Specialized human capital and unemployment*

Saman Darougheh†

Job Market Paper

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Abstract

I propose and show that workers in occupations that are employable in more industries ("broader" occupations) are better insured against industry-specific shocks. In an industry-specific recession, workers in broader occupations are hence less likely to be unemployed because of mismatch. Using geographical variation in occupation-level broadness, I show that during the Great Recession, unemployed in broader occupations had higher job-finding rates than unemployed in more specialized occupations. Moreover, the recession affected particularly sectors that employ many specialists. These facts together with the strong rise of unemployment would lead you to believe that recessions that hit mismatch-prone labor markets lead to larger unemployment responses. I test this theory in a Lucas (1974) island setting where both intra-island labor markets and inter-island mobility are frictional. In the model, shocks to mismatch-prone labor markets lead to heterogenous but not larger unemployment responses. Industries propagate productivity shocks to the occupations that they employ. Broad workers respond to productivity shocks to any of their industries by relocating to other industries. They thereby progagate the shock to the broad workers in the remaining industries: The original shock is weakened, but affects more individuals. Specialists are hit harder but respond by switching occupations – and thus partly offset the aggregate unemployment impact of a shock to specialist industries. I conclude that the composition of industries and occupations affected during the Great Recession was not a key driver of the sharp rise in aggregate unemployment. (JEL E24, J22, J24, J63, J64)

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†PhD Candidate, Institute for International Economic Studies, Stockholm University. E-mail: saman.darougheh@iies.su.se. Web: https://sites.google.com/view/sdarougheh

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 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.

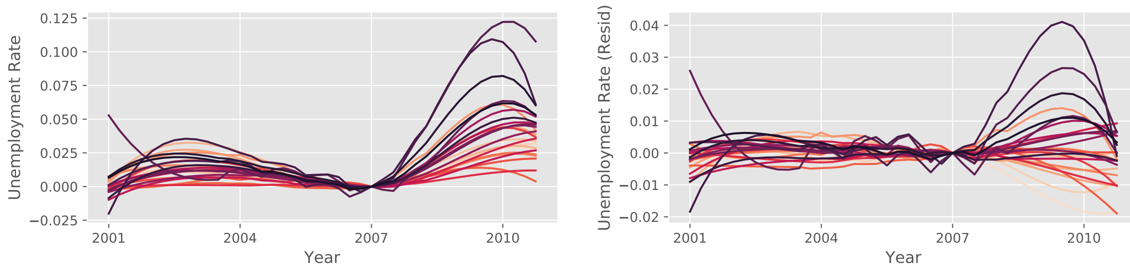
There are many potential dimensions of mismatch, and they all require some adjustment friction that prevents job seekers from adjusting to the requirements of the vacancies. To see which dimensions are most important in explaining unemployment, I carry out an empirical investigation that lets the data 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 is among the most important predictors of their unemployment status[1]. This is in line with the mismatch idea: Occupation-specific human capital and occupational licensing might impede the unemployed from changing their occupation in response to labor demand in other 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 difference could potentially be explained by the industries that employ workers in these occupations: Construction-related occupations simply have larger unemployment responses because the construction industry faced a large downturn during the recession. The right-hand panel shows that this is not the case: I residualize the individual-level unemployment status with individual demographics and full interactions of industry, state and year. Yet, after controlling for all these factors, occupations still display heterogenous unemployment dynamics during the Great Recession.

In this paper, I provide a novel explanation for occupation-specific unemployment responses to aggregate shocks. I use the notion of task-based human capital (Gathmann and Schönberg, 2010) to distinguish between occupations whose tasks are specialized and used

[1]For details on the empirical exercise see Appendix B.

Figure 1: Occupations responded differently during great recession



Left: Occupation-specific unemployment rates. Right: Occupation-specific unemployment rates, residualized against individual demographics, and all combinations of industry, state and year fixed effects. All unemployment rates fit through a Savitzky-Golay filter and normalized in 2007. Data: CPS.

by very few industries, from those whose tasks are general and used in many different industries. I call occupations with more general tasks "broader" occupations. Previous research has found that a larger share of human capital is occupation-specific than industry-specific (Kambourov and I. Manovskii, 2009). This implies that unemployed are c.p. 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 to sample job offers from, I argue that they are less dependent on any single industry and thereby better insured against industry-specific shocks.

I measure each the broadness of each occupation using the dispersion of its workers across industries. Then, I estimate the extent to which occupation-specific broadness dampened the impact of the Great Recession on the unemployment risk using data from the CPS. 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 occupation's unemployment response 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 in that period, and find that the job-finding rates of broader occupations were up to 38% higher than those of specialists.

In the Great Recession, the pool of unemployed consisted of much more specialized workers than in previous recessions. As I show in the empirical section, the unemployment responses for specialized workers during the Great Recession were much higher. Does this suggest that the disproportionally large shock to workers in specialist occupations contributed to the strong rise in unemployment during the Great Recession? This hypothesis is in essence a microfoundation of mismatch unemployment: Unemployed are "stuck" in their occupation. A shock to an industry that hires specialists ("specialist industry") will cause mismatch unemployment since these unemployed are unable to respond to the relatively higher demand in other industries that have no use for their specialized occupation. In contrast to that, shocks to industries that employ broad individuals ("broad industries") should cause less mismatch unemployment: These shocks will transmit to workers that can relocate to unaffected industries without changing their occupation, and who are hence less mismatch-prone.

To test that theory, I propose a model that features frictional unemployment, frictional mobility, and a continuum of occupations that are either specialized and employable at a single industry, or broad and employable at a continuum of industries. Every occupation is a Lucas and Prescott (1974) type island with a Diamond-Mortensen-Pissarides (DMP) style labor market. 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 on specialist occupations, and broad occupations' labor markets 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.

Surprisingly, these cross-sectional results do not imply that shocks to broad industries lead to smaller aggregate unemployment responses. 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 workers is proportional to the broadness of the occupation: An occupation that is employable in e.g. 5 industries will only be affected by 1/5th of each industry-specific shock, but that shock will affect 5 times as many individuals. The difference between shocks to broad or specialist industries then boils down to whether strong shocks to few workers lead to more aggregate unemployment, or 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 that concentrate on the broad industries.

The model predicts that recessions in more mismatch-prone sectors 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 Şahin et al. (2014) who show empirically that the degree of mismatch was not worse during the Great Recession than in other recessions.

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 tasks. 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 on 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. Kambourov and Iourii Manovskii (2009) first demonstrated that more human capital is occupation 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) on Portuguese administrative data.

Conceptually, the transferability of human capital relates to the structure of labor markets: Within which boundaries are unemployed searching for jobs? While Nimczik (2016) estimates labor markets non-parametrically, human-capital based approaches provide testable theoretical foundations. Using the task-based approach, Macaluso (2016) finds that unemployed 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 by what dimension of portability of human capital we relate to mismatch unemployment during the Great Recession. Relatedly, Gottfries and Stadin (2016) suggest that mismatch is a more important determinant of unemployment than imperfect information. A complementary story to human-capital based mismatch is geographical mismatch: Yagan (2016) shows that the convergence of geographical labor markets hit by an asymmetric shock is slow, suggesting that geographical mismatch contributes to employment responses.

Instead of looking at cross-sectional heterogeneity in mismatch unemployment during the Great Recession, one might compare total mismatch unemployment during the Great Recession with that 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 from other recessions. My quantitative results support that finding: Shocks to more mismatch-prone labor markets will lead to a higher variance of unemployment responses across labor markets, but not larger unemployment responses. 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 (2013) and Helm (2016). 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 heterogenous geographical presence of industries across labor markets. While they focus on homogenous industry exposure on 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 I. Manovskii (2009) model mismatch as caused by frictional mobility across frictionless labor markets. Shimer and Alvarez (2011) develop a tractable framework in which relocation costs time and hence raises unemployment. All these environments are stationary economies: Individual labor markets are affected by idiosyncratic shocks that wash out in the aggregate. In these papers, mobility is either random, or local labor markets are non frictional. I contribute to this literature by developing an environment in which individuals move to the best available occupation during relocations, and local labor markets are DMP islands. In Pilossoph (2013) and Chodorow-Reich and Wieland (2018), 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 human capital

This section defines the concept of specialized human capital, and introduces the link to unemployment risk. Firms are grouped into industries depending on what type of goods they produce, while workers are grouped into occupations depending on what type of tasks they typically perform at work.

More specifically, allow me to juxtapose the case of managers and carpenters. Managers' typical tasks are team-leadership and strategy-planning, and used by firms in many different industries in their production process. Electricians' typical tasks are installation and maintaining of wires and electrical equipment. These tasks are used in much fewer industries, mainly by firms in the construction industry. I categorize the broadness of an occupation by the degree to which the demand for their typically performed tasks are well-spread across many industyries. The exemplary managers would be broader than the engineers.

Notice that broadness is a moment of the IO 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 occupation-level broadness will change.

2.1 Broadness and unemployment risk

Notice that *conceptially*, broadness is defined via the production network, and not in relation to unemployment risk. However, it may have implications for unemployment risk.

Take again the case of electricians and managers. Assume that both are employable by the construction sector, but the managers also are employable in finance. In this very simplistic example, the construction sector has with equal probability either low or high number of hires $h_c \in \{x, 2x\}$ from each occupation, while finance hires $h_f = x$ in each state of the world. Consider a two-period setup where in period 1 agents have to choose between the two occupations, and in period 2 random hiring realizes. Given labor force ℓ_o and hires h_o, an occupations job-finding probability f in a frictionless environment is h_o/ℓ_o, when we ensure $h_o < \ell_o, o \in \{e, m\}$. Assume that all workers get a fixed wage $w > b$, where b denotes the worker's outside option.

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

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

$$
\begin{aligned}
U_e = U_m \Rightarrow \mathbf{E}[f(\ell_e, h_c)] &= \mathbf{E}[f(\ell_m, h_c + h_f)] \\
\Rightarrow \ell_e &= \frac{3}{5}\ell_m \\
\mathrm{Var}\left[f(\ell_e, h_c)\right] - \mathrm{Var}\left[f(\ell_m, h_c + h_f)\right] &= \frac{1}{2}\left(\frac{125}{9} - 13\right)\left(\frac{x}{\ell_m}\right)^2 > 0
\end{aligned}
$$

As shown above, an equal average job-finding rate ensures that the occupation with more volatile hires also has a more volatile job-finding rate. Here, the fraction of unemployed is equal to those that did not find a job, $u = 1 - f$. Therefore, broader occupations both have less volatile job-finding rates and less volatile unemployment rates. This result extends to a dynamic setup as long as separation rates are not correlated with broadness.

If a productivity shock enforces a negative correlation between hires and separations, the result is even stronger in a dynamic setup.

In the example, one of the industries had constant hires. One can show that broader occupations have less volatile unemployment rates even if hires in all industries are random. This is true as long as hires are not perfectly correlated across all industries.

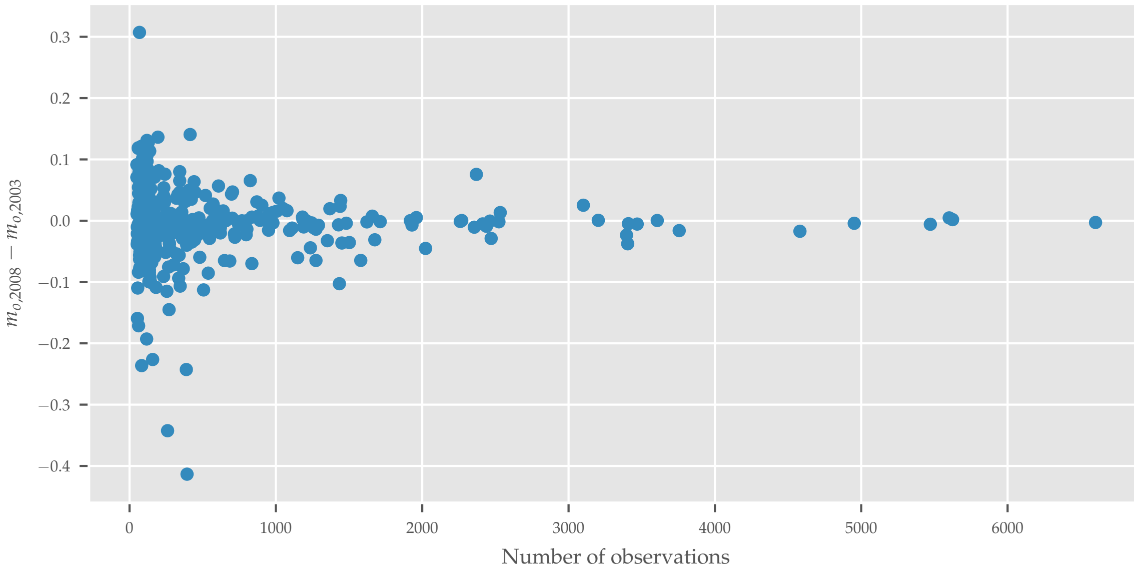
Several general equilibrium effects potentially dampen these effects. First, individuals might adjust their occupation after the shock has realized. The degree to which this happens depends on the costs of changing occupation, among other the opportunity-cost of not using their occupation-specific human capital. Second, individuals might not be willing to change their industry, if they have accumulated high human capital in their previous industry. While Kambourov and I. Manovskii (2009) show that on average there is less human capital associated with industries than occupations, this need not be true for all occupation-industry pairs. Third, as workers in more specialized occupations are "stuck", firms that do employ them might be able to bargain lower wages. This could lead to higher profits, and thereby more jobs in industries that hire from specialized occupations. Finally, prices of industries that employ more specialized occupations might interact with the aforementioned profit response.

In the remainder of this paper, I will first show empirically that despite the potential general equilibrium interactions, broadness does provide an insurance value in response to aggregate shocks. Then, I will develop a general equilibrium model that incorporates these effects, confirm that broadness does provide insurance-value also in general equilibrium, and perform aggregate shocks.

2.2 Measuring broadness

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

Figure 2: Measured broadness does not change for occupations with many observations



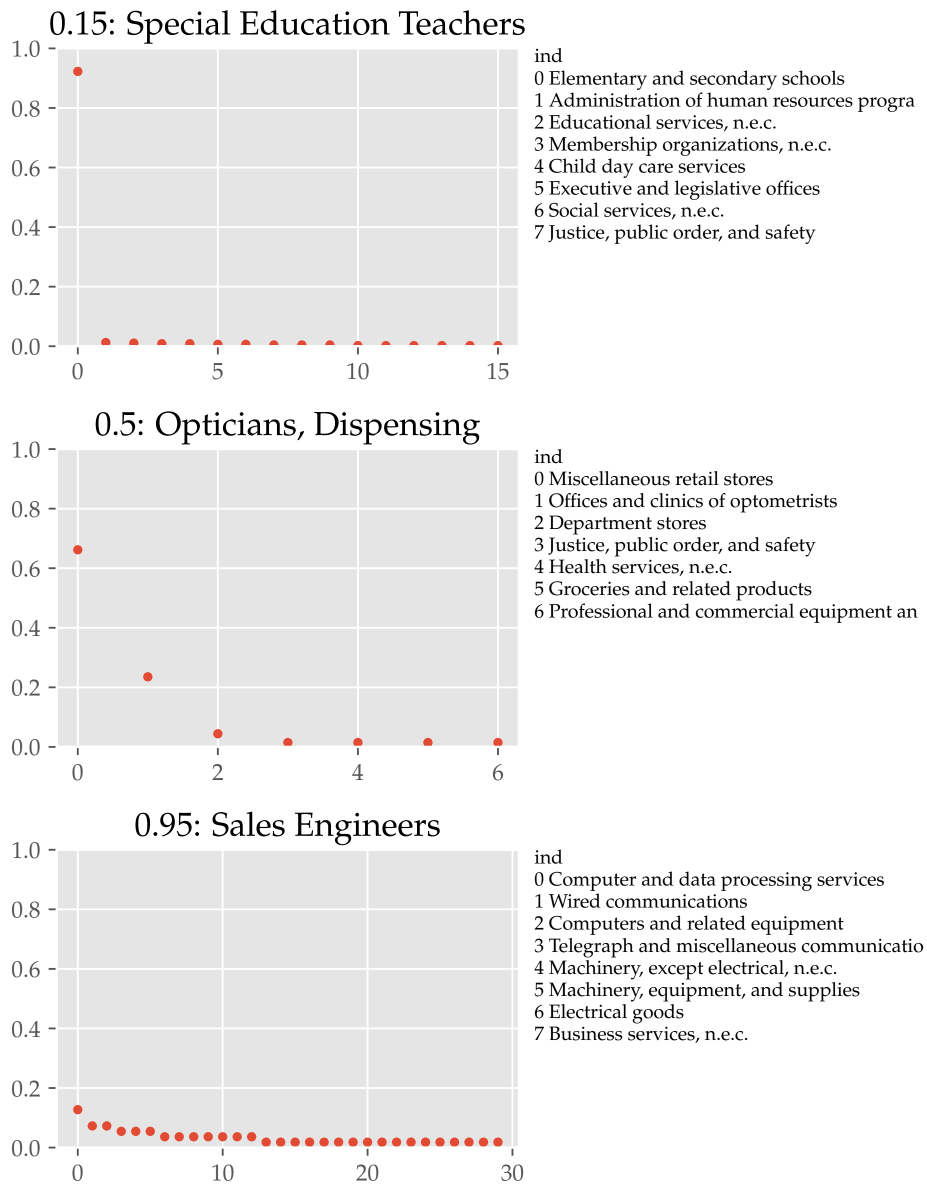
For each occupation, the difference in measured broadness between 2008 and 2003 is plotted against the *minimum* number of observations for that occupation in either year.

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

For the remainder of this section, I will describe the morphology of broadness. First, figure 2 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 contributed to measurement error and less to actual structural change. This is in line with an argument that firms cannot change their production function very quickly and hence do not respond to short-run fluctuations in the composition of labor supply and distribution of wages (Sorkin, 2015). Therefore, unless indicated differently, in the remainder of the paper, I will use several years of data to compute a more precise estimate of broadness.

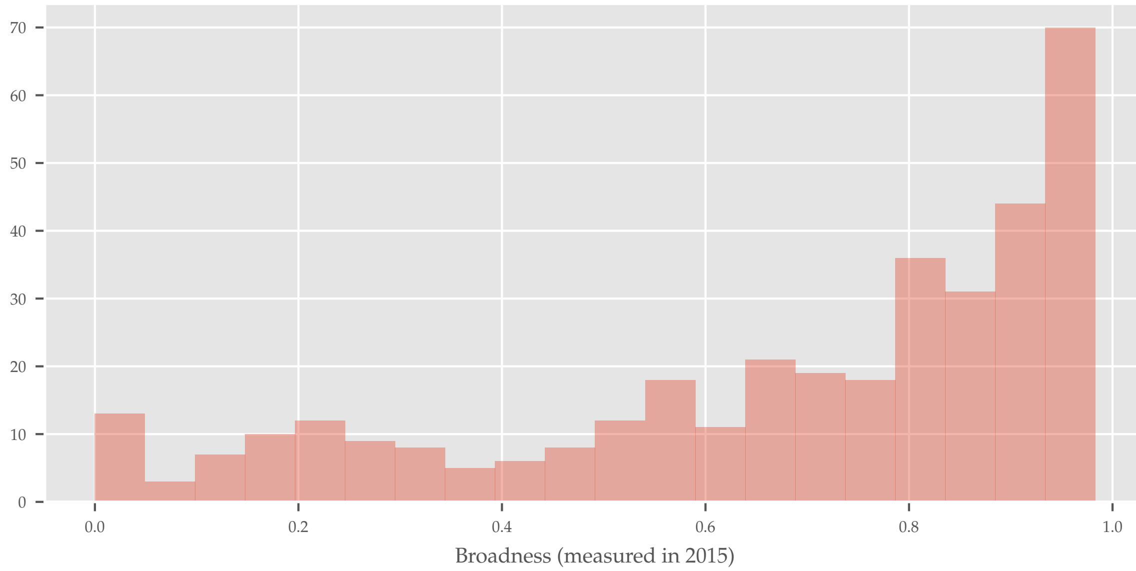
To provide some intuition for different employment structures that mask behind the

Figure 3: Three exemplary occupations across the support of broadness



Broadness for three exemplary occupations with low (0.15), intermediate (0.5) and high (0.95) levels of broadness. For each occupation, the industries on the right list the industries with the highest employment shares.

Figure 4: Distribution of occupations across broadness



Broadness has full support, and most occupations are very broad.

one-dimensional measure of broadness, Figure 3 plots the cross-sectional distribution of employment for teachers, opticians and sales engineers. Note that teachers, like most specialized occupations, have most their employment in a single industry. Opticians mostly work in retails and clinics. As most very broad occupations, sales engineers work in a large variety of industries – the highest of which only contributes to an employment share of 18%.

I plot the distribution of broadness across occupations in Figure 4. While broadness has full support, most occupations are very broad.

3 Empirical investigation

Having developped a measure of broadness, I will devise an empirical strategy to identify the relationship between broadness, and the change in unemployment rates during the great recession.

3.1 Did broader occupations have a lower unemployment response during the great recession?

We focus at the impact of the great recession, and analyze whether less broad occupations had a higher unemployment response during the great recession. Naively, one would want to regress occupation-level unemployment *responses* during the great recession against occupation-level broadness. However, occupations vary among other dimensions than their industry-network. To isolate the impact of broadness from other occupation-fixed characteristics, I use that occupation-industry networks vary geographically. For example, consider programmers in New York City with those in Silicon Valley: The former will to a large extent be employable in the finance sector, while the latter have access to many more industries, making them differentially broader. This allows me to compute broadness $m_{o,z}$ for each occupation o and state z, as in (2). To reduce noise, I will group occupations into 26 major groups, and use several years of data prior to the recession to compute $m_{o,z}$.

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

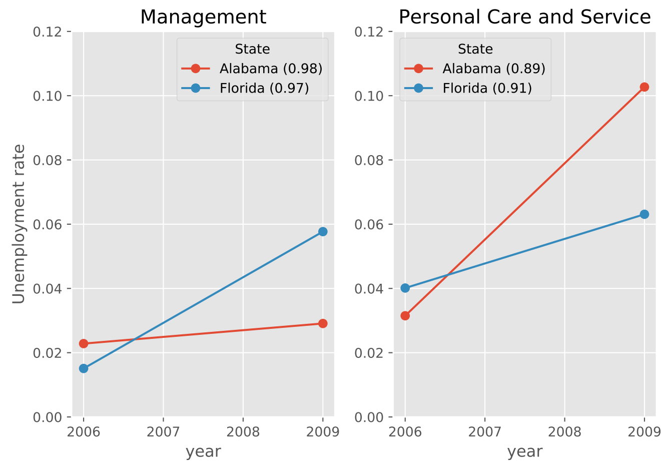
My identification setup is schematized by Figure 5. For each occupation and state, I regress the difference in unemployment rates between 2006 and 2010 against the occupation-state level of broadness. Broadness is computed using data between 2002 and 2006. I use data prior to the Great Recession to prevent 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 2002.

I choose 2006 and 2010 two years since they characterize the peak and trough of unemployment during that period. The regression setup is summarized by (3).

$$
u_{o,z,2010} - u_{o,z,2007} = \alpha m_{o,z} + \beta_z \text{state}_z + \eta_o \text{occupation}_o + \epsilon_{o,z} \tag{3}
$$

Figure A.2 draws the regression line against all observations. Table 1 summarizes the empirical results after standardizing $m_{o,z}$. The baseline result is displayed in column

Figure 5: The regression setup



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

(3): On average, one standard deviation increase in broadness is associated with a reduced *increase* in the unemployment To put this into perspective, the mean increase in occupation-state specific unemployment rates between 2007 and 2010 weighted by cell sizes was by 0.034 (unweighted: 0.04), implying that 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 estimates in columns (2).

Finally, I controll for two types of heterogeneities across occupation$\times$state bins: Individual level characteristics and industry of last employment, interacted with state. The former controls for demographics that are potentially associated with a lower reemployment rate. The latter controls for differential exposure of different industries to the recession, potentially by state. To be precise, in each year, I residualize individual-level broadness and unemployment status for a quadratic term in age, three racial groups, three education groups, two sex groups, and 223×51 industry-by-state groups. I then compute cell-means

Table 1: Broader occupations' unemployment rates less responsive to recession

Dependent variable: Difference in unemployment rates between 2007 and 2010

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

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

for each state, occupation and year, and then compute the inter-year difference as before. The findings are summarized in column (4) in Table 1, and scattered in Figure **??**: 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 variation post-residualization at the occupation×state dimension is picked up 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×state and influence unemployment changes that are picked up by $m_{o,z}$.

To provide more evidence, the next section will perform individual-level regressions on a subset of the data.

3.2 Did unemployed in broader occupations have a higher job-finding rate during the great recession?

So far, we have seen that at the occupation-level, broadness is associated with a reduced unemployment response during the great recession. While the occupation-level aggregates have described the relationship between broadness and unemployment responses, I will now find evidence for the mechanism at play. One key role of broadness in differential unemployment responses comes from the job-finding margin: Unemployed in broader occupations can sample job offers from more industries and hence have a higher matching rate.

In this section, we will test this relationship: Did unemployed in broader occupations have a higher job-finding rate during the great recession? Naively, one would run a regression with individual-level job-finding probabilities on the left-hand side, and the individual's broadness (as measured in the previous occupation) on the right-hand side. As before, unobserved occupation characteristics that correlate with occupation-level broadness will lead to biased results, and we will use occupation$\times$state-level broadness to difference out occupation-fixed effects.

Another potential bias comes from non-random selection. Unemployed ability is expected to correlate with market tightness: It is reasonable to expect that finding a job is easier in labor markets with lower unemployment rate. Therefore, a randomly drawn unemployed from a low-unemployment labor market is expected to be less able than a randomly drawn unemployed 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 from a broader occupation are on average more less able than those drawn from a less broad occupation. This selection bias will be weaker in labor markets with a larger inflow of unemployed. Therefore, I will focus here on unemployed coming from the construction sector. Two thirds of these unemployed had been employed in construction-related occupations that would have aggregated into a single major occupation. Therefore I am now using the unaggregated occupation definition of which there are 303 in my sample. However, as these occupations are unevenly represented, most of the power will come from about 30 occupations with more than 500 observations.

The setup is then as follows: fix any particular month, and focus at all unemployed individuals whose last employment was in the construction sector. Figure **??** displays the distribution of broadness across states for three typical occupations of the construction sector. Compute for all of these the probability of being employed in the subsequent months. 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

Table 2: Job-finding rates are higher for individuals in broader occupations

Dependent variable: Monthly probability of being hired

	(1)	(2)	(3)	(4)	(5)	(6)
(std, over all) Broadness	-0.0175***	0.00838	0.0724**	0.0794***	0.0600*	0.0714**
	(0.00672)	(0.0151)	(0.0291)	(0.0289)	(0.0327)	(0.0339)
Occ FE	Yes	Yes	Yes	Yes	Yes	Yes
State x Month FE	No	No	No	No	Yes	Yes
Indiv Demographics	No	No	No	Yes	Yes	Yes
Only male	No	No	No	No	No	Yes
Observations	335290	43487	7865	7864	7756	7173

Data from CPS. Sample: Unemployed in construction sector in 2008 and 2009. Standard errors in parentheses. SE two-way clustered at state and occupation level. *** significant at 0.01, ** at 0.05, * at 0.10.

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. To do so, I create one fixed-effect for each state and month. The regression I am estimating is given by (4).

$$f_{j,o,z,t} = \alpha m_{o,z} + \beta_o \text{occ}_o + B_1 X_j + \gamma_{z,t} \text{state x month}_{z,t} + \epsilon_{j,o,z,t} \tag{4}$$

Table 2 shows the results. Columns (1)-(4) build the regression by adding controls, column (5) shows the main specification. The average monthly job-finding rate in that period for that sample amounted to 0.18. One standard-deviation increase in job-finding rates corresponds to an increase in monthly job-finding rates of 0.06, or one third. Column (5) is only significant at the 10% level, but this lack of precision can be attributed to the relatively small number of observations that has to carry both many fixed effects, and a binary outcome variable that is quite heterogenous. To make this point, I focus in column (6) on the subset of males. The point estimate increases to 0.07 (38%), while standard errors stay the same.

4 Model

Now we want to understand whether the documented dampening effect of broadness onto unemployment responses implies that recessions that indirectly affect broader occupations are less potentent than those that concentrate more on narrow occupations.

Empirically, the difference in average broadness of unemployed across the dot-com recession and the great recession, together with the differential aggregate unemployment response suggests so. However, it is difficult to devise a clean empirical strategy to compare across two recessions. Therefore, I build a model that is supposed to address this question.

The model needs to feature occupations that differ in their level of broadness, hence it will feature both industries and occupations with a non-symmetric production network. Unemployment will be caused by frictional labor markets in each occupation. The possibility of relocation across occupations limits the impact that any occupation-specific effect may have. To show that my results are robust to that, I allow for costly migration across occupations. First, I will develop the model's stationary environment. Then, I subject it to unexpected productivity shocks that differentially affect occupations by their broadness, to shed light on the original question.

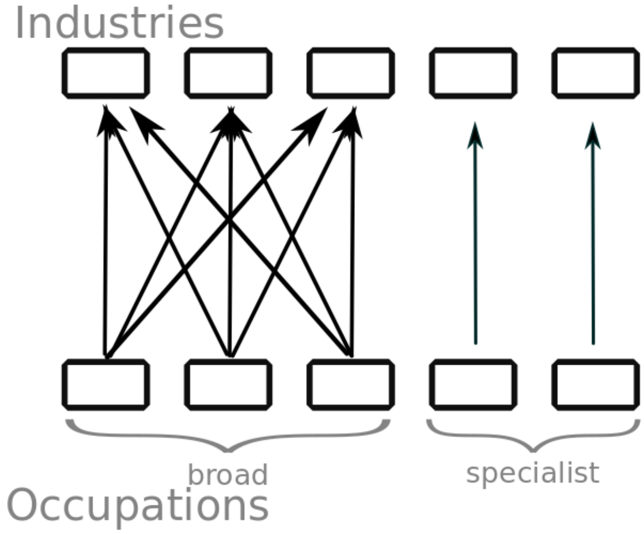
The discrete-time model consists of several layers of building blocks.

In the aggregate, final output is produced by aggregating the output from a continuum of industries that are hit by idiosyncratic shocks. The model is stationary: All aggregate variables such as total output and average unemployment will stay constant over time.

In the meso level, there exists a continuum of occupations and industries. Industries produce using an intermediate good (a labor service) from the occupations. Occupations are not ex-ante identical: They differ in the demand structure for the output that they produce.

The model features two type of occupations. A measure γ of occupations are labelled "broad": They provide a service that is employed by a large number of industries. A measure $1-\gamma$ of occupations are labelled "specialists" and provide a service that is only used by a single industry. This IO network is illustrated in Figure (6). Idiosyncratic productivity shocks hit industries in each period. Because of their distinct demand structure, broad and specialist occupations are affected by these shocks differentially.

Figure 6: The input-output structure between occupations and industries



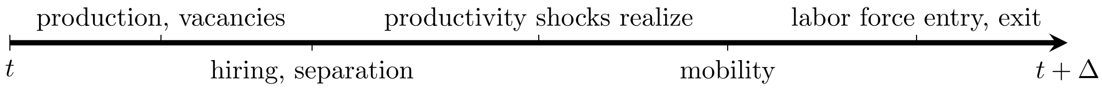
At the micro level, each single occupation is made up by Diamond-Mortensen-Pissarides type frictional labor market with occupation-specific firms and workers who inhabit that occupation. One-worker firms in each occupation produce the intermediate good that is used by industries to produce an industry-specific output. One can think about these occupations as islands in the Lucas and Prescott (1974) sense. Mobility across islands is frictional: Unemployed can change islands only after incurring a fixed cost that is meant to capture occupation-specific human capital and red tape. Additionally, employed and unemployed exit the labor force at exogenous rate ζ. New workers enter the labor force at the same rate, decide which occupation to enter first, and beginn their careers unemployed.

I will now describe these building blocks in more detail.

4.1 Final sector

There is a measure 1 of industries that each produces intermediate output $y(i)$. The final sector produces aggregate output Y by integrating these with elasticity θ.

Figure 7: Timing of events within each period



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

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

4.2 Specialist industries

Each industry i permits a competitive equilibrium in which firms produce the intermediate output $y(i)$ at zero profit. Each specialist industry is linked to a unique specialist occupation whos input $z(i)$ its firm use for production. While the environment is dynamic, I ignore time indices until necessary for ease of exposition.

$$y(i) = A(i)z(i) \tag{7}$$

where $A(i)$ is the industry-specific idiosyncratic productivity shock. Denote the industry-specific and occupation-specific prices as $p(i)$ and $p_z(i)$. Perfect competition implies

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

4.3 Specialist occupations

Each occupation is made up by a DMP environment. The timing is as in Figure 7. First, production happens, followed by separations and hiring. Then, industry-specific productivity shocks materialize. Unemployed then have the option of changing occupation. Finally a share ζ of workers exits the labor force, and are replaced by a new cohort.

The main innovation compared to the canonical DMP setup is labor market mobility after the realization of productivity shocks.

I will first describe this reallocation problem, and then describe the production setup.

Denote the relevant state variable of each specialist occupation as Ω - we will soon establish what it consists of. Note that all the following variables are particular for specialist occupations and not broad occupations; I will drop a subscript s for ease of notation.

Denote the value of staying in such an occupation as $U^{\text{stay}}(\Omega)$. I assume that relocation is targeted and workers have perfect information: If they decide to leave, they will relocate to the occupation that delivers the highest attainable utility $\overline{U}$. As they have to pay a fixed cost k, we can define the value before the leaving stage as

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

Unemployed and vacancies match in a search market with tightness $m(\Omega)$. The value of staying consists of unemployment benefits b and either becoming employed (E) at rate $f(m(\Omega))$, or staying unemployed and being allowed to change occupation again. Both employed and unemployed workers exit the labor force at exogenous rate ζ with terminal value 0. This implies that the effective discount rate ρ is a sum of both impatience and the exit rate: $\rho = \tilde{\rho} + \zeta$.

$$U^{\text{stay}}(\Omega) = b\Delta + e^{-\rho\Delta}\left[(1 - e^{-f(m(\Omega))\Delta})\mathbb{E}[E(\Omega')] + e^{-f(\Omega')\Delta}\mathbb{E}[U(\Omega)]\right] \tag{9}$$

Each specialist occupation o produces an output that is used by a single industry. Each one-worker firm in this occupation produces one unit of output. To price its output, we need to chain the demand function for the final good (6) with those of the industry (8) to get

$$p_s(o) = A(o)\left(\frac{Y}{A(o)(1-u(o))\ell(o)}\right)^{\frac{1}{\theta}}$$

Realizing that Y and $\overline{U}$ will be a constant, the three state variables to each occupation's recursive problem are hence its occupation-specific unemployment rate and labor force, and its connected industry's productivity: $\Omega = \{a, u, \ell\}$.

Let E and J denote the value functions for employed and firms: Matches produce one unit of output sold at price $p_z(\Omega)$, which the firm receives and pays the worker wage $w(\Omega)$.

Matches separate naturally at rate δ, when the worker immediately becomes the option of changing occupation U, and the firm simply disappears. As indicated before, matches separated due to labor force exit yield a continuation value of zero for both employed and firms.

$$E(\Omega) = w(\Omega)\Delta + e^{-(\tilde{\rho}+\zeta)\Delta}\mathbb{E}\left[e^{-\delta\Delta}E(\Omega') + (1-e^{-\delta\Delta})U(\Omega')\right] \tag{10}$$

$$J(\Omega) = [p_s(\Omega) - w(\Omega)]\Delta + e^{-(\tilde{\rho}+\zeta+\delta)\Delta}\mathbb{E}[J(\Omega')] \tag{11}$$

Vacancies pay a fixed cost c each period and match at rate q. Free entry determines the market tightness:

$$0 = -c\Delta + (1 - e^{-q(m(\Omega))\Delta})e^{-\tilde{\rho}\Delta}\mathbb{E}[J(\Omega')] \tag{12}$$

Wages satisfy continuous Nash bargaining with workers' bargaining power β.

$$\beta J(\Omega) = (1-\beta)(E(\Omega) - U(\Omega) \tag{13}$$

It is left to describe the transition for Ω. For now, we will take the law of motion for the labor force $g_{l;s}(a', a, u, \ell)$ as given. Productivity a follows an AR(1) process, and the law of motion for the unemployment rate has to be corrected for changes due to migration:

$$g_{u;s}(a, u, \ell, \ell') = 1 - e^{-\zeta\Delta}(1 - \tilde{u}(a, u, \ell))\frac{\ell}{\ell'} \tag{14}$$
$$\tilde{u}(a, u, \ell) = (1 - e^{-\delta\Delta})(1-u) + e^{-f(m(a,u,\ell))\Delta}u$$

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

To summarize the specialist occupations, we define a partial equilibrium.

Definition 1. *A* Stationary Recursive Specialist Occupation Partial Equilibrium *is given*

- *A price function* $p_{z;s}(\Omega)$
- *A law of motion for labor* $g_{\ell;s}(\Omega)$

- *A leaving utility* $\overline{U}$

and contains

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

such that

1. *Given* $\{g_{u;s}, w\}, \overline{U}, Y$*:* $\{J_s, E_s, U_s^{stay}, U_s\}$ *satisfy* (9)-(11)
2. *Given* $\{J_s, E_s, U^{stay}\}$*: Wages satisfy Nash bargaining* (13)
3. *Given* $\{J_s\}$*:* m *satisfies free-entry* (12)
4. *Law of motion* $g_{u;s}$ *is consistent with* $\{m\}$ (14)

4.4 Broad industries

Firms in each broad industry i employ a CRS production function with elasticity of substitution θ_b. They use labor services from all broad occupations:

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

where as before, $A(i)$ is 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. As before, there is perfect competition in each sector. The firms' problem is to optimize their input composition taking as given the price vector of inputs and their level of output (15).

$$\begin{aligned} &\min_{\{z(i,o)\}_o} \int_{[0,\gamma]} p_z(o) z(i,o) do \qquad (15) \\ &\text{s.t. } y(i) = A(i) \left[\int_{[0,\gamma]} z(i,o)^{\frac{\theta_b - 1}{\theta_b}} do \right]^{\frac{\theta_b}{\theta_z - 1}} \end{aligned}$$

The appendix shows that the solution is given by (16), where P_x is the price-index associated with producing $x(i)$. Optimal input composition is identical across industries, as they only differ in their productivities. This difference in productivities only affects their level of output, but not the composition of $x(i)$.

$$\frac{z(i,o)}{x(i)} = \left(\frac{P_x}{p_z(o)}\right)^{\theta_b}, \forall i, o \tag{16}$$
$$P_x = \left[A_x \int_{[0,\gamma]} p_z(o)^{1-\theta_b}\right]^{\frac{1}{1-\theta_b}}$$

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

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

The question remains as to how x is distributed across industries. The appendix uses feasibility (17) and a rewritten firm's problem to show that each industry will use a share of total intermediate goods that relates to both their individual productivity $A(i)$, an average productivity-index across broad industries A_b, and the elasticity of substitution across industries θ (18).

$$x = \int_{[0,\gamma]} x(i)di \tag{17}$$

$$\frac{x(i)}{x} = \left(\frac{A(i)}{A_b}\right)^{\theta-1} \tag{18}$$
$$A_b = \left[\int_{[0,\gamma]} A(i)^{\theta-1} di\right]^{\frac{1}{\theta-1}}$$

Finally, the appendix shows how one can use this result, together with prices implied by perfect competition (19), to compute P_x in closed-form (20).

$$p(i) = \frac{P_x}{A(i)} \tag{19}$$

$$P_x = A_x \left(\frac{Y}{x} A_b^{\theta-1} \right)^{\frac{1}{\theta}} \tag{20}$$

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

Definition 2. *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* $\{p_z(o)\}_o, P_x$*,* $\forall i$ (16)
2. *Industry choice: Intermediate output consistent with zero profits,* $\forall i$ (19)
3. *Feasibility:* $x(i)$ *add up to* x (17)

4.5 Broad occupations

One-worker firms and unemployed in broad occupations look similar to those in specialist occupations. The main difference lies in the demand function for their good. The price of the output produced by each industry i chains the contribution towards the intermediate good x, and the price of that intermediate good:

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

P_x will be constant in a stationary environment, and the relevant state variables for each broad occupation remain $\Omega_b = \{u, \ell\}$. Note that this is intuitive: The only difference between broad and specialist occupations is that the former are not depending on any particular occupation, hence the absence of any productivity in their state vector. Taking that into account, the structure within broad occupations is similar to that of narrow occupations: The valuefunctions in this environment are given by (21)-(23),

$$J_b(\Omega_b) = [p_b(\Omega_b) - w_b(\Omega_b)]\Delta + e^{-(\rho+\delta)\Delta} J_b(\Omega_b') \tag{21}$$

$$E_b(\Omega_b) = w_b(\Omega_b)\Delta + e^{-\rho\Delta}\left[e^{-\delta\Delta} E_b(\Omega_b') + (1 - e^{-\delta\Delta}) U_b(\Omega_b')\right] \tag{22}$$

$$U_b^{\text{stay}}(\Omega_b) = b\Delta + e^{-\rho\Delta}\left[e^{-f(m_b(\Omega_b))\Delta} U_b(\Omega') + (1 - e^{-f(m_b(\Omega_b))\Delta}) E_b(\Omega_b')\right] \tag{23}$$

where

$$U_b(\Omega_b') = \max\{U_b^{\text{stay}}(\Omega_b'), \overline{U} - k\}$$

Note that moving within or across broad and specialist occupations is equally costly: Broadness is defined via the diversity of industries that demand an occupation's inputs. There is ex-ante no reason to believe that skill requirements are similar for broad and specialist occupations, which would have suggested to impose different migration cost k for broad-broad and broad-specialist migrations. As a result, the highest attainable utility for unemployed $\overline{U}$ is the same for individuals that are currently in broad, and in specialist occupations.

Free-entry is similar to before:

$$0 = -c\Delta + (1 - e^{m_b(\Omega_b)}) e^{-\tilde{\rho}\Delta} J_b(u, \ell) \tag{24}$$

Laws of motion similar as in the specialist case:

$$\begin{aligned} \tilde{u}_b(u, \ell) &= (1 - e^{-\delta\Delta})(1 - u) + e^{-f(m_b(u,\ell))\Delta} u \\ g_{u;b}(u, \ell, \ell') &= 1 - e^{-\zeta\Delta}(1 - \tilde{u}_b(u, \ell)) \frac{\ell}{\ell'} \end{aligned} \tag{25}$$

Also here wages are determined by Nash bargaining:

$$\beta J_b(\Omega_b) = (1 - \beta)(E_b(\Omega_b) - U_b(\Omega_b)) \tag{26}$$

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

- *Law of motion* $g_{\ell;b}(\Omega_b)$,
- *Prices and wages* $\{p_b(\Omega_b), w_b(\Omega_b)\}$,
- *Leaving threshold* $\underline{U}$

a collection of

- *Value functions* $\{J_b(\Omega_b), E_b(\Omega_b), U_b(\Omega_b)\}$,
- *Rates* $\{m(\Omega_b), u(\Omega_b)\}$
- *Law of motion* $\{g_{u;b}(u, \ell, \ell')\}$

such that

1. $\{J_b, E_b, U_b\}$ *correct given* $\{p_z, w_b\}$ (21)-(23)
2. *Law of motion for* u *consistent with* m, ℓ' (25)
3. *Wages satisfy Nash bargaining* (26)
4. *Free-entry:* $m(i)$ *consistent with* $J_b(u, \ell)$ (24)

4.6 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.

Unemployed can pay 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 an unemployed the highest expected utility. This highest utility in each sector is denoted as U_b and U_s.

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

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

As mentioned before, 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 $\overline{U}$. The present-discounted value of moving net of migration cost k will be denoted $\underline{U}$.

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

It is optimal for unemployed to leave whenever their next period's value $U_b(\Omega_b')$ or $U_s(\Omega_s')$ is below $\underline{U}$. All unemployed 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 (27). Remember that workers exit labor force at rate ζ. There are four cases to distinguish: (i) If without mobility, next period's utility would be between the boundaries $(\underline{U}, \overline{U})$, no mobility occurs. (ii) If without mobility, next period's utility would surpass the upper threshold, a mass enters with a size that will bring that utility down to exactly $\overline{U}$. Since $U_b(u, \ell)$ is strictly decreasing in ℓ, such a size always exists. Whenever next period's utility was to be below $\underline{U}$, unemployed will leave. However, since there is only a finite mass of unemployed ready to leave, this leaves two cases: (iii) all unemployed leave and utility stays at or below $\underline{U}$, or (iv) sufficiently many unemployed leave such that utility will be exactly $\underline{U}$. The law of motion for the specialist occupations' labor force (28) follows the same spirit.

$$g_{\ell;b}(u, \ell) = \begin{cases} e^{-\zeta\Delta}\ell & \text{if } U_b(g_{u;b}(u, \ell, e^{-\zeta\Delta}\ell), e^{-\zeta\Delta}\ell) \in (\underline{U}, \overline{U}] \\ x : U_b(g_{u;b}(u, \ell, \ell' = x), x) = \overline{U} & \text{if } U_b(g_{u;b}(u, \ell, e^{-\zeta\Delta}\ell), e^{-\zeta\Delta}\ell) \geq \overline{U} \\ (1 - \tilde{u}_b(u, \ell))e^{-\zeta\Delta}\ell & \text{if } U_b(g_{u;b}(u, \ell, e^{-\zeta\Delta}\ell), e^{-\zeta\Delta}\ell) < \underline{U} \\ x : U_b(g_{u;b}(u, \ell, \ell' = x), x) = \underline{U} & \text{otherwise} \end{cases} \tag{27}$$

$$g_{\ell;s}(a', a, u, \ell) = \begin{cases} \ell & U(a', g_u(a, u, \ell, \ell), \ell) \in [\underline{\mathrm{U}}, \bar{U}] \\ x : U(a', g_u(a, u, \ell, \ell' = x), \ell' = x) = \bar{U} & U(a', g_u(a, u, \ell, \ell), \ell) > \bar{U} \\ \ell(1 - \tilde{u}(a, u, \ell)) & U(a', 0, \ell(1 - \tilde{u}(a, u, \ell))) < \underline{\mathrm{U}} \\ x : U(a', g_u(a, u, \ell, \ell' = x), \ell' = x) = \underline{\mathrm{U}} & \text{else if } U(a', g_u(a, u, \ell, \ell), \ell) < \underline{\mathrm{U}} \end{cases} \tag{28}$$

4.7 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.

4.8 Connection between industries and occupations

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

$$A(i) \sim \log \text{Normal}(\text{s.t. stationary AR (1)}) \qquad \forall i \in [0,1] \tag{29}$$

$$(u(i), \ell(i)) \sim G_s(a, u, \ell | a = a(i)) \qquad \forall i \in (\gamma, 1] \tag{30}$$

Industries $i < \gamma$ 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:

$$z(o) = (1 - u(o))\ell(o)\,, \forall o \in [0,1] \tag{31}$$

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

$$p_b(u, \ell) = \left(\frac{x}{\ell(1-u)}\right)^{\frac{1}{\theta_b}} P_x \tag{32}$$

$$p_s(a, u, \ell) = a\left(\frac{Y}{a(1-u)\ell}\right)^{\frac{1}{\theta}} \tag{33}$$

Feasibility in terms of labor:

$$L = \gamma \int_{\mathcal{U}\times\mathcal{L}} \ell dG_b(u,\ell) + (1-\gamma) \int_{\mathcal{A}\times\mathcal{U}\times\mathcal{L}} \ell dG_s(a,u,\ell)$$
$$L = L_b + (1-\gamma) \int_{\mathcal{A}\times\mathcal{U}\times\mathcal{L}} \ell dG_s(a,u,\ell) \tag{34}$$

where L is a parameter.

Definition 4. *A* General Equilibrium *is , given ξ, 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 consistent with industry output* (5)
2. *$z(i)$ is consistent with occupation-level output* (31)
3. *Specialist industry states consistent with specialist occupation distribution* (30)
4. *$\underline{U}$ is consistent with G_b, G_s*
5. *Prices are consistent with industry-level demand and feasibility* (32)-(33)
6. *Laws of motion for labor are consistent with $\{\underline{U}, \overline{U}\}$* (27)-(28)
7. *$\{G_b, G_s\}$ are consistent with 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 $\{Y, \{z(o)\}_{i\in[0,\gamma]}$: $\{x, x(i), p_z\}$ solve* Broad Industry PE
11. *Given $\{L_b, p_b(u,\ell), \underline{U}, \overline{U}\}$: $\{J_b, E_b, U_b, m, u, g_{u;b}\}$ solve* Recursive Broad Occupation PE
12. *Feasibility w.r.t L* (34)

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	
μ	0.000	Mean innovation, specialist log-productivity	Normalization
μ_b	0.000	Mean innovation, broad log-productivity	Normalization
θ	4.500	Elasticity, Final sector	
Network			
A_x	2.337	Productivity (x)	Labor force distribution
γ	0.680	Measure of broad occupations	CPS
$\overline{\theta}$	0.500	Elasticity, broad industries	High complementarity
Occupations			
A	1.355	Matching productivity	Literature
α	0.510	Matching elasticity	Literature
c	0.117	Vacancy posting cost	Average unemployment rate
h	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	0.104	Moving cost	double foo

All rates in quarterly units.

4.9 Calibration

The model is calibrated to match relevant features of the data. Several of these are labor market

The unit of time is a quarter. To match flows in and out of unemploymnet, the length of period is smaller. Here, I trade off precision and computational complexity.

In this paper, I am making a point about differential responses between specialist and broad occupations. Broad occupations and industries differ on other dimensions that has 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 than those typically measured for aggregate productivity. 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.

Network I have empirically measured the average broadness of the economy to be 0.68, and set γ to match that average broadness. The labor-force weighted average broadness of the economy was similar, 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. The rise and fall of construction-specific demand together with relative weak outside options for blue-collar workers in the construction sector allowed me 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 is at the lower end of the distribution, I pick $\overline{\theta} = 0.5$, but will perform robustness checks for this parameter.

Occupations Shimer (2007) makes the point that perfectly competitive local labor markets can display 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 setup labor-market-level matching parameters. α is set to a median value. As explained in Shimer (2005), the level of market tightness is anyhow meaningless. I set A to his chosen value and calibrate c to match an average unemployment rate of U.

To generate reasonable unemployment responses to an aggregate productivity shock, I calibrate home production and bargaining power following Hagedorn and Iourii Manovskii (2008). While this does affect absolute responses of unemployment rates to a productivity shock, *relative* unemployment rates across occupations will not be affected.

Finally, k will the govern the rate at which workers respond to shocks by changing occupations. Unfortunately, there is no causal evidence on the link between occupation-specific shocks and exit rates. Moreover, even the unconditional rate at which unemployed change occupations is not well-documented. This is because occupation data is noisly measured. Since occupation changes are measured as differences in individual-specific occupation tags, measurement error attributes to an upwards-bias in estimated occupational transition rates. The CPS introduced dependent coding in 1995 to address this issue. However, unemployed agent's occupation tags are still measured without dependent coding. I summarize this issue in the appendix and argue that 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 unemployeds' value function, and compute the corresponding 20s and 80s percentile. k is set to match the difference in those. Notice that the resulting k is small: The costs of changing occupations are around 1/10s of the workers average quarterly wage.

4.10 Steady state

Table 4 displays key statistics of the steady state of the economy. As most of the labor force is in broad occupations and industries are substitutes, production of total output draws more from broad industries, who in equilibrium sell their intermediate goods at lower prices. However, this large difference in prices is not visible in wages: Because of free-entry into the firm market, differences in sector-level prices are basically eaten up by differential entry cost, as more vacancies enter into specialist occupations.

Table 4: Key statistics of the steady state

Moment	Value	Description
Industries		
Y	0.9585	Total output
y_b	0.5872	Total output, broad ind
y_s	0.2187	Total output, narrow ind
P_b	1.1150	Price index, broad
P_s	1.3887	Price index, specialist
Occupations		
v_b	0.3157	Vacancies, broad
$\mathbf{E}[v_s]$	0.3430	Vacancies, specialist
u_b	0.0491	Unemp, broad
$\mathbf{E}_\ell[u_s]$	0.0512	Unemp, narrow occ (weighted average)
$std[u_s]$	0.0137	Unemp, narrow occ (weighted std)
$\mathbf{E}[w_b]$	1.0007	Wage, broad occ
$\mathbf{E}[w_s]$	1.0025	Wage, narrow occ (average)
L_b	0.6823	Measure broad labor

5 Aggregate Experiments

Having set up the machinery, we will now conduct a series of experiments. In each of these, we will shock the productivity of a subset of industries for 12 quarters. After that, the change in productivity reverses, and the economy will converge back to the initial steady state. The initial shock can be thought about as a zero-probability event, often referred to as "MIT shock". As soon as the initial shock hits, all agents have perfect foresight about the remainder evolution of the process.

Section 5.1 is directed towards explaining the empirical findings: we focus on the differential responses by broadness to the same aggregate shock. In Section 5.2, we compare different recessions: Are recessions that affect mainly specialized occupations worse in terms of aggregate fluctuations?

5.1 Crosssectional Experiments

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

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

5.1.1 Indescriminate shock

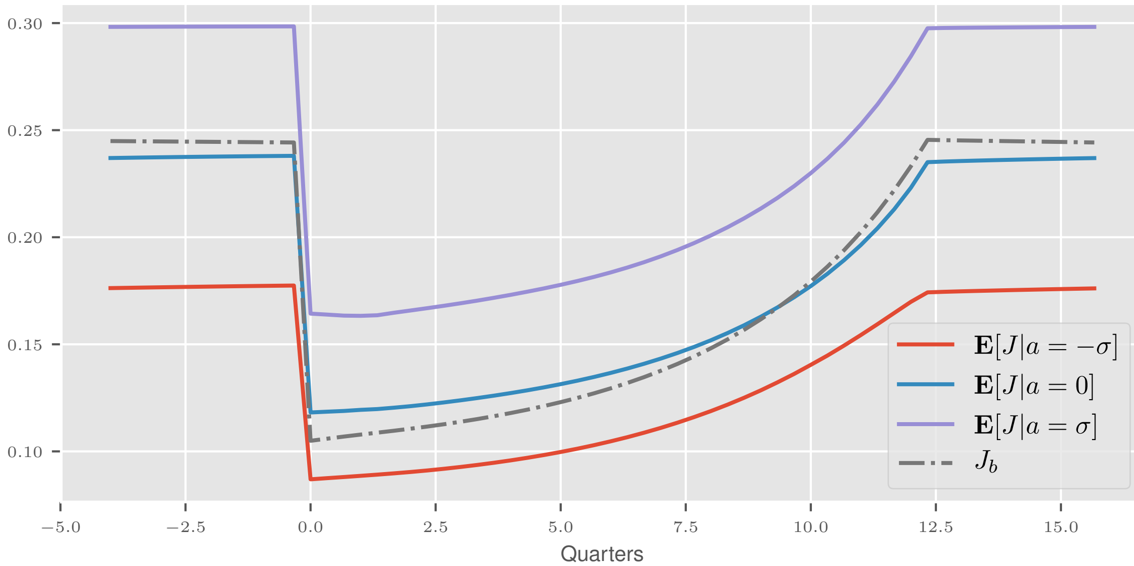
Here, we play through an experiment in which productivity in each sector is reduced for a finite number of periods. I will now denote the industry-specific shock $A(i,t)$ as a sum of an industrys-specific AR(1) process $\tilde{A}(i,t)$, and an aggregate component $A(t)$. For clarity of exposition, $A(t)$ will not dissolve geometrically. Instead, it will switch between any non-zero value during the periods of the experiment, $t \in \mathcal{T}$, and zero else. The shock structure is summarized in (35).

$$\begin{aligned} A(i,t) &= A(t) + \tilde{A}(i,t) \\ \tilde{A}(i,t) &= \phi A(i,t-1) + \epsilon_t \\ A(t) &= \begin{cases} \mu & \text{if } t \in \mathcal{T} \\ 0 & \text{else} \end{cases} \end{aligned} \tag{35}$$

As it turns out, broad occupations fare *worse* than specialists throughout the episode. Figure 8 displays the impact of the aggregate shock onto firm values at the occupation level. As the aggregate productivity enters multiplicatively with idiosyncratic productivity, firms with high idiosyncratic productivity are affected more by the aggregate shock. This leads to a compression of firm values during the aggregate shock. Firms in broad occupations face no idiosyncratic shocks as they are diversified across industries. Prior to the aggregate shock, broad firms had the same value as the median productivity specialist firms. However, their values drop more during the recession. This is because of the interaction of idiosyncratic with aggregate shocks: Specialist firms' upside from a positive shock dominates the downside from a negative shock. The riskiness of their output has positive value, which is why broad firms (who lack this value) lose more on value during the recession than their specialist counterparts.

Figure 9 separates the effects into the three main layers of the model. As all industries are affected, relative productivity changes are equal in both broad and specialist industries.

Figure 8: Interaction between aggregate and idiosyncratic shocks



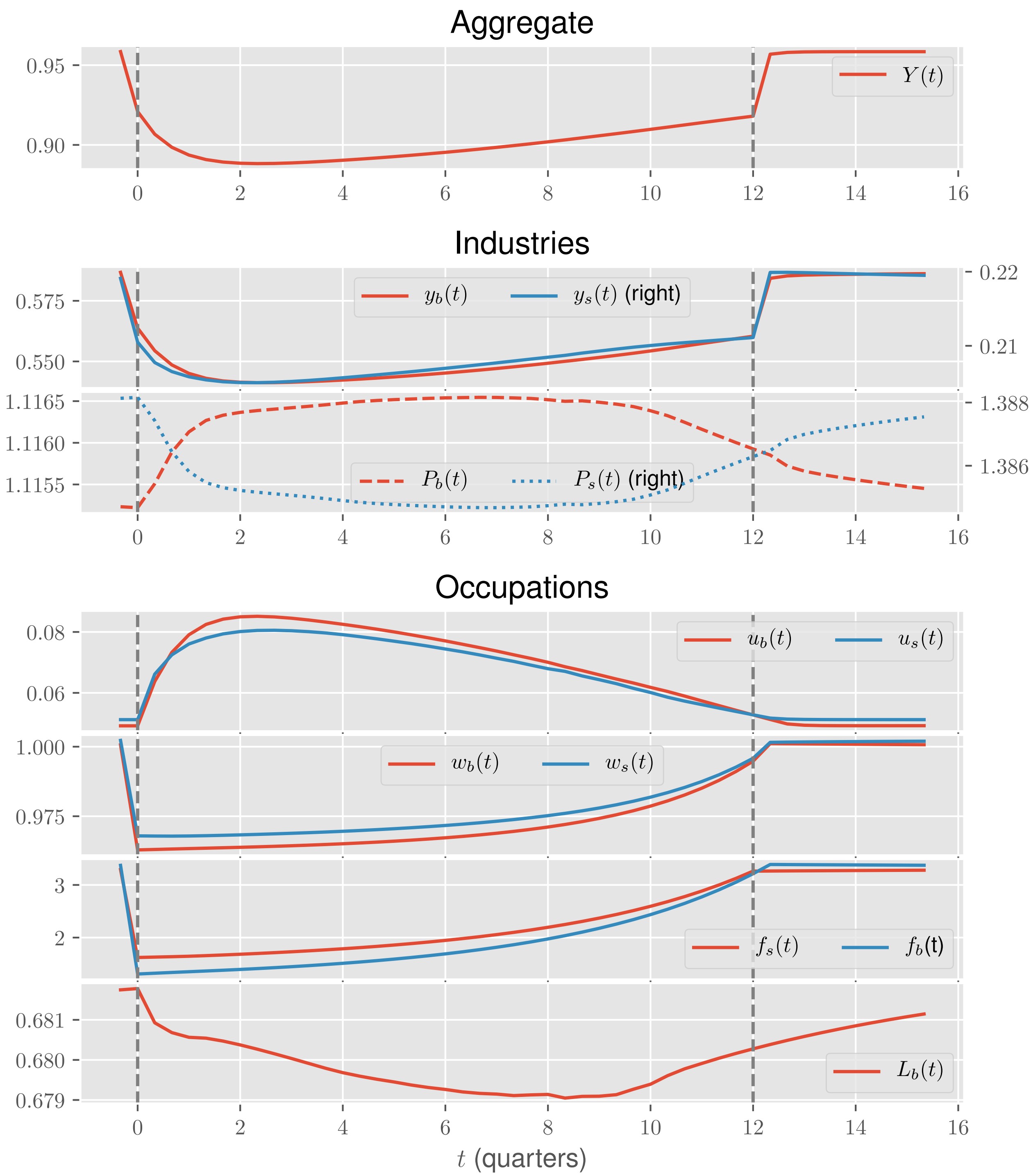
Aggregate shock leads to a compression of firm values across idiosyncratic productivity shocks. The upside from an increase in productivity is now larger than the downside from a decrease in productivity: Riskiness is valuable. Therefore, broad occupations are affected more by the aggregate shock.

The shock hits in time 0. Notice that unemployment is frictional, and production is timed to happen before adjustments through hirings and separations can happen: The initial output response in $Y(0)$ is purely coming from the change in productivity. Labor market responses then result in further reduction of output in subsequent periods.

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

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

Figure 9: Response of the economy to an indescriminate shock



5.1.2 Lilien-type recession

Now we focus on an aggregate shock that does not affect all industries in the same manner, for example an oil-price shock that affects industries differentially by their dependency. Denote the set of affected industries by $\mathcal{I}$. I adjust the previous shock structure as in (36).

$$
\begin{aligned}
A(i,t) &= \begin{cases} A(t) + \tilde{A}(i,t) & \text{if } i \in \mathcal{I} \\ \tilde{A}(i,t) & \text{else} \end{cases} \\
\tilde{A}(i,t) &= \phi A(i,t-1) + \epsilon_t \\
A(t) &= \begin{cases} \mu & \text{if } t \in \mathcal{T} \\ 0 & \text{else} \end{cases}
\end{aligned} \tag{36}
$$

To ensure a proper comparison between broad and specialist occupations, I ensure that the specialist and broad industries are equally represented in $\mathcal{I}$. Figure 10 summarizes the effects for level of aggregation.

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

5.2 Longitudinal Experiments

Here, we want to find out whether aggregate shocks lead to worse aggregate outcomes if they affect disproportionally more specialist occupations. To that end, I compare the outcome of two shocks: One that focusses exclusively on specialist industries, and one that focusses exclusively on broad industries.

The shock setup is as in (36), but $\mathcal{I}$ is different: in both recessions, the measure of affected industries is equal.

Figure 10: Response of the economy to a Lilien-type recession

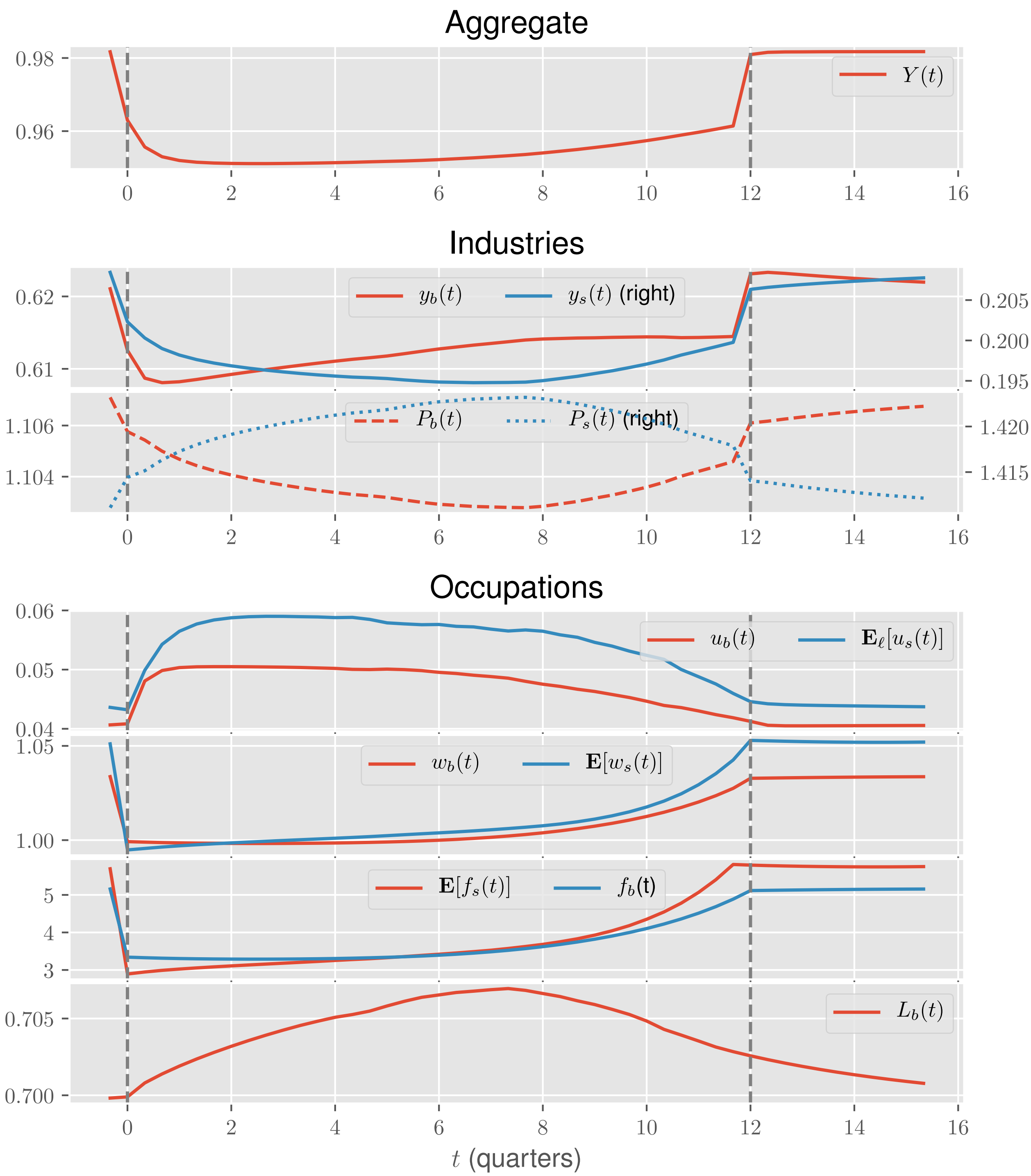


Figure 11 compares the outcomes on the aggregate level: Aggregate output responses are similar in both shocks. Panels 2 and 3 display the differential responses of broad and specialist sectors to each shock: Each sector's output immediately drops responding to its own productivity shock. Sectors do not immediately respond to the shock that happens at the other type, but throughout the experiment aggregate output is produced increasingly using the type of intermediate output that is not affected.

Figure 12 compares the main variable of interest: Panel 1 displays aggregate unemployment responses in each shock. Surprisingly, aggregate unemployment is not mitigated in the broad recession: The unemployment response in broad recessions is roughly equal or larger than those of specialist recessions. Panels 2 and 3 decompose this into the cross-sectional unemployment response for each recession. Panel 2 compares the in-type responses: It displays broad occupation's unemployment in the broad recession against the specialists' unemployment response in the specialist recession. We recover that specialists' unemployment rate is more sensitive. A large drop of unemployment in the first period is caused by massive exit out of specialist occupations – which is the main offsetting force. Panel 2 displays the responses each occupation's unemployment response to a recession in the other sector. Here is no slow build-up of unemployment, it instead spikes immediately. This is a result of the immediate relocation in the first period that leads to a spike in unemployment in the destination occupations.

Finally, Figure 13 displays the reasons behind the differential unemployment responses. The first panels displays job-finding rates: Specialists are more sensitive to in-type and other-type shocks than broad occupations. Panels 2 and 3 show the immediate response of mobility to each shock, which together yield total labor force in broad occupations (panel 4). These large responses in labor force equilibrate unemployment responses across different types of shocks.

Figure 11: Comparing broad and specialist recessions I

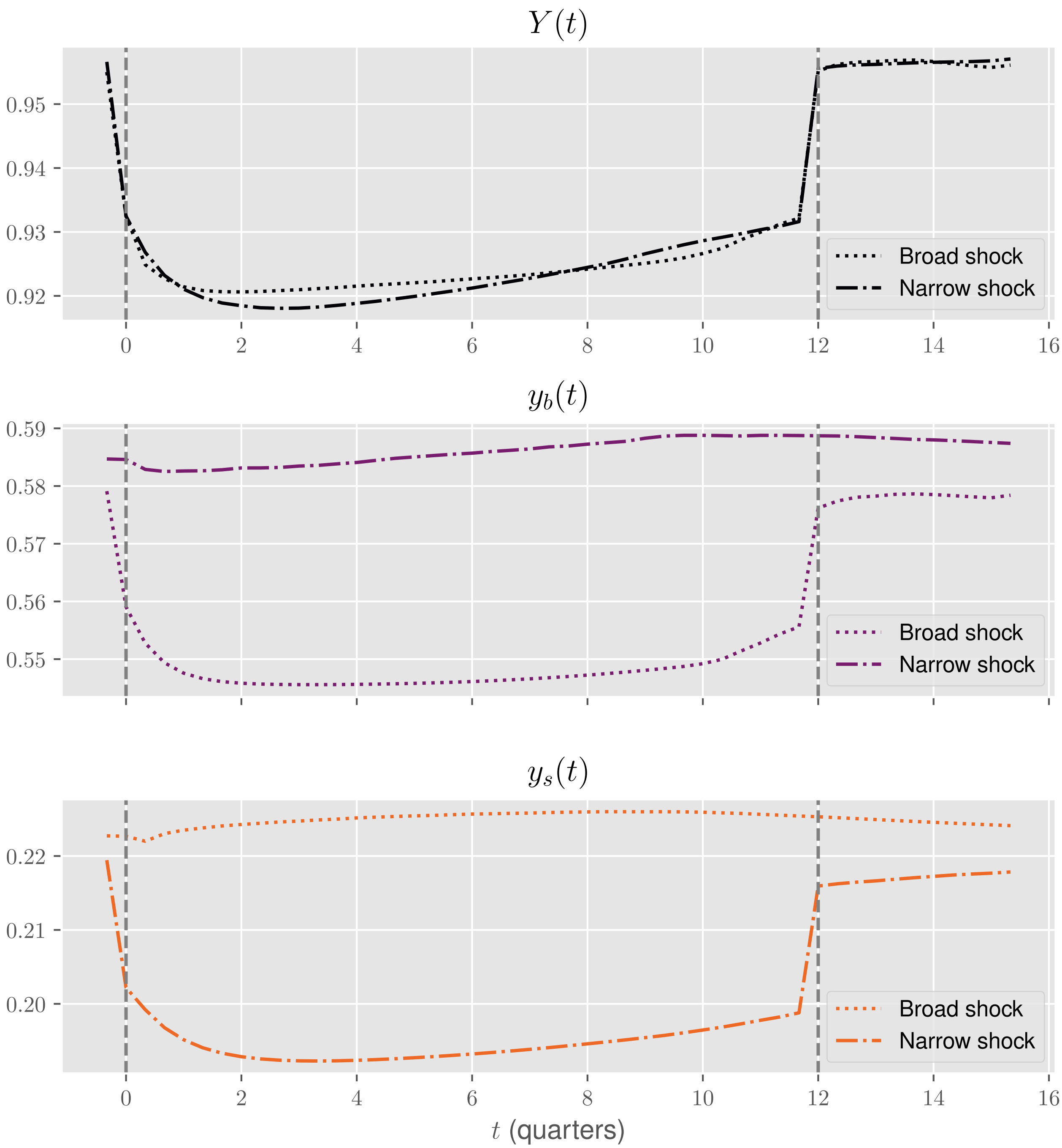


Figure 12: Comparing broad and specialist recessions II

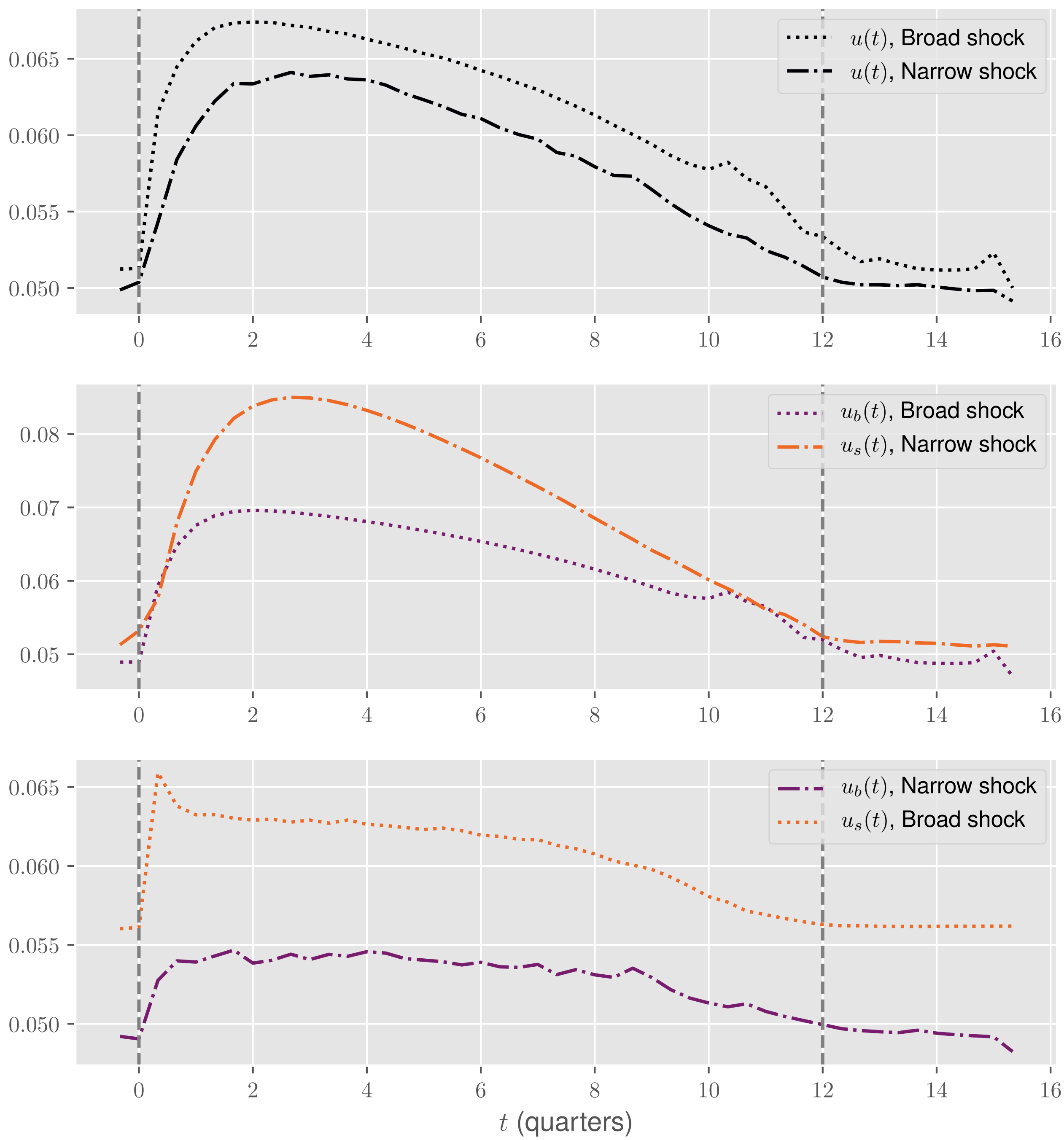
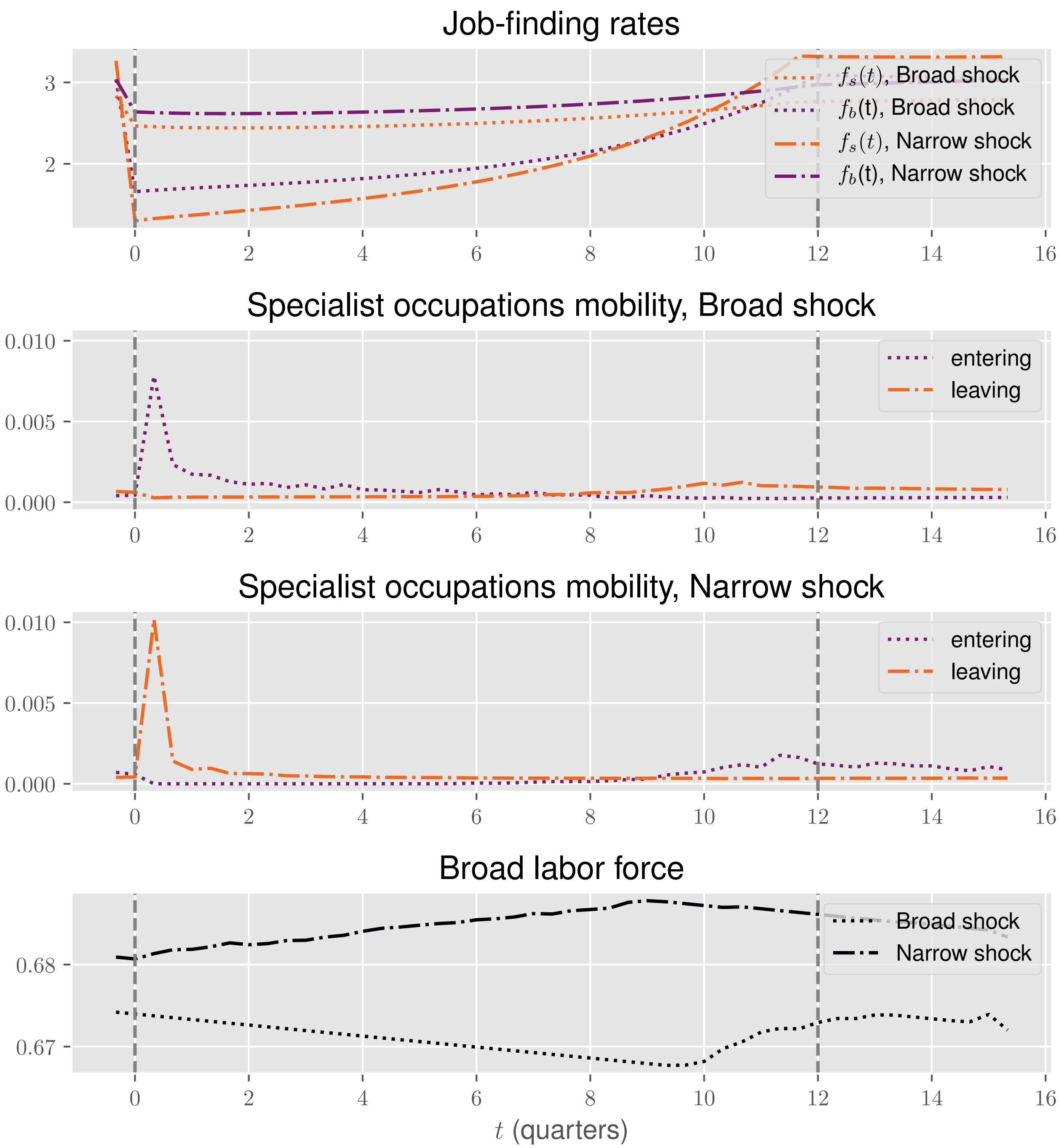


Figure 13: Comparing broad and specialist recessions III



6 Conclusion

In this paper, I develop a measure of occupation-specific broadness based on the dispersion of employment links across industries. A theory that is based on the finding that more human capital is in occupations than in industries predicts that broader occupations with access to more industries are less affected by industry-specific shocks. Fundamentally, this is one microfoundation of mismatch unemployment. I show that broader occupations' unemployment rates responded much less during the Great Recession, and thereby provide further evidence for the findings in Kambourov and Iourii Manovskii (2009). I demonstrate in a model that shocks to more specialized labor markets do not yield larger unemployment responses. This does not depend on the particular calibration, but is a fundamental property of broadness: Broadness implies insurance against shocks, but also a larger labor market. In this paper, I emphasize large empirical differences in the cross-section that do not imply significant differences in the aggregate. The results demonstrate the need for micro-founded macroeconomic models to draw inference from microeconomic evidence.

The findings can be extended to other types of mismatch: We should not in general expect that shocks to more mismatch-prone markets generate larger unemployment responses. However, they can generate larger welfare losses, as few individuals are hit particularly hard. A corollary is that there is not necessarily a direct link between aggregate unemployment responses and welfare.

On the empirical side, we simulatenously observe a large insurance-value of occupation-specific broadness, and a substantial share of unemployed that change occupations. A potential explanation is that occupation-specific human capital varies strongly in the cross-section: Unemployed are either unaffected by broadness due to a lack of human capital and switch occupation, or are affected and do not switch. Studying the cross-sectional heterogeneity in human capital and labor market mobility in a heterogenous-agent framework appears promising.

A large literature has assessed the degree to which mismatch in labor markets contributed to the large unemployment response during the Great Recession. A key motivation is that one of the sectors affected in the recession was construction, which features a particular large number of mismatch-prone specialists. In this paper, I do not argue whether mismatch was specially large during the Great Recession. 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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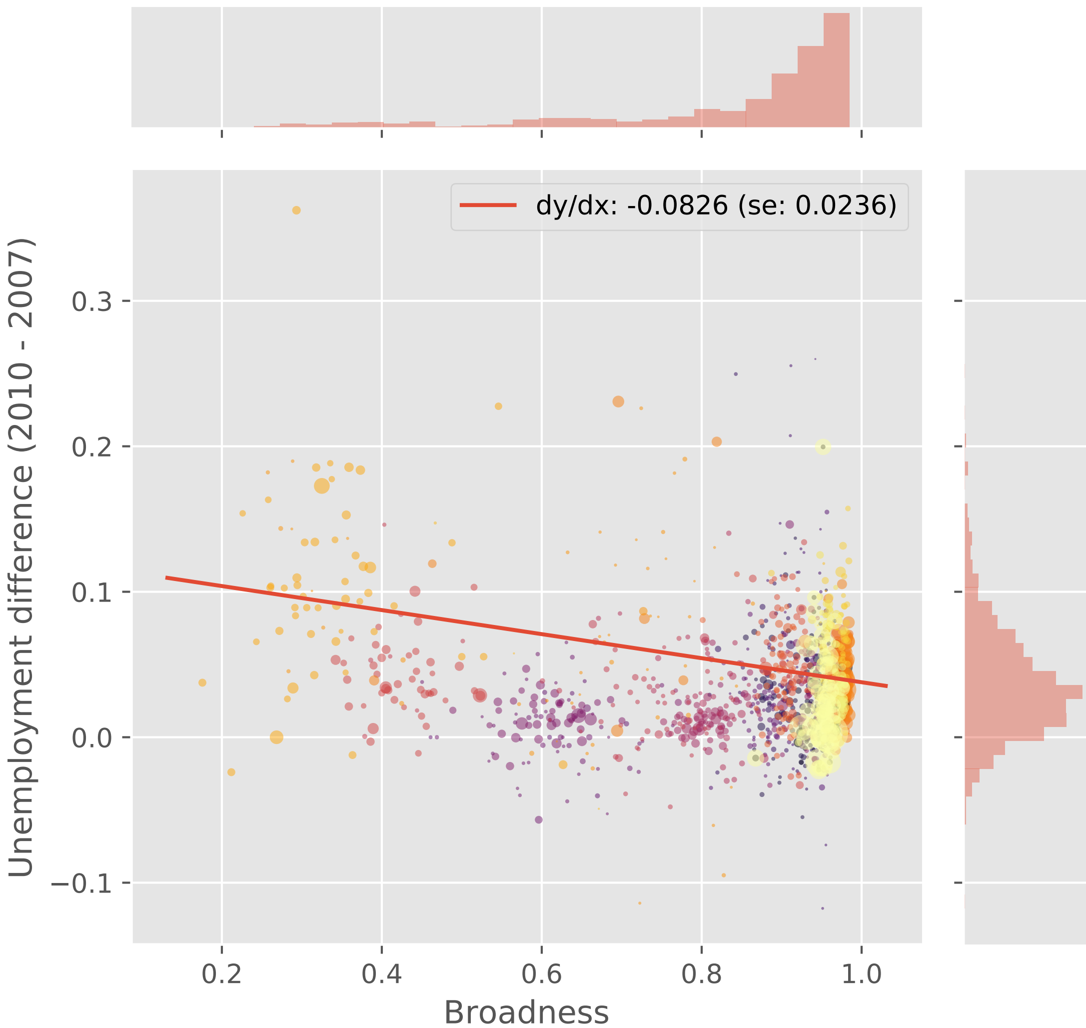
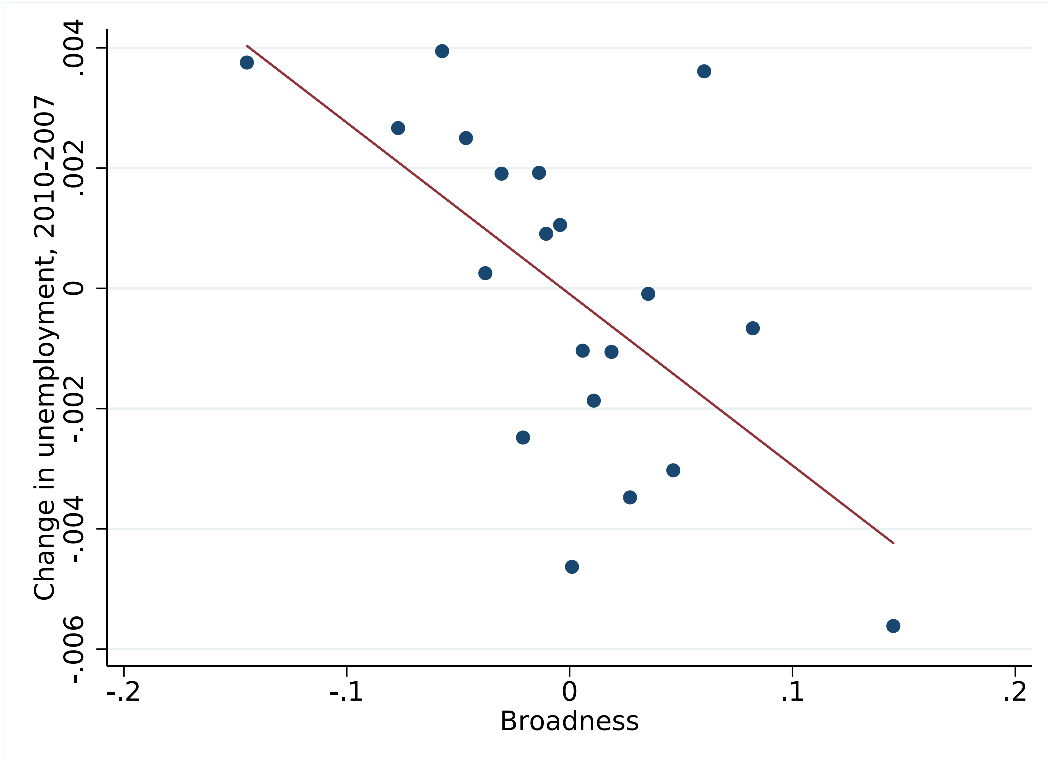
A Figures

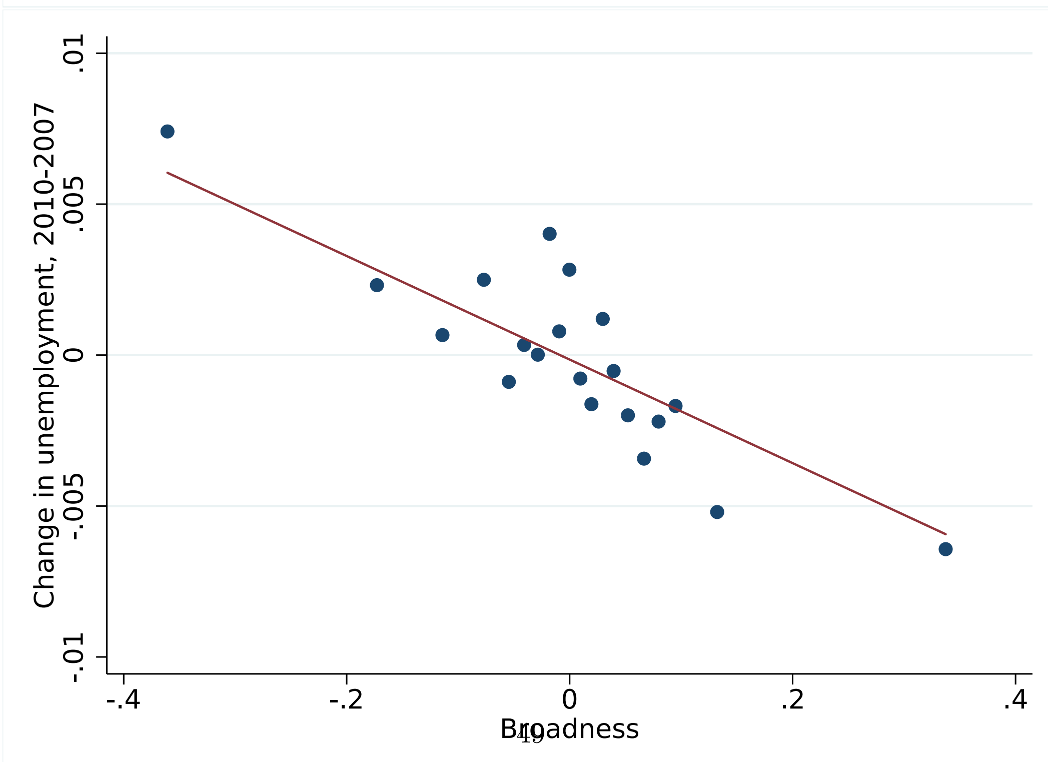
Figure A.1: Broader occupations unemployment responses were mitigated



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

Figure A.2: Broader occupations unemployment responses were mitigated





Occupation-specific unemployment responses during the great recession as a function of their broadness. Top panel: Only controlling for occupation and state-fixed effects, correponding to column (3) in table 1. Bottom panel: Also controlling for individual demographics, and state-year fixed effects, corresponding to column (4).

B Classification

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

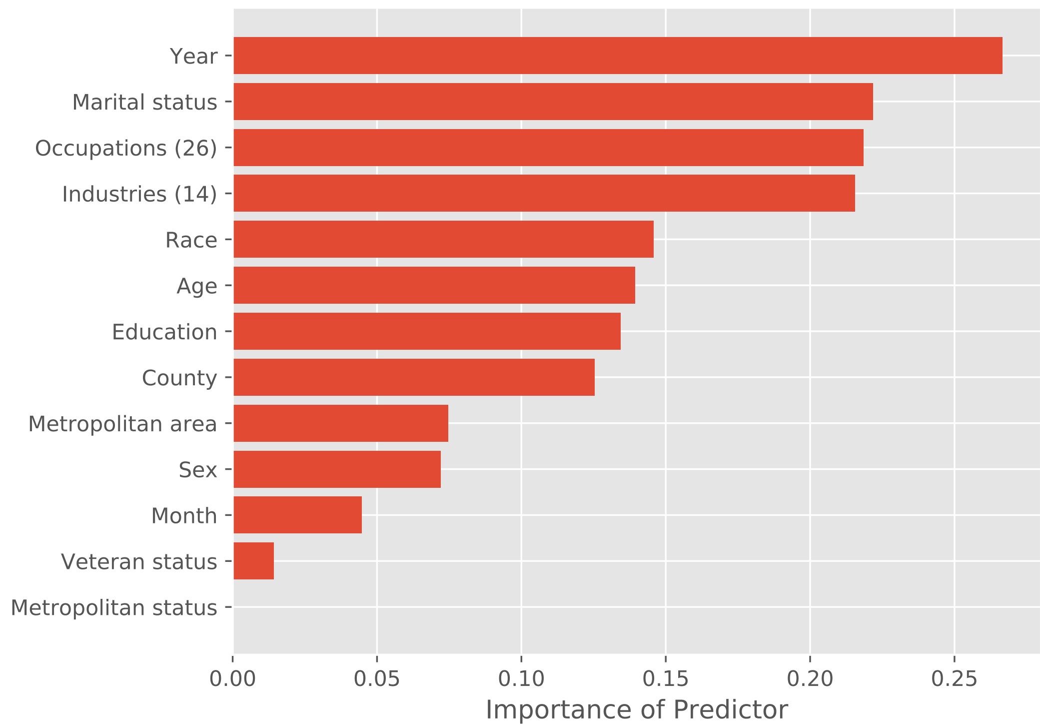
Shapley values are a solution concept in game theory: They uniquely distribute a surplus to a coalition of players. Shapley values are the unique distribution that satisfies the following four important characteristics for a given player set: They (i) distribute the total surplus ("efficiency"), attribute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

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

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

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

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



The for most important predictors of unemployment status in sample. Less important and not displayed: Age, sex, education, county, metropolitan area, month, veteran status. Data: CPS.