: a one-standard deviation increase in broadness mitigates the unemployment response of the occupation by half. As suggested by the theory, these changes in unemployment rates stem from differences in job-finding rates. I focus on the construction industry, as it had a large inflow of unemployed workers in that period, and find that the job-finding rates of broader occupations were up to 38% higher than those of specialists.

I then connect these strong cross-sectional findings to the literature that estimates the impact of mismatch on aggregate unemployment responses. I first confirm that there was more mismatch during the Great Recession: the pool of unemployed workers in the Great Recession consisted of much more specialized workers than in previous recessions. These are largely driven by the slump in the construction sector that affected many specialized occupations. Taken at face value, the empirical cross-sectional results would suggest that the high degree of mismatch during the Great Recession can explain a large share of the strong and persistent unemployment response during that recession. How can we then make sense of the findings of (Şahin et al., 2014), who argue that mismatch had a

Figure 1: Dispersion of 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. Computation explained in Appendix A.

limited contributed to the aggregate unemployment response during the Great Recession?

To reconcile the cross-sectional and aggregate findings, I propose a model that features a continuum of occupations that are either specialized and employable in a single industry, or broad and employable in many industries. Industries either buy input from broad or specialized occupations: “broad industries” only employ broad occupations, while “specialized industries” buy from a single specialized occupation each. Every occupation is a Lucas and Prescott (1974) type island with a Diamond-Mortensen-Pissarides (DMP) style frictional labor market. The model will uncover an important general equilibrium channel that explains the missing impact of mismatch on aggregate unemployment: broad occupations are insured against aggregate shocks since they can fall back to other industries. By using these other industries as an outside option, they spread the original shock to more industries and affect more workers.

In the model, the unemployed can change occupations at any time, but incur a cost when doing so. The general equilibrium model replicates the empirical insurance value of broadness in the cross-section: the unemployment rate of broad occupations increases less in response to a shock onto broad industries, than the unemployment rate of specialist occupations in response to a shock to specialist industries. Both shocks generate a similar DMP-style response within the directly affected occupations, as a fall in productivity will imply a lower market tightness and higher unemployment. Aggregate output falls in both cases and causes prices in the remaining sectors to fall. If the value of being in the affected occupations falls enough, the unemployed incur the moving cost and switch to other occupations. A shock to broad industries additionally allows for adjustment across industries: workers in the affected broad occupations can costlessly relocate to other broad industries. As output

in other broad industries rises, their prices fall: the labor supply response spreads the impact of the shock across all broad industries. The direct impact on broad occupations is hence smaller than the impact on specialist occupations, and the labor markets of broad occupations do not deteriorate as much. This is not true for aggregate shocks that affect all industries equally: broadness does not insure against shocks that perfectly correlate across all industries.

So, the model replicates the direct effect of broadness on occupation-level unemployment. However, this does not imply that shocks to broad industries lead to smaller aggregate unemployment responses than those to specialized occupations. This is because a shock to any broad industry does not only affect the workers that are employed in that industry but also the broad workers in other industries. The size of the affected worker force is proportional to the broadness of the occupation: an occupation that is employable in e.g. 5 industries will only be affected by one fifth of each industry-specific shock, but that shock will affect 5 times as many individuals. The difference between shocks to broad or specialized industries then boils down to whether strong shocks to few workers lead to more aggregate unemployment than weak shocks to many workers. An important nonlinearity in this framework is that workers will switch occupations whenever their occupation deteriorates too much: specialists will respond to the large devaluation of their occupation by switching to more productive occupations, thereby improving the aggregate unemployment rate. As the value of broad occupations never falls as much, they tend to migrate less. In the quantitative simulations, aggregate unemployment responds more to recessions concentrated on broad industries.

The model predicts that recessions that generate more mismatch do not lead to larger unemployment responses. This suggests that the large unemployment response during the Great Recession was not caused by mismatch, in line with the findings of Şahin et al. (2014). The model explains these findings by emphasizing the strong crowding-out effect that workers in thick markets generate when responding to shocks.

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 and Schönberg (2010) focus on occupational mobility, while I analyze mobility within occupations and across industries. Both papers are related to a larger literature on the portability of human capital. Becker (1962) looks at firm-specific versus general human capital. Neal (1995) and Shaw (1984) focus on occupation and industry-specific human capital. Kambojov 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 (2017) 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 from 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. My quantitative results support that finding: shocks which generate more mismatch lead to a higher variance of unemployment responses across labor markets, but not larger volatility of aggregate unemployment. A priori, the large unemployment response during the Great Recession is not indicative of mismatch. Herz and Van Rens (2011) and Barnichon and Figura (2015) perform related longitudinal decompositions of mismatch unemployment.

Conceptually, my empirical variation stems from geographical heterogeneity in industry exposure, similar to Autor, Dorn, and Hanson (2013b) and Helm (2019). Here, the variation in industry exposure is not used as a shift-share instrument, 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 homogenous 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-type structure.

On the theoretical side, I integrate the canonical DMP framework of the frictional labor market with the idea of multiple labor markets as in Lucas and Prescott (1974). In a similar fashion, Shimer (2007) and Kambourov and Manovskii (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 two ways. First, I contribute to this literature by integrating the notion of industries into the occupational framework in a tractable way. Second, 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.

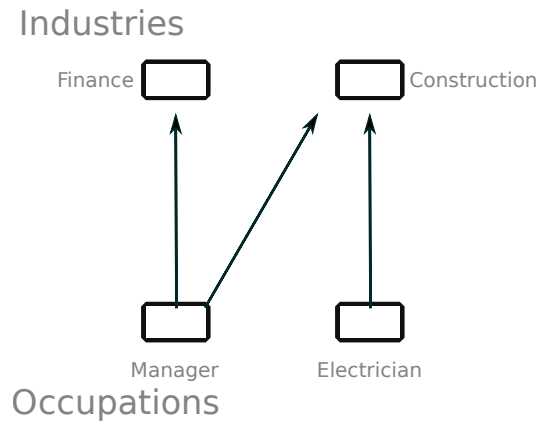
In sections 2 and 3, I first describe the concept of broad and specialized human capital, and measure its impact on unemployment responses. Building on these cross-sectional results, section 4 describes the model, and section 5 analyzes aggregate shocks.

2 Broad and specialized occupations

This section introduces the notion of specialized occupations and relates it to unemployment risk and the notion of mismatch unemployment. 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 similar input compositions in production. In this paper, the focus is on the composition of different occupations that are being used in production. Conceptually, occupations can be thought of as categories of workers depending on their typically performed tasks: workers who perform similar tasks will be assigned the same occupation.

I now juxtapose managers and electricians. Managers are used by firms in many different industries in their production process. Electricians are employed in much fewer industries, mainly by

Figure 2: Stylized occupation-industry network



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

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 well-spread across many industries. The exemplary managers would be broader than electricians.

Notice that 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 mismatch

Many studies refer to situations in which the matching of workers to firms is suboptimal with the term “mismatch”. In this paper, I follow a literature that does not concern with the allocation of workers to firms, but focuses on their allocation to labor markets. The benchmark allocation of workers to labor markets is one that a social planner would choose that is unconstrained by frictions regarding the relocation of workers across markets. Differences in total unemployment between the competitive equilibrium and the benchmark allocation are referred to as “mismatch unemployment”. It is important to stress that “mismatch unemployment” is not a normative term. The notion is being used for accounting purposes, and to answer how much of aggregate unemployment can be

explained by differences to the benchmark allocation. It is useful to understand the causes underlying fluctuations in aggregate unemployment, even if they are efficient.

Broadness was defined as a metric of the production network, and not in relation to mismatch. However, broadness may have implications for mismatch and thereby for unemployment risk. I demonstrate this using again the stylized case of managers and electricians.² For simplicity, assume that workers are completely stuck in their occupation, but free to move across industries. Now, imagine that the productivity in the firms in the construction sector falls so much that firms in that sector are no longer hiring, and many workers have been laid off. Since both sectors use managers in their production function, the unemployed managers 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 can not respond that easily to industry-level labor demand. Since they are in a less broad occupation, they are more likely to be mismatched across industries, and thereby at a higher risk of being unemployed.

We assumed that workers are stuck in their occupations, but can change industries flexibly. This simplifying assumption will not hold in reality. We do not need this strong simplifying assumption, it is sufficient that the adjustment costs across occupations are on average higher than across industries. Why would this be the case? First, Kambourov and Manovskii (2009a) have spawned a large literature that demonstrates that more human capital is specific to occupations than to industries. Giving up human capital (and changing the 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.

To confirm the argument brought forward, I will now empirically measure broadness and provide evidence which suggests that individuals in broader occupations were indeed less mismatched during the Great Recession.

2.2 Measuring broadness

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

²I provide a simple static model in Appendix C that formalizes the argument brought forward here.

occupation's level of broadness.

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

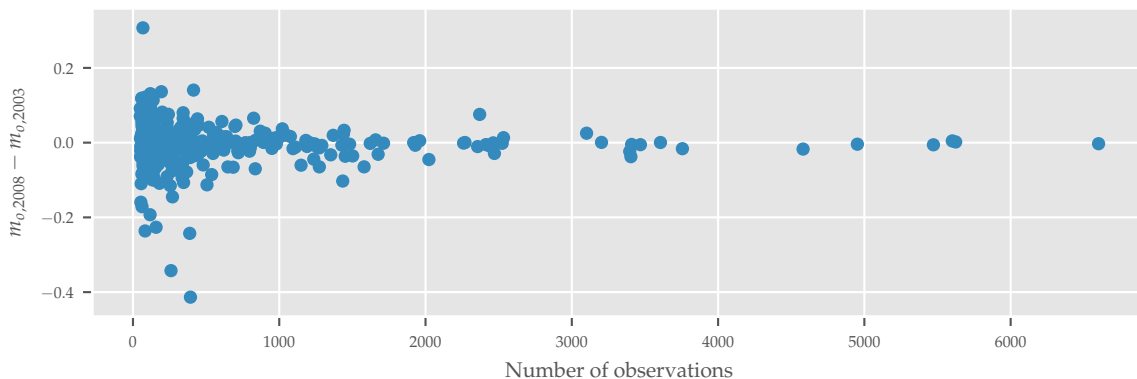
This measure of broadness is ad hoc and not suggested by any particular model. It has several attributes that make it attractive. First, it is well-known: much research around trade or competition involves the Herfindahl Index, and researchers are likely to be familiar with its properties. Secondly, it is stable: any metric of broadness necessarily is 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 will face few observations.

The suggested measure is more robust to noise in such scenarios than alternative specifications, for example one that counts for each occupation the number of industries with positive employment. Another measure that comes to mind evolves around occupational mobility and builds on shares $s_{o,i}$ that do not measure raw employment, but reemployment out of unemployment. Such a measure would ensure that the unemployed can indeed move across industries and we do not simply observe many unconnected occupation-by-industry submarkets. However, it is much more noisy for two reasons. First, by relying on the unemployed it ignores 95% of the data and reduces the already relatively low sample size. Second, measuring mobility across occupations or industries is prone to mismeasurement, since a wrong coding of occupations in either of two periods will generate a falsely identified move (Kambourov and Manovskii, 2009b). Together, this implies that a metric based on movers is much more noisy.

For the remainder of this section, I will describe the morphology of broadness. First, Figure 3 plots changes in occupation-specific broadness across time against the number of observations used to compute broadness. Note that 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 an 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). Therefore, unless otherwise indicated, in the remainder of the paper, I will use several years of data to compute a more precise estimate of broadness.

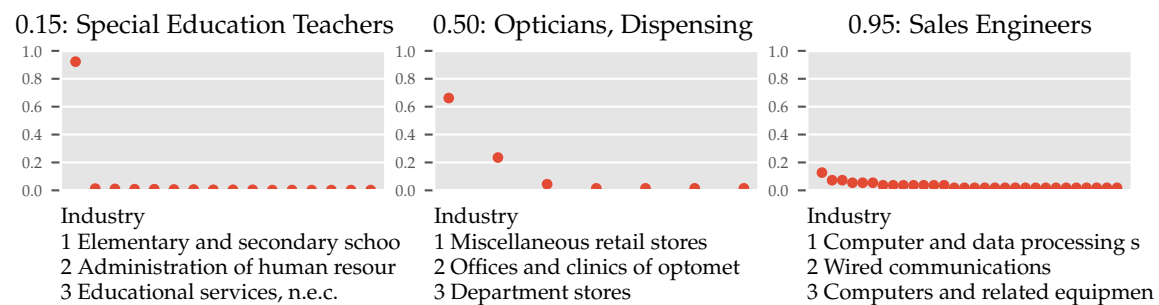
To provide some intuition for different employment structures that are hidden behind the one-

Figure 3: 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.

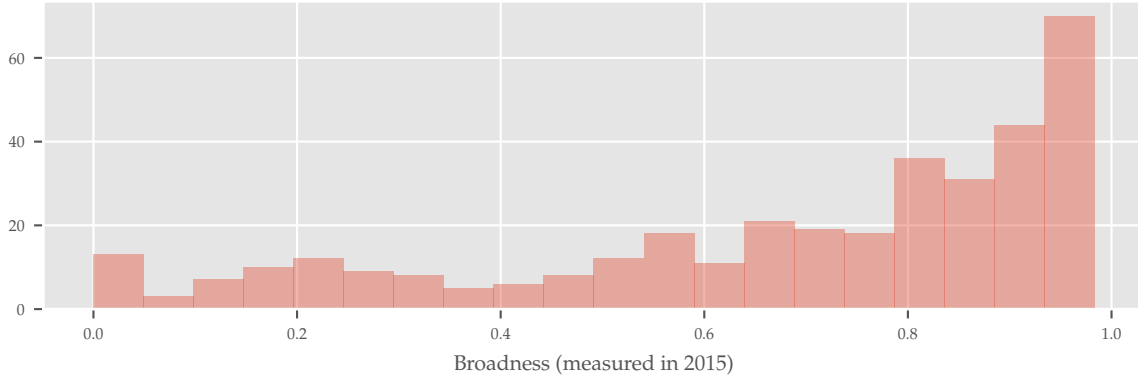
Figure 4: Three exemplary occupations across the support of broadness



dimensional measure of broadness, Figure 4 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 at. 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 5. 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.

Figure 5: Distribution of broadness across occupations



3 Empirical investigation

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. In this section, I will first compare individuals that were all previously employed in the construction sector, and show that those in broader occupations had higher job-finding rates than their peers in more specialized occupations. In a similar setup, I will then compute average unemployment changes for each occupation, and show that unemployment increases during the Great Recession were smaller for broader occupations.

In what follows, we 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 an 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 there are different industries present in different US states, occupations will be differentially broad across US states. This allows me to compute broadness $m_{o,z}$ for each occupation o and state z , as in (2).

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

Figure 6: Geographical heterogeneity of broadness



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 6 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.

3.1 Did the unemployed in broader occupations have a higher job-finding rate during the Great Recession?

In this section, we will test whether the unemployed in broader occupations had higher job-finding rates during the Great Recession. As before, unobserved occupation characteristics that correlate with occupation-level broadness will lead to biased results, and I will use occupation-by-state-level broadness to difference out occupation-fixed effects.

Here, I focus on unemployed workers coming from the construction sector. 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.

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

Dependent variable: monthly probability of being hired				
	(1)	(2)	(3)	(4)
Broadness	0.0724 ** (0.0293)	0.0794 *** (0.0253)	0.0600 * (0.0353)	0.0714 ** (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.

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 6 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 sex.

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

Table 1 shows the results. Columns (1)–(2) build the regression by adding controls and column

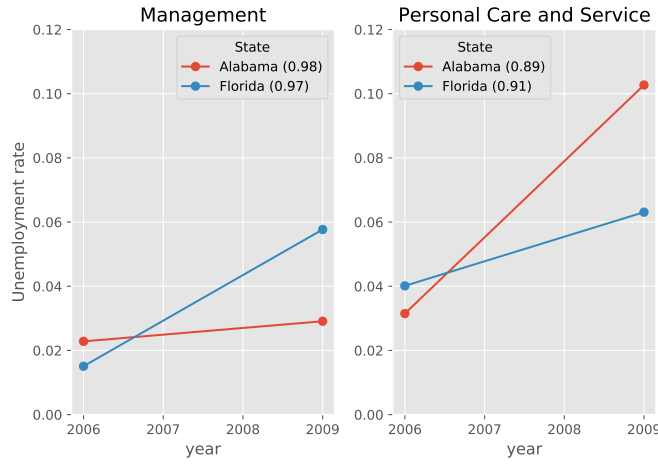
(3) shows the main specification. The average monthly job-finding rate in that period for that sample amounted to 0.18. A one standard-deviation increase in the job-finding rates corresponds to an increase in monthly job-finding rates of 0.06, or 30%. Column (3) is only significant at the 10% level, 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 there are several common selection issues that I try to address 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 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 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 than being unemployed in a market with lower broadness. Therefore, we expect that randomly drawn unemployed workers from a broader occupation are on average less able 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.

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

The setup with individual-level regressions on job-finding rates helps us cleanly isolate the impact of broadness. 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 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 (4).

Figure 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.

$$u_{o,z,2010} - u_{o,z,2007} = \alpha m_{o,z} + \Lambda_z + \Theta_o + \epsilon_{o,z} \quad (4)$$

Figure H.11 draws the regression line against all observations. Table 2 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

Table 2: 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 (0.00912)	-0.0153 (0.00992)	-0.0168** (0.00769)	-0.0273** (0.0103)
Occ FE	No	Yes	Yes	Yes
State FE	No	No	Yes	Yes
Individual Demographics	No	No	No	Yes
Industry \times State	No	No	No	Yes
<i>N</i>	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.

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 applying the Frisch–Waugh–Lovell theorem: in each year, I partial out individual-level broadness and unemployment status for a quadratic term in age, three racial groups, three education groups, two sex groups, and 223 \times 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 2. 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 .

4 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 faced 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 occupations 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.

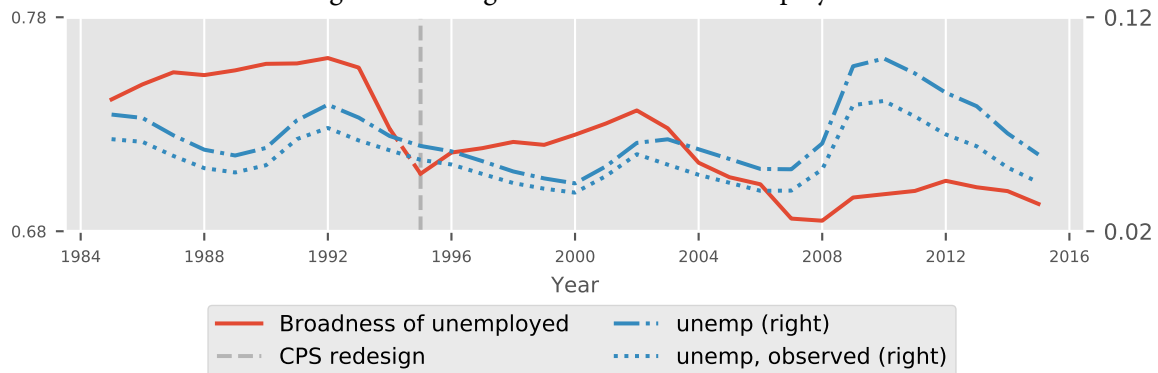
A large literature discussed the extent to which mismatch unemployment was relevant in explaining the large unemployment response during the Great Recession. We now show that indeed, the type of industries and occupations affected during the Great Recession suggests a high relevance of mismatch unemployment.

Figure 8 displays the average broadness of the unemployed over time. Two features are remarkable. First, average broadness appears to be counter-cyclical. 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.

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 be 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 in managers and programming and lead 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 degree of

Figure 8: Average broadness of the unemployed



Unemployment rates against the degree of broadness of the unemployed. 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 E for more information on the computation and robustness checks.

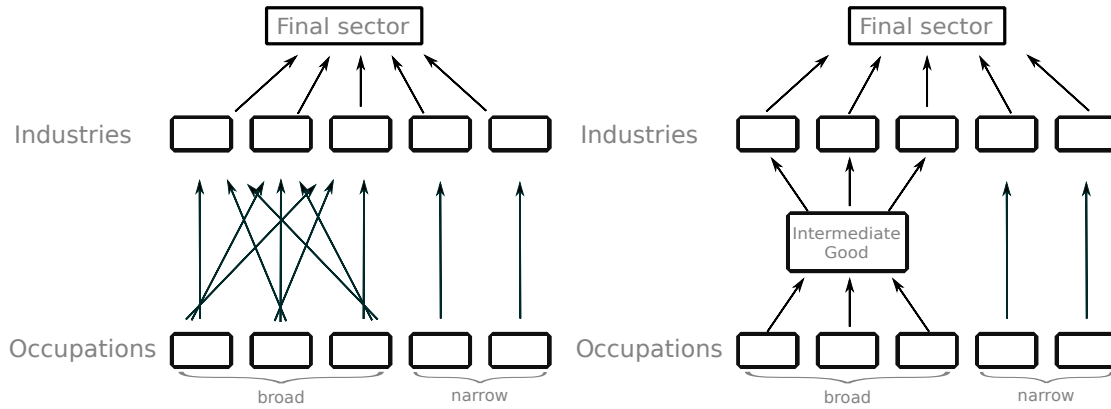
broadness among the unemployed and aggregate unemployment fluctuations. It is difficult to devise a clean empirical strategy to compare two recessions. Therefore, I build a model to test the relationship between mismatch and aggregate unemployment fluctuations. The model will confirm the findings by 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 floors the risk one may face at 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 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 and Prescott (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

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



The production network of the economy. Notice that the two networks are isomorphic, as Section 4.3 shows.

across islands is frictional: the unemployed can change islands only after incurring a fixed cost that captures 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 labelled “broad”: they provide a service that is employed by a large number of industries. A measure $1-\gamma$ of occupations is labelled “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 to equilibria 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.

4.1 Final sector

There is a unit measure of industries that each 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.

$$Y = \left[\int_{[0,1]} y(i)^{\frac{\theta-1}{\theta}} di \right]^{\frac{\theta}{\theta-1}} \quad (5)$$

$$p(i) = \left(\frac{Y}{y(i)} \right)^{\frac{1}{\theta}} \quad (6)$$

4.2 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 (7), 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 (8)

$$y(i) = A(i)z(i) \quad (7)$$

$$p(i) = \frac{p_z(i)}{A(i)} \quad (8)$$

4.3 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 (9).

$$\begin{aligned} \min_{\{z(i,o)\}_o} \int_{[0,\gamma]} p_z(o)z(i, o)do & \quad (9) \\ \text{s.t. } y(i) = A(i) \left[\int_{[0,\gamma]} z(i, o)^{\frac{\theta_b-1}{\theta_b}} do \right]^{\frac{\theta_b}{\theta_b-1}} & \end{aligned}$$

The appendix shows that optimal input composition is given by (10), 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 $x(i)$.

$$\begin{aligned} \frac{z(i, o)}{x(i)} = \left(\frac{P_x}{p_z(o)} \right)^{\theta_b}, \quad \forall i, o & \quad (10) \\ P_x = \left[A_x \int_{[0,\gamma]} p_z(o)^{1-\theta_b} \right]^{\frac{1}{1-\theta_b}} & \end{aligned}$$

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:

$$\begin{aligned} x &\equiv \left[A_x \int_{[0,\gamma]} z(o)^{\frac{\theta_b-1}{\theta_b}} do \right]^{\frac{\theta_b}{\theta_b-1}} \\ x &= \int_{[0,\gamma]} x(i) di & (11) \end{aligned}$$

The question remains as to how x is distributed across industries. The appendix answers this question by using feasibility (11) and a rewritten firm's problem to compute equilibrium $x(i)$ shares (12). 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 (12).

$$\frac{x(i)}{x} = \left(\frac{A(i)}{A_b} \right)^{\theta-1} \quad (12)$$

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

Finally, the appendix shows how one can use this result, together with prices implied by perfect competition (13), to compute P_x in closed-form as in (14).

$$p(i) = \frac{P_x}{A(i)} \quad (13)$$

$$P_x = A_x A_b \left(\frac{Y}{A_b x} \right)^{\frac{1}{\theta}} \quad (14)$$

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

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

- aggregate output Y ,
- 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 $\{p_z(o)\}_o, P_x, \forall i$ (10)
2. Industry choice: intermediate output consistent with zero profits, $\forall i$ (13)
3. Feasibility: $x(i)$ add up to x (11)

4.4 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

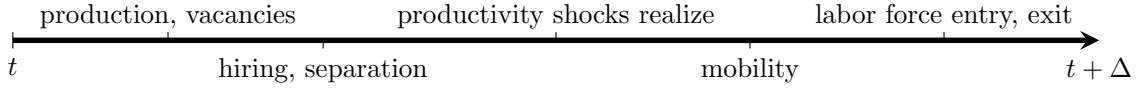
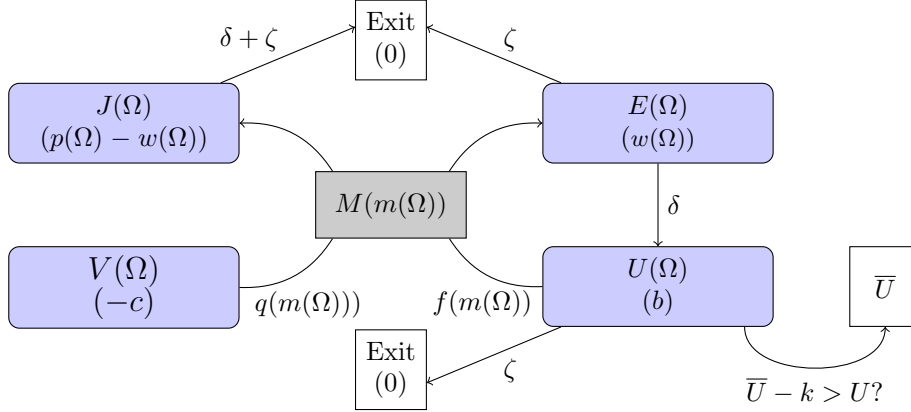


Figure 11: Dynamics within each occupation



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 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 receives wage $w(\Omega)$. The value 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 are nonstandard. 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 \bar{U} . We take \bar{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

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

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: $\rho = \bar{\rho} + \zeta$.

$$U^{\text{stay}}(\Omega) = b\Delta + e^{-\rho\Delta} \left[\left(1 - e^{-f(m(\Omega))\Delta}\right) \mathbb{E}[E(\Omega')] + e^{-f(\Omega')\Delta} \mathbb{E}[U(\Omega)] \right] \quad (15)$$

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

$$E(\Omega) = w(\Omega)\Delta + e^{-(\bar{\rho}+\zeta)\Delta} \mathbb{E} \left[e^{-\delta\Delta} \mathbb{E}[E(\Omega')] + (1 - e^{-\delta\Delta}) \mathbb{E}[U(\Omega')] \right] \quad (16)$$

$$J(\Omega) = [p_s(\Omega) - w(\Omega)]\Delta + e^{-(\bar{\rho}+\zeta+\delta)\Delta} \mathbb{E}[J(\Omega')] \quad (17)$$

$$V(\Omega) = -c\Delta + \left(1 - e^{-q(m(\Omega))\Delta}\right) e^{-\bar{\rho}\Delta} \mathbb{E}[J(\Omega')] \quad (18)$$

In equilibrium, market tightness is governed by free entry, (19), and wages are determined by Nash bargaining with workers' bargaining power β , (20).

$$V(\Omega) = 0 \quad (19)$$

$$\beta J(\Omega) = (1 - \beta)(E(\Omega) - U(\Omega)) \quad (20)$$

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 structure 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 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 (6), industry-level technology (7), and free-entry, (8), to compute p_s (21). 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 to compute 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 $\Omega_s = \{a, u, \ell\}$.

$$p_s(a, u, \ell) = a \left(\frac{Y}{a(1-u)\ell} \right)^{\frac{1}{\theta}} \quad (21)$$

$$p_b(u, \ell) = \left(\frac{x}{(1-u)\ell} \right)^{\frac{1}{\theta_b}} \cdot P_x \quad (22)$$

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 (22). 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:

$$\begin{aligned} g_{u;s}(a, u, \ell, \ell') &= 1 - e^{-\zeta\Delta}(1 - \tilde{u}(a, u, \ell)) \frac{\ell}{\ell'} \\ \tilde{u}(a, u, \ell) &= (1 - e^{-\delta\Delta})(1 - u) + e^{-f(m(a,u,\ell))\Delta} u \end{aligned} \quad (23)$$

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.

$$\begin{aligned} \tilde{u}_b(u, \ell) &= (1 - e^{-\delta\Delta})(1 - u) + e^{-f(m_b(u,\ell))\Delta} u \\ g_{u;b}(u, \ell, \ell') &= 1 - e^{-\zeta\Delta}(1 - \tilde{u}_b(u, \ell)) \frac{\ell}{\ell'} \end{aligned} \quad (24)$$

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 \bar{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 $\{g_{u;s}, w\}, \bar{U}, Y: \{J_s, E_s, U_s^{stay}, U_s\}$ satisfy (15)-(17)
2. Given $\{J_s, E_s, U_s^{stay}\}$: wages satisfy Nash bargaining (20)
3. Given $\{J_s\}$: m satisfies free-entry (19)
4. Law of motion $g_{u;s}$ is consistent with $\{m\}$ (24)

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 \bar{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 $\{g_{u;b}, w\}, \bar{U}, Y: \{J_b, E_b, U_b^{stay}, U_b\}$ satisfy (15)-(17)
2. Given $\{J_b, E_b, U_b^{stay}\}$: wages satisfy Nash bargaining (20)
3. Given $\{J_b\}$: m satisfies free-entry (19)
4. Law of motion $g_{u;b}$ is consistent with $\{m\}$ (25)

4.5 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 .

$$\bar{U}_b = \max_{(u,\ell):g_b(u,\ell)>0} U_b(u, \ell)$$

$$\bar{U}_s = \max_{(a,u,\ell):g_s(a,u,\ell)>0} U_s(a, u, \ell)$$

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 originating and destination occupation. Therefore, the relevant variable for the optimization problem is the best attainable utility of any of those, denoted \bar{U} . The present-discounted value of moving net of the migration cost k will be denoted \underline{U} .

$$\bar{U} = \max\{\bar{U}_b, \bar{U}_s\}$$

$$\underline{U} = \bar{U} - k$$

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 $U_s(a, u, \ell) < \underline{U}$. In what follows, I will describe the law of motion for the labor force in the broad occupations (25).

To understand mobility, denote by $U'(g_\ell)$ next-period utility as a function of mobility at the end of this period. There are four cases to distinguish. In case (i) $U'(0) \in (\underline{U}, \bar{U})$. If without mobility, next period's utility is strictly between the boundaries, there is no incentive for workers to leave. Moreover, as occupation does not belong to the set of "best occupations for the unemployed to enter", no worker will enter. In case (ii) $U'(0) \geq \bar{U}$: next period's utility would be at or above \bar{U} . In equilibrium, \bar{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 $U'(g_\ell) \geq \bar{U}$. Thus, we know that mobility will be such that $U'(g_\ell) = \bar{U}$. Next, we have to deal with $U'(0) \leq \underline{U}$. Whenever that is the case, unemployed workers will leave the occupation. The measure leaving is such that either (iii) all unemployed workers have left, but next-period's utility remains below the threshold, or (iv) the utility has moved to the threshold \underline{U} – whatever requires fewer mobility. The law of motion for the specialist occupations' labor force (26) follows the same spirit.

$$\begin{aligned}
g_{\ell;b}(u, \ell) &= \begin{cases} e^{-\zeta\Delta\ell} & \text{if } U_b(g_{u;b}(u, \ell, e^{-\zeta\Delta\ell}), e^{-\zeta\Delta\ell}) \in (\underline{U}, \bar{U}) \\
x : U_b(g_{u;b}(u, \ell, \ell' = x), x) = \bar{U} & \text{if } U_b(g_{u;b}(u, \ell, e^{-\zeta\Delta\ell}), e^{-\zeta\Delta\ell}) \geq \bar{U} \\
(1 - \bar{u}_b(u, \ell))e^{-\zeta\Delta\ell} & \text{if } U_b(g_{u;b}(u, \ell, e^{-\zeta\Delta\ell}), e^{-\zeta\Delta\ell}) < \underline{U} \\
x : U_b(g_{u;b}(u, \ell, \ell' = x), x) = \underline{U} & \text{otherwise} \end{cases} \tag{25} \\
g_{\ell;s}(a', a, u, \ell) &= \begin{cases} e^{-\zeta\Delta\ell} & U(a', g_u(a, u, \ell, e^{-\zeta\Delta\ell}), e^{-\zeta\Delta\ell}) \in (\underline{U}, \bar{U}) \\
x : U(a', g_u(a, u, \ell, \ell' = x), \ell' = x) = \bar{U} & U(a', g_u(a, u, e^{-\zeta\Delta\ell}, e^{-\zeta\Delta\ell}), \ell) \geq \bar{U} \\
(1 - \bar{u}(a, u, \ell))e^{-\zeta\Delta\ell} & U(a', 0, e^{-\zeta\Delta}(1 - \bar{u}(a, u, \ell))) \leq \underline{U} \\
x : U(a', g_u(a, u, \ell, \ell' = x), \ell' = x) = \underline{U} & \text{else if } U(a', g_u(a, u, e^{-\zeta\Delta\ell}), e^{-\zeta\Delta\ell}) \leq \underline{U} \end{cases} \tag{26}
\end{aligned}$$

4.6 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 at each occupation o . Third, the distribution and flows of labor across occupations have to be consistent with the (constant) aggregate labor force.

4.7 Connection between industries and occupations

Industries are lined up on the unit interval. 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 $G_s(\tilde{a}, u, \ell)$:

$$A(i) \sim \log \text{Normal}(\text{s.t. stationary AR (1)}) \quad \forall i \in [0, 1] \quad (27)$$

$$(u(i), \ell(i)) \sim G_s(a, u, \ell | a = a(i)) \quad \forall i \in (\gamma, 1] \quad (28)$$

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:

$$z(o) = (1 - u(o))\ell(o) \quad , \forall o \in [0, 1] \quad (29)$$

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

$$p_b(u, \ell) = \left(\frac{x}{\ell(1-u)} \right)^{\frac{1}{\theta_b}} P_x \quad (30)$$

$$p_s(a, u, \ell) = a \left(\frac{Y}{a(1-u)\ell} \right)^{\frac{1}{\theta}} \quad (31)$$

Feasibility in terms of labor is stated as follows:

$$\begin{aligned}
L &= \gamma \int_{\mathcal{U} \times \mathcal{L}} \ell dG_b(u, \ell) + (1 - \gamma) \int_{\mathcal{A} \times \mathcal{U} \times \mathcal{L}} \ell dG_s(a, u, \ell) \\
L &= L_b + (1 - \gamma) \int_{\mathcal{A} \times \mathcal{U} \times \mathcal{L}} \ell dG_s(a, u, \ell)
\end{aligned} \tag{32}$$

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 (5)
2. $z(i)$ is consistent with occupation-level output (29)
3. Specialist industry states consistent with specialist occupation distribution (28)
4. \underline{U} is consistent with G_b, G_s
5. Prices are consistent with industry-level demand and feasibility (30)-(31)
6. Laws of motion for labor are consistent with $\{\underline{U}, \bar{U}\}$ (25)-(26)
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 (8)
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 $\{Y, \{z(o)\}_{o \in [0, \gamma]}\}$: $\{x, x(i), p_z\}$ solve Broad Industry PE
11. Given $\{L_b, p_b(u, \ell), \underline{U}, \bar{U}\}$: $\{J_b, E_b, U_b, m, u, g_{u; b}\}$ solve Recursive Broad Occupation PE
12. Feasibility w.r.t L (32)

Table 3: 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	4.322	Productivity (x)	Labor force distribution
γ	0.500	Measure of broad occupations	Illustration
$\bar{\theta}$	0.500	Elasticity, broad industries	High complementarity
Occupations			
A	1.355	Matching productivity	Literature
α	0.510	Matching elasticity	Literature
c	0.127	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.

4.8 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. While the discount rate appears small, together with the labor force exit rate, they add up 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 of 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 for 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, $\bar{\theta}$ 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, $\bar{\theta}$ 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-collared and white-collared workers in the construction sector. Recognizing that the chosen split and sector are at the lower end of the distribution for $\bar{\theta}$, I choose $\bar{\theta} = 0.5$. 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 Petrongolo and Pissarides (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 there-

fore 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 D 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 .

4.9 Steady state

This model nests occupational directed search with random search in each occupation. Moreover, each occupation has decreasing returns to scale. These components, together with the exogenous labor force exit rate, ensure that the steady state is unique. 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.

Table 4 summarizes some aggregate statistics of the steady state. As most of the labor force is in broad occupations and industries are substitutes, the production of total output draws more from broad industries, which in equilibrium sell their intermediate goods at lower prices. However,

Table 4: Key statistics of the steady state

Moment	Value	Description
Industries		
Y	0.9619	Total output
y_b	0.3980	Total output, broad ind
y_s	0.3887	Total output, narrow ind
P_b	1.2166	Price index, broad
P_s	1.2231	Price index, specialist
Occupations		
v_b	0.3139	Vacancies, broad
$E[v_s]$	0.4249	Vacancies, specialist
u_b	0.0492	Unemp, broad
$E[u_s]$	0.0564	Unemp, narrow occ (weighted average)
$std[u_s]$	0.0216	Unemp, narrow occ (weighted std)
$E[w_b]$	1.0000	Wage, broad occ
$E[w_s]$	1.0020	Wage, narrow occ (average)
L_b	0.5050	Measure broad labor

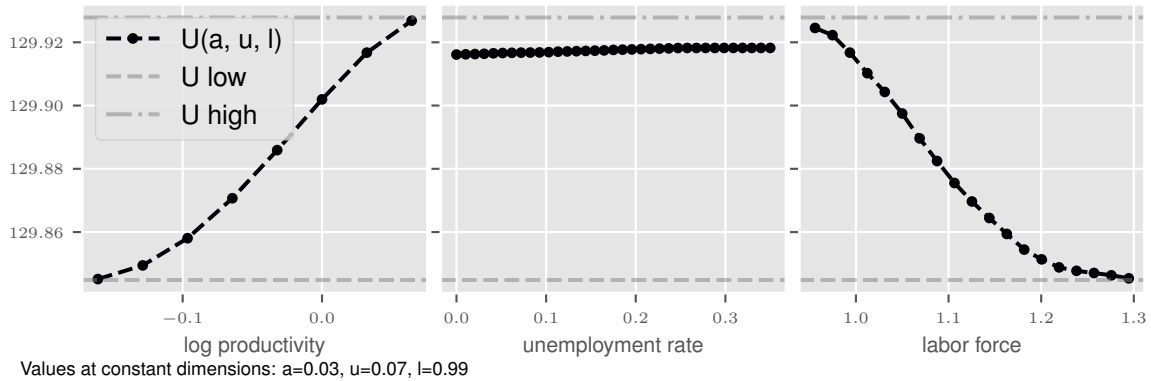
this large difference in prices is not visible in wages: because of free entry of firms, differences in sector-level prices are dominated by differential entry costs, as there are more vacancies in specialist occupations.

4.9.1 Mobility and compensating differentials

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.

Higher productivity will imply a higher total production of the industry-level good, which lowers industry prices and hence occupation-level prices. However, each firm in each industry is able to produce more output, 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. The less intuitive dimension is the unemployment rate: a higher unemployment rate increases the value of the unemployed. This is because we are

Figure 12: Value function of the unemployed

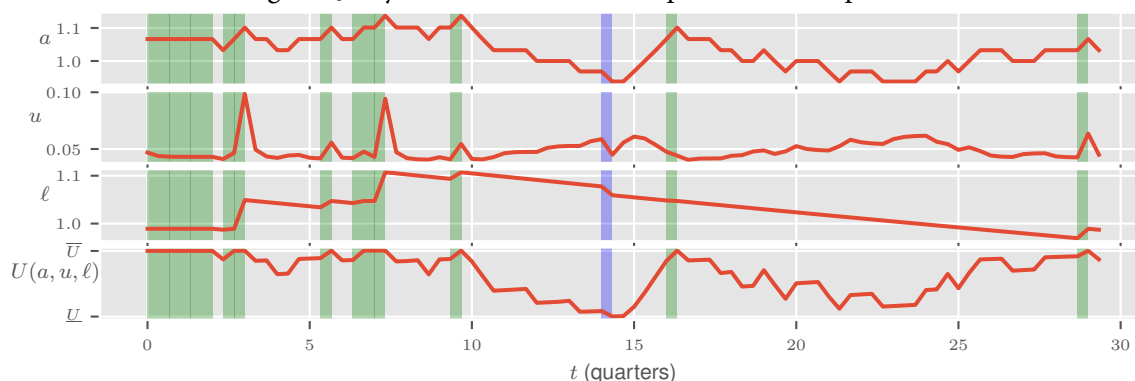


holding all other dimensions constant. In this class of models, free entry pins down a rate of market tightness: a higher unemployment rate will, *ceteris paribus*, simply mean a higher vacancy rate, and will not affect the job-finding rate. Additionally, a higher unemployment rate implies that a smaller share of workers are employed, which leads to a higher price of the occupation-level good.

The key take-away from the value functions is that individuals typically want to enter into an occupation that has high productivity and a low labor force, and leave those with 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 \bar{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 \bar{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 these spikes in u vanish quickly: mobility does not contribute largely to measured unemployment fluctuations.

Whenever the occupation is not at the upper boundary, we have no mobility into that occupation. Exogenous labor force exit will slowly reduce the labor force present in the occupation. This acts as a stabilizing factor: we observe much more directed mobility into an occupation than out of it. In this particular simulation, there is only one episode where active exit out of an occupation was necessary. That episode is highlighted in purple. As unemployed individuals are those that exit the occupation,

Figure 13: Dynamics of a simulated specialized occupation



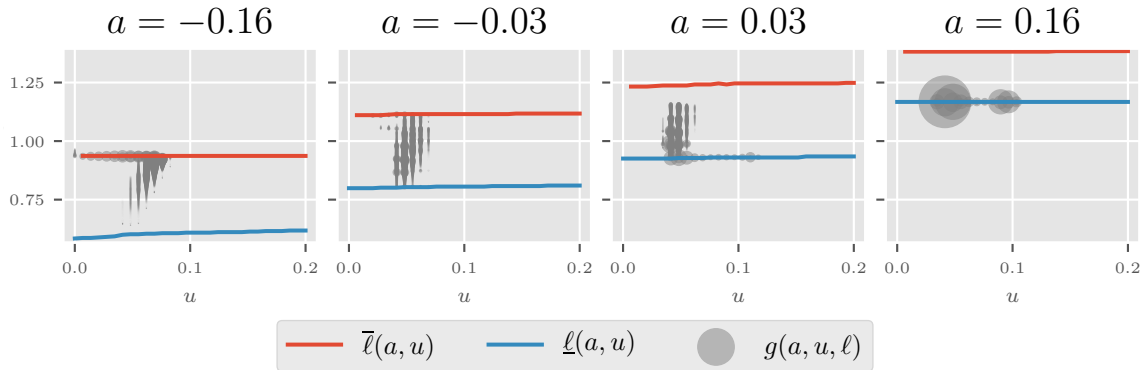
Dynamics of a simulated specialized occupation. First three panels draw the evolution of the state vector $\{a, u, \ell\}$, and the fourth panel depicts the evolution of the value function.

we observe a sharp decline in both labor force and unemployment rate.

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 blue and red lines denote the lower and upper boundary of the labor force for any given unemployment rate and productivity. Notice that these boundaries increase in both productivity and unemployment rates, as the value functions also increase in a and u . Occupations move in this state space for three reasons. First, productivity shocks will shift occupations across these panels. Second, an occupation's (u, ℓ) adjusts if it finds itself outside of $(\underline{\ell}, \bar{\ell})$ at the new productivity state a' . Third, unemployment rates change anytime 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 a slow depreciation of labor, until occupations are pushed towards $\underline{\ell}$.

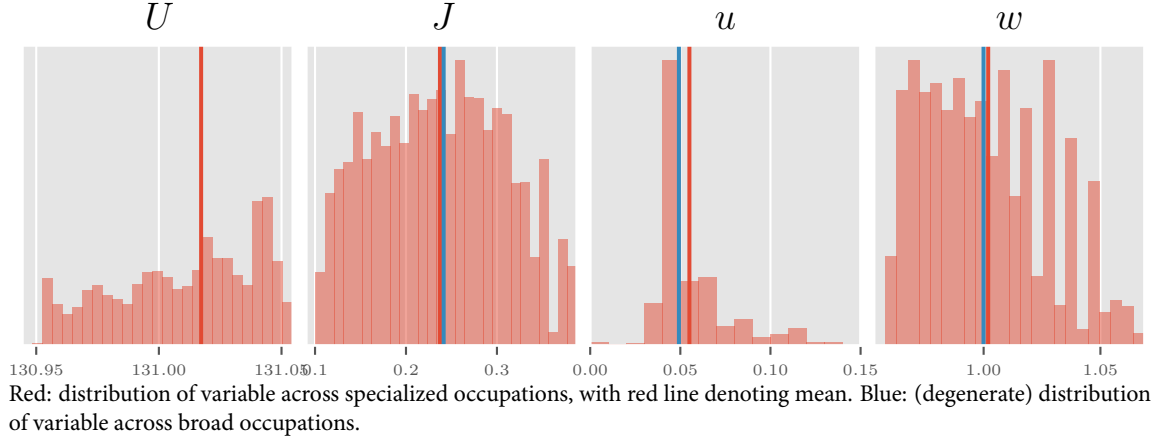
Notice that many occupations with the lowest productivity state have a higher unemployment rate than occupations with the highest productivity state. This is because unemployment rates are not only a function of the job-finding rate, but also of mobility: occupations with high productivity states will 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.

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.

Figure 15: Key labor market variables in specialized and broad occupations



Red: distribution of variable across specialized occupations, with red line denoting mean. Blue: (degenerate) distribution of variable across broad occupations.

4.9.2 Compensating differentials and wage profiles

Now we highlight wage formation in this model. Figure 15 displays a few labor market characteristics for both broad and specialized occupations. The first panel displays the distribution of the utilities of the unemployed in specialized occupations against those in broad occupations. The distribution of labor markets in broad occupations is degenerate on (u, ℓ) , which is why U_s collapses on a single value, indicated by the blue line. Without exogenous mobility, any $U_b \in [\underline{U}, \bar{U}]$ would be consistent with a steady state. As we have chosen $\zeta > 0$, $U_b = \bar{U}$ is the unique equilibrium: for any $U_s < \bar{U}$ we have positive exit but no entry, inconsistent with the defined steady state.

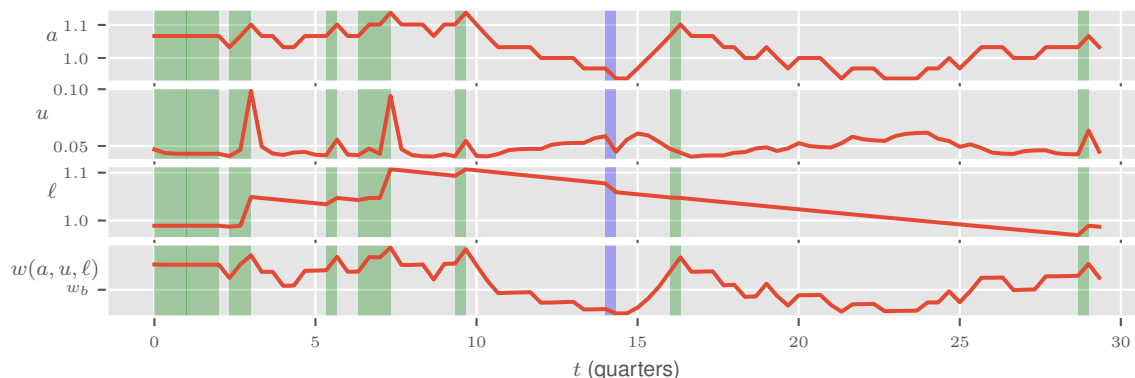
This will mean that average U_b is higher than average U_s in this economy in any equilibrium with non-zero k . The strict relationship between U and J implies that also $J_b > \mathbf{E}[J_s]$, as can be seen in the second panel. From the free-entry condition, this will imply a strictly higher market tightness in broad occupations, and thus a higher job-finding rate in broad occupations. As the third panel shows, this higher job-finding rate leads to a lower unemployment rate on average in broad occupations. Wages are on average equal in the two economies: there is no compensating differential for choosing the more risky specialized occupations. This is because agents are risk-neutral.

However, there are still some interesting wage dynamics going on in specialized occupations. To see these, Figure 16 again considers the simulated specialized occupation that we have seen earlier. Now, instead of plotting the evolution of utilities U_s , we plot the evolution of wages w_s . 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 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 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.

Figure 16: Evolution of wages in specialized occupations



Dynamics of a simulated specialized occupation. First three panels draw the evolution of the state vector $\{a, u, \ell\}$, and the fourth panel depicts the evolution of wages.

5 Aggregate shock

Having set up the machinery, we can now turn to the effects from 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 faring similarly in such a recession. Appendix F.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 F.2. Qualitatively, this targets a period like that 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 the specialized occupations.

Now, we turn our attention back to different types of recessions: Those that generate mismatch

because they affect specialized occupations. We contrast them against recessions that affect broad occupations and hence generate less mismatch. 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* lead to larger output losses, but not to larger or more persistent unemployment responses.

$$\begin{aligned}
 A(i, t) &= \begin{cases} A(t) + \tilde{A}(i, t) & \text{if } i \in \mathcal{I} \\ \tilde{A}(i, t) & \text{else} \end{cases} & (33) \\
 \tilde{A}(i, t) &= \phi A(i, t-1) + \epsilon_t \\
 A(t) &= \begin{cases} \mu & \text{if } t \leq T \\ 0 & \text{else} \end{cases}
 \end{aligned}$$

Equation (33) 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 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 0.2: 20% of industries are affected by the recession.

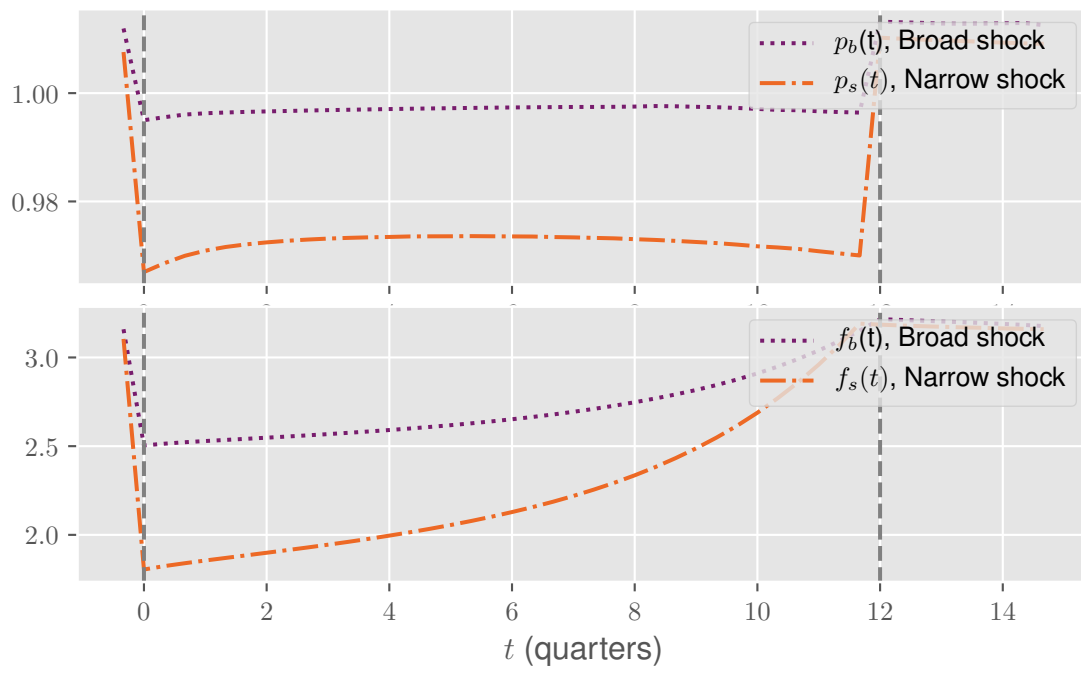
This recession is unexpected by the agents. As soon as the initial shock hits, all agents have perfect foresight about the remaining evolution of the process. This type of zero-probability aggregate shocks are often referred to as “MIT shocks”³

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 affected, and I refer to that recession as a “broad recession”. The other recession draws the measure 0.2 of industries among those with $i > \gamma$, and I call that recession a “narrow recession”.

The top panel in figure 17 compares the evolution of the prices of occupation-specific goods across both recessions. I contrast the value of broad goods in broad recessions against that of specialized goods in specialized recessions. As established earlier, workers in broader occupations are insured

³Studying 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 17: Cross-sectional responses



against industry-specific recessions as they can sell their good to unaffected sectors. This insurance manifests itself in a lower sensitivity of the price of the occupation-level good. The bottom panel plots the evolution of job-finding rates. The consequence of the price evolution is that the job-finding rates of the unemployed in broad occupations are less responsive than that of specialized occupations.

These are the implications of the direct effect. They qualitatively track what we measured in the empirical section. However, we have to take into account the size of the populations affected by each shock. The first panel in Figure 18 compares the relative labor forces that are directly affected by the shock in each type of recession: shocks in specialized industries directly affect the specialized occupations that are connected. As a measure 0.2 of industries are shocked in each scenario, and the labor force has been calibrated to be equally distributed among broad and specialized occupations, a measure 0.2 of workers is affected in the specialized recession. In contrast to that, the recession in measure 0.2 of broad industries affects *all* workers in broad industries. In the model, this is because the reduction of occupation-level prices affects both firms that had been selling to the affected industries, and those that had been selling to industries which are not affected.

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.

The second panel in Figure 18 addresses the question of mobility by comparing the relative changes in the labor forces. In this model, moving entails a fixed cost. Therefore, individuals that incur larger losses are more likely to change occupations. Workers in specialized occupations are not insured against the shock: They fare worse in the recession and respond more by changing occupations. Workers that change occupations always target the best available labor market and therefore dampen the impact of the aggregate productivity shock on the unemployment rate.

The response of the aggregate unemployment rate is a composite of all these effects: how hard are workers hit in the cross-section, how many of them are directly affected by either recession, and to what extent do they respond by changing occupation. Figure 19 compares the aggregate unemployment responses of the whole economy in both types of recessions. The aggregate unemployment rate response is roughly similar in both types of recessions. The reason for the unemployment rates being similar is the aforementioned general equilibrium effect: broadness insures the individual, not the whole occupation. Thus, a shock to specialized occupations affects few workers a lot, while a shock to broad occupations affects many workers a little bit. Which type of recession leads to a larger unemployment response is model-specific. In this model, the important nonlinearity is the

Figure 18: Comparison compositions

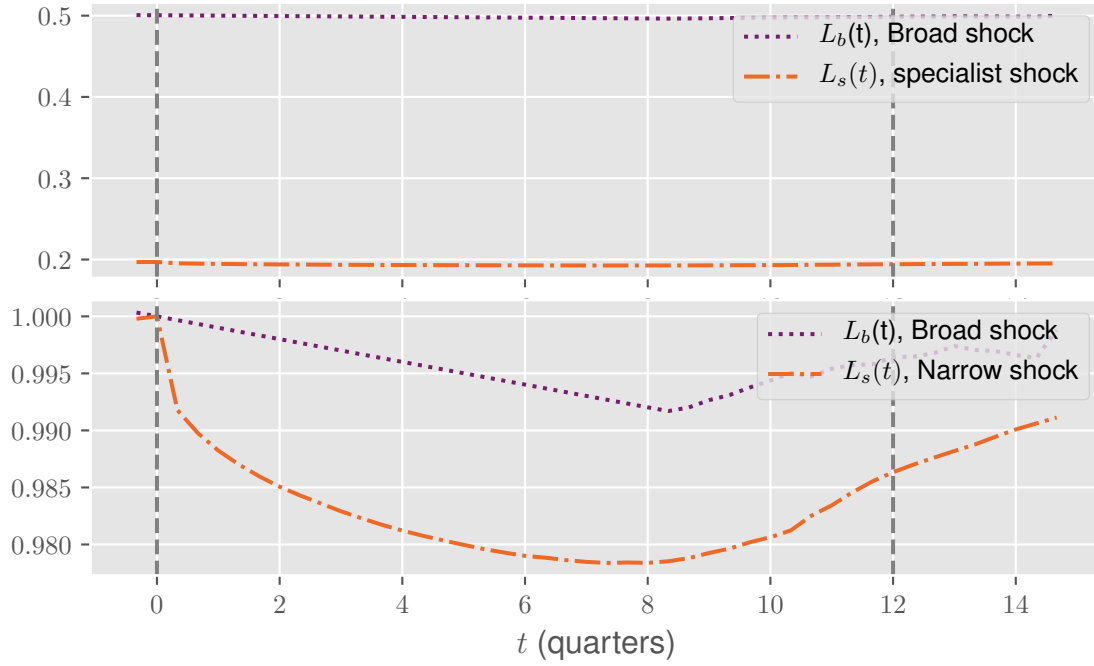


Figure 19: Aggregate unemployment response

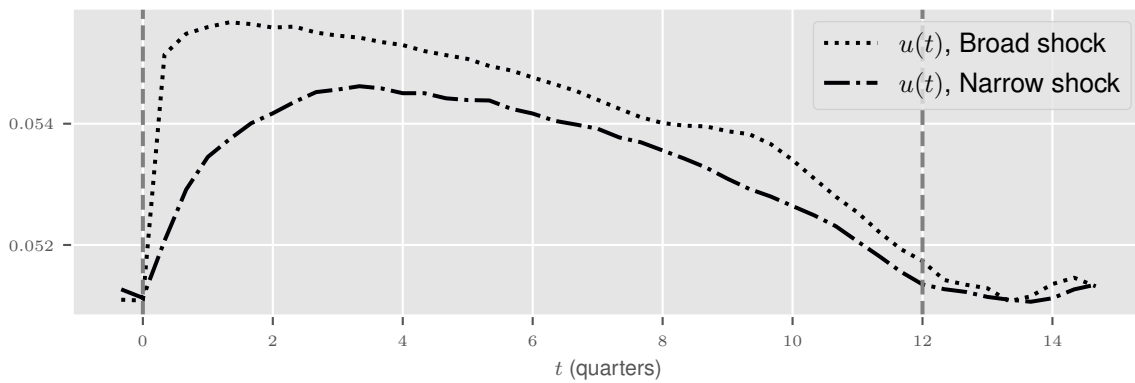
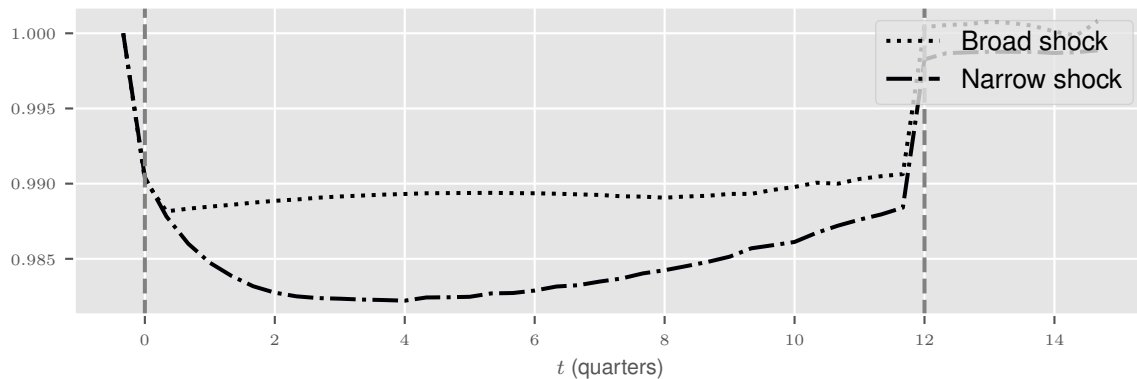


Figure 20: Aggregate output response



aforementioned occupation-switching. A shock to specialized occupations leads to larger relocation of labor. These relocating workers move to labor markets with higher job-finding rates and thereby improve the aggregate unemployment rate.

This does not imply that a shock to broad occupations leads to a larger welfare drop. Here, the appropriate welfare measure is aggregate consumption. The aggregate consumption is computed by subtracting the vacancy costs and the mobility costs from the aggregate output. The vacancy costs are comparable in both recessions, and the mobility costs are larger in the specialized recession. Therefore, it is sufficient to show that the output losses are larger in the specialized recession than in the broad recession (Figure 20), to conclude that the shock to specialized industries leads to larger welfare losses. Why are the output losses larger in a specialized recession? In the broad recession, firms in the broad occupations sell their output flexibly to unaffected industries. Firms in specialized occupations do not have this option when their industries are affected in a specialized recession. They continue to sell their output to the industries affected by the productivity shock. Therefore, a shock to specialized industries leads to a larger misallocation of labor and larger output losses.

6 Conclusion

Understanding the determinants of unemployment is key in 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. I do so by modeling mismatch as a result of adjustment frictions across occupations and industries. The key variation - differences in broadness across occupations - is an important determinant of unem-

ployment risk in the cross-section. For policy makers, this is a concept that can be readily applied to estimate exposure of occupations to unemployment fluctuations and guide labor market policies. The externalities of occupational mobility leave room for welfare gains of policy improvements. For example, occupational retraining could be targeted at more specialized occupations to provide insurance to workers that are particularly affected by a recession.

These strong cross-sectional results are contrasted by the missing effect of mismatch in the aggregate. In the model, recessions that cause more mismatch do not lead to larger unemployment fluctuations. This is because the direct effect is confronted by a general equilibrium effect caused by workers in broad occupations that switch industry and thereby spread the impact of the recession onto more product markets. These two effects are of similar order of magnitude. The exact qualitative difference between broad and narrow recessions is ambiguous and depends on the nonlinearities built into the model. Quantitatively, these two effects roughly offset each other: the large cross-sectional implications of mismatch do not carry over to the aggregate. Thereby, this paper explains how Şahin et al. (2014) found that mismatch did not contribute largely to the rise of unemployment during the Great Recession despite the large differences in exposure across sectors.

Recessions that cause more mismatch do not cause larger unemployment responses, but they do lead to larger losses of output and welfare. This is because they lead to more misallocation of labor. Therefore, there is potential room for regulation: policy makers should pay more attention to sectors that employ specialized occupations, as fluctuations in these sectors are more costly. One way to do so is by regulating those sectors more. Alternatively, monetary policy could be targeted more towards stabilizing these sectors (Bouakez, Rachedi, and Santoro, 2018). During the Great Recession, some policy makers have been using such arguments to defend stabilizing policies in the housing market. However, a full macroeconomic analysis is still warranted.

An extensive literature has assessed the degree to which a mismatch in labor markets contributed to the large unemployment response during the Great Recession. A key motivation behind this analysis is that one of the sectors affected in the recession was construction, which features a particularly large number of mismatch-prone specialists. In this paper, I do not address whether mismatch unemployment was especially large during the Great Recession. Rather, my results suggest that a shock of similar size to other sectors might have caused less mismatch, but not smaller unemployment responses.

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