

# Search and Mismatch

Saman Darougheh



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Academic dissertation for the Degree of Doctor of Philosophy in Economics at Stockholm University to be publicly defended on Friday 25 October 2019 at 14.00 in Nordenskiöldsalen, Geovetenskapens hus, Svante Arrhenius väg 12.

## Abstract

I define occupations that are employed in more industries as “broader” occupations. I study the implications of occupation-level broadness for mismatch of unemployed and vacancies across occupations and industries. In the cross-section, workers in broader occupations are better insured against industry-level shocks and less at risk of being mismatched. Using geographical variation in occupation-level broadness, I show that during the Great Recession, unemployed workers from broader occupations had higher job-finding rates and smaller increases in unemployment than those previously employed in more specialized occupations. I contrast these cross-sectional results to the aggregate implications of mismatch. To that end, I build a model where the resulting mismatch of an industry-level shock depends on how specialized the affected occupations are. The model extends the Lucas (1974) island setting with frictional intra-island labor markets and frictional inter-island mobility. Workers in broader occupations are insured against industry-level productivity shocks because they can stay in their occupation but work in other unaffected industries. When individuals from broad occupations move to other industries, they propagate the shock to more workers. This strong general equilibrium mechanism offsets the direct effect. The results indicate that recessions which cause more mismatch lead to larger unemployment risk for workers in specialized occupations, but do not cause larger fluctuations of the aggregate unemployment rate.

I develop a model of the consumer good market where the individual’s search decision is consistent with balanced-growth preferences. Here, optimal search is independent of income but increases with the time endowment. I characterize the potentially multiple equilibria and test whether the model can replicate differences in observed shopping behavior across employed and unemployed individuals. Using the American Time Use Survey, I show that unemployed individuals have an almost 50% larger time endowment available for leisure and shopping. Meanwhile, they only spend 18% more time shopping than the employed. In the calibrated model, however, unemployed households will spend around twice as much time shopping as employed households. I argue that consumer-goods search models are not yet ready for business cycle analysis, and discuss ways of reconciling the model with the data.

We study the impact of worker protection in an environment with heterogeneous match productivity and a constrained wage setting. Firms can either employ costly screening to determine the match quality, or hire workers out of their applicant pool at random, learn about the match quality, and disengage from bad matches. Thus, layoff protections intervene with a firm’s ability to screen matches. In our calibration, a policy that prevents layoffs reduces unemployment and increases consumption in the new steady state. However, the economy becomes more susceptible to productivity shocks. Two additional channels transmit productivity shocks when layoffs are regulated. First, the value of hiring at random is more volatile when separating bad matches is no longer an option. Second, additional screening in recessions worsens the composition of the unemployed pool. Consequently, recessions will be long lasting and hiring is lower even after the TFP shock has receded. We conclude that economies potentially have a higher average output under layoff regulations, but that this comes at the cost of higher volatility and jobless recoveries.

**Keywords:** *labor market, unemployment.*

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## Abstracts

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**Consumer good search: theory and evidence** I develop a model of the consumer good market where the individual’s search decision is consistent with balanced-growth preferences. Here, optimal search is independent of income but increases with the time endowment. I characterize the potentially multiple equilibria and test whether the model can replicate differences in observed shopping behavior across employed and unemployed individuals. Using the



American Time Use Survey, I show that unemployed individuals have an almost 50% larger time endowment available for leisure and shopping. Meanwhile, they only spend 18% more time shopping than the employed. In the calibrated model, however, unemployed households will spend around twice as much time shopping as employed households. I argue that consumer-goods search models are not yet ready for business cycle analysis, and discuss ways of reconciling the model with the data.

**Worker protection and heterogeneous match quality** We study the impact of worker protection in an environment with heterogeneous match productivity and a constrained wage setting. Firms can either employ costly screening to determine the match quality or hire workers out of their applicant pool at random, learn about the match quality, and disengage from bad matches. Thus, layoff protections intervene with a firm's ability to screen matches. In our calibration, a policy that prevents layoffs reduces unemployment and increases consumption in the new steady state. However, the economy becomes more susceptible to productivity shocks. Two additional channels transmit productivity shocks when layoffs are regulated. First, the value of hiring at random is more volatile when separating bad matches is no longer an option. Second, additional screening in recessions worsens the composition of the pool of unemployed workers. Consequently, recessions will be long lasting and hiring is lower even after the TFP shock has receded. We conclude that economies potentially have a higher average output under layoff regulations, but that this comes at the cost of higher volatility and jobless recoveries.

Moonlight floods the whole sky  
from horizon to horizon; How  
much it can fill your room  
depends on its windows.

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Jalāl ad-Dīn Muhammad Rūmī



## Acknowledgments

My parents are my role models for the importance of discipline, power of will, and following one's interests. Their support throughout the process made this thesis possible.

Tracing back the origins of this thesis, it was Helge Braun's excellence in teaching that motivated me to study macroeconomics and try my luck at an academic career. I appreciate the Stockholm School of Economics for accepting me into the PhD program, where I met then-colleagues and now-friends from whom I benefited then, and hopefully will do for a lifetime. I shared an office with Karl Harmenberg, who inspired me to study Mathematics beyond the requirements of the degree, and who introduced me to "The Rise of the Meritocracy" – a single book powerful enough to completely shift my moral compass in favor of egalitarianism. I believe that this made me a better person, and I am very grateful. The other member of that office was Gustaf Lundgren, who is active in two communities that argue for the sake of arguing and often debate factoids while having no firm opinion on the matter: The Debate Society and Academic Economists. These environments have not rendered him a cynic, and I'm partly less of a cynic and a contrarian due to his influence<sup>1</sup>. The insanity of the author might have reduced the quality of this thesis. I spent many hours in and out of school with members of the "other office" at SSE; I would like to thank Eleonora Freddi, Marta Giagheddu and Nadiia Lazhevskaja for keeping me sane.

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<sup>1</sup>I am aware that some might say I should've paid more attention.

their patience with me at that time, and hope to apply in the future what I have learned in these years.

Many more people at the institute affected the direction that my research took: Torsten Persson on how to conceptually think about theory and data, Jon de Quidt on irrationality and the instability of preferences, Arash Nekoei and Josef Sigurdsson on the value of microeconomic work for a macroeconomist, Sirus Dehdari on theoretical econometrics, Richard Foltyn and Jonna Olsson on the importance of getting the nitty-gritty details right. The whole macroeconomic research group at the institute was of tremendous help and I appreciate Timo Boppart, Tobias Broer, John Hassler, Alexandre Kohlhas and Kathrin Schlafmann for great support throughout the years.

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Saman Darougheh  
Stockholm, Sweden  
September 2019

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# Introduction

An entrepreneur envisions a profitable enterprise by producing and selling a good. For that purpose, he needs workers who have specific skills, but who are also a good match with his work environment. After hiring these workers and producing, he needs to sell his product. The profitability of the enterprise depends on how strong the competition is, and at what price he can sell the good.

The self-contained essays in this thesis relate to these three stages of economic activity, and their relationship to unemployment.

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

First, I focus on the role of occupation-industry networks in hiring. I observe that occupations are not equally employed in all industries. Some occupations are specialized in very few industries, while others are what I refer to as “broad”: they are employable in many industries. Individuals have a hard time changing occupations: when industries that employ specialized occupations face adverse shocks, unemployed workers in these specialized occupations are left behind and cannot adjust to a change in the industrial structure. I analyze the implications of this mismatch between industrial labor demand and occupational labor supply for unemployment risk across workers and different recessions.

I test the theory empirically using data from the so-called “Great Recession” in 2008. I show that in the United States, workers in broader occupations found jobs faster: unemployment was particularly high for workers in specialized occupations like electricians who had a hard time adjusting to the implosion of



the construction sector during that recession.

In a second stage, I look across recessions. I compare the Great Recession, which particularly loaded onto specialized occupations, with the 2002 bursting of the dot-com bubble that affected broad occupations such as programmers and managers. In the model, both recessions led to comparable unemployment, but they had different output responses: the Great Recession affected specialized occupations that could not easily relocate to more productive sectors. Consequently, misallocation of labor is higher in that recession, which led to the mentioned larger loss of output.

**Consumer good search: theory and evidence** I develop a theory of households that use some of their leisure to search for low prices of goods and purchase them at the cheapest price available - a process commonly referred to as “shopping”. In recent years, many economists have integrated consumer good search into their models and made new predictions about the behavior of the macroeconomy. The paper cautions against reduced-form modeling of shopping behavior by analyzing in detail the cost-benefit analysis of consumer good search. One aim is to use the theory to try to understand the shopping decisions of employed and unemployed households. Empirically, unemployed households have much more leisure than employed households. The model predicts that the unemployed should spend much more time shopping than we observe in the data. I conclude that consumer good search is not yet ready for macroeconomic analysis. I suggest several ways of realigning the theory with the evidence. However, one should think carefully about in which of these ways to proceed: they differ vastly in their implications for macroeconomic outcomes.

**Worker protection and heterogeneous match quality** In the last essay, I study the relevance of the work environment for the hiring decision together with Gustaf Lundgren. Our theory starts with the basic assumption that firms have different work environments, and workers have different work environment requirements. A random worker-firm pair is going to be highly productive if the environment and the requirements align, and unproductive otherwise. In our theory, firms can - and will - expend costs to

detect potentially good matches among their applicants. In a world without employment protection, an alternative approach is to hire workers, find out the match quality during employment, and lay off the worker if the match turns out to be bad. In this environment, we study the introduction of legislature aimed at protecting workers. We show that this change improves the economy's trend performance, but increases the volatility of unemployment: worker protection renders the economy much more susceptible to aggregate shocks.



# Chapter 1

## Occupation-industry mismatch in the cross-section and the aggregate<sup>\*</sup>

### 1.1 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,

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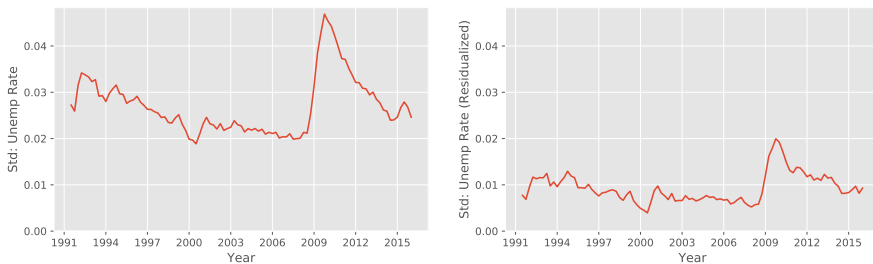
I carry out an empirical investigation that lets the data speak without imposing any structural assumptions. I perform a machine learning exercise where the individual unemployment status is predicted out of sample using independent variables from the CPS. I find that an individual's occupation and industry are among the most important predictors of their unemployment status.<sup>1</sup> 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 1.1. 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.

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

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<sup>1</sup>For details on the empirical exercise see Appendix 1.B.

**Figure 1.1:** 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 1.A.

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 measure 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's cross-sectional 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 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 findings to the literature that estimates the impact of mismatch onto aggregate unemployment responses (Şahin et al., 2014). I first

show that 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. I therefore consider the hypothesis that recessions that cause more mismatch - by hitting sectors that are connected to less broad occupations - lead to larger unemployment responses.

To that end, I propose a model that features a continuum of occupations that are either specialized and employable at a single industry, or broad and employable at 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 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 onto 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 workers 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 that concentrate 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 Şahin et al. (2014). They show empirically that the degree of mismatch was not worse during the Great Recession than in other recessions. The model explains those 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 ana-



lyze 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. Kambourov and Manovskii (2009b) 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) 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 from 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 (2013) 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 is 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.

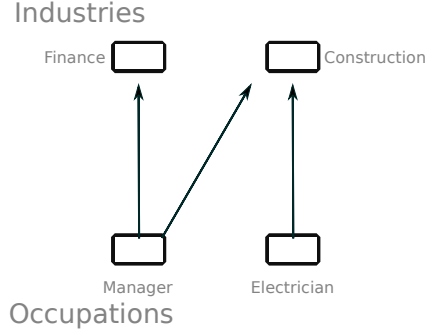
In sections 2 and 3, I first describe the concept of broad and specialized human capital, and measure its impact on unemployment responses. Building on these cross-sectional results, section 4 describes the model, and section 5 analyzes aggregate shocks.

## 1.2 Broad and specialized occupations

This section introduces the notion of specialized occupations and connects it to unemployment risk. 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 the case of 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 firms in the construction industry. This stylized occupation-industry matrix is displayed in Figure 1.2. 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.

**Figure 1.2:** Stylized occupation-industry network

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

### 1.2.1 Broadness and mismatch

In this paper, mismatch refers to a situation in which unemployed job-seekers are looking to be employed in occupations which are different from those that firms are posting vacancies in. In such scenarios, the unemployed will have a more difficult time finding a job, and will face higher unemployment risk. Broadness was defined as a metric of the production network, and not in relation to mismatch. However, broadness may have implications for unemployment risk. I demonstrate this using again the stylized case of managers and electricians. The strong assumptions put forward here will be relaxed in the quantitative model.

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

The general form of preferences for each occupation  $o$  is

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

which for both occupations boils down to

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

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

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

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

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

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

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

In this example, an equal average job-finding rate ensures that the occupa-

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

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

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

Several general equilibrium mechanisms potentially dampen these effects. First, individuals might adjust their occupation after the shock has been realized. The degree to which this happens depends on the costs of changing occupations, among other the opportunity cost of not using their occupation-specific human capital. As I show in Appendix 1.C, a significant number of unemployed workers does not change their occupation – thereby dampening the expected effect from occupation switching. Second, individuals might not be willing to change their industry – e.g. if they have accumulated human capital in their previous industry. While Kambourov and Manovskii (2009a) show that, on average, there is less human capital associated with industries than occupations, this need not be true for all occupation-industry pairs. Third, as workers in more specialized occupations are more dependent on firms in fewer industries, those firms might be able to bargain lower wages. This could lead to higher profits, and thereby more jobs in industries that hire from specialized occupations. Finally, the prices of industries that employ more specialized occupations might interact with the

aforementioned profit response.

To address these issues, I do two things. In the remainder of this section, I empirically measure broadness and provide evidence which suggests that individuals in broader occupations were less mismatched during the Great Recession. Second, the general equilibrium model developed later on incorporates most of these channels and shows that broadness still provides an insurance-value against unemployment risk.

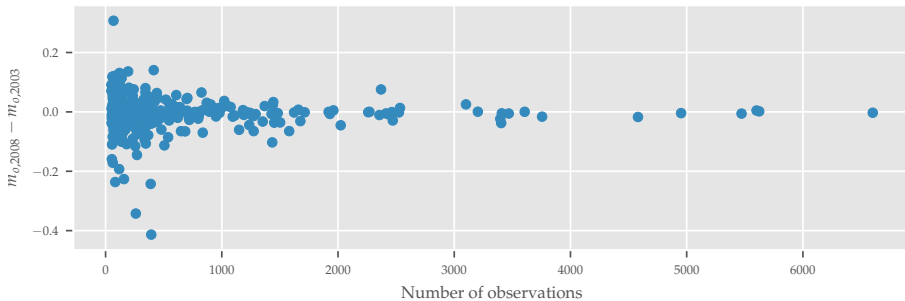
### 1.2.2 Measuring broadness

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 (1.1). We have that  $m_o \in [0, 1]$  and increases in an occupation's level of broadness.

$$\begin{aligned} s_{o,i} &= \frac{E_{o,i}}{\sum_i E_{o,i}} \\ m_o &= 1 - \sum_i s_{o,i}^2 \end{aligned} \tag{1.1}$$

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

**Figure 1.3:** 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.

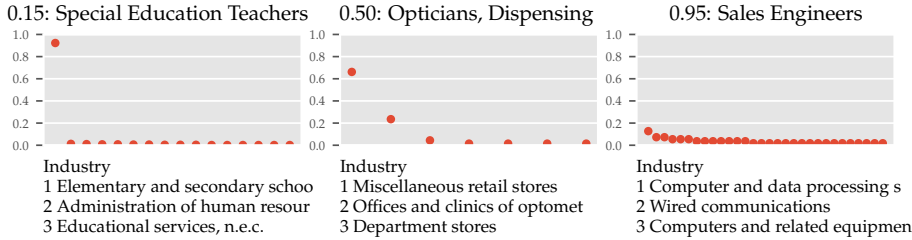
not measure raw employment, but reemployment out of unemployment. Such a measure would ensure that the unemployed can indeed move across industries and we do not simply observe many unconnected occupation-by-industry submarkets. However, it is much more noisy for two reasons. First, by relying on the 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 1.3 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 hid-



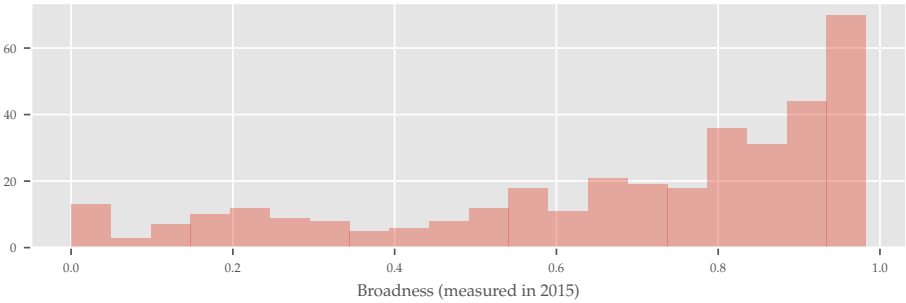
*Figure 1.4: Three exemplary occupations across the support of broadness*



den behind the one-dimensional measure of broadness, Figure 1.4 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 1.5. 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 1.5: Distribution of broadness across occupations*



### 1.3 Empirical investigation

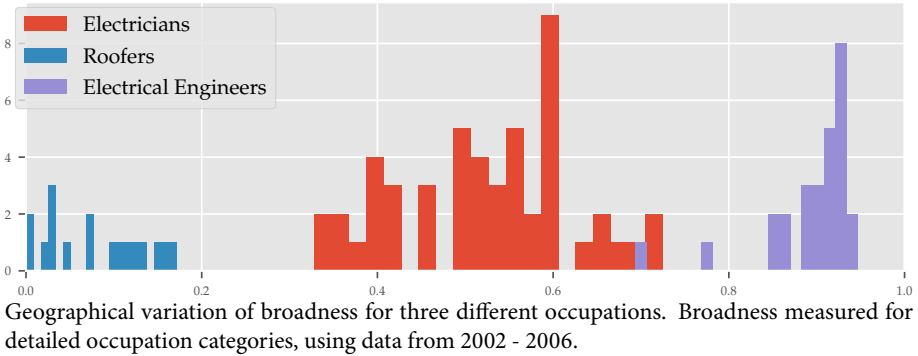
Having developed a measure of broadness, I will now devise an empirical strategy to identify the relationship between broadness and the change in unemployment rates during the Great Recession. In this section, I will first compare individuals that were all previously employed in the construction sector, 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 (1.2).

$$\begin{aligned} s_{o,i,z} &= \frac{E_{o,i,z}}{\sum_i E_{o,i,z}} \\ m_{o,z} &= 1 - \sum_i s_{o,i,z}^2 \end{aligned} \tag{1.2}$$

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 1.6 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 differ-

*Figure 1.6: Geographical heterogeneity of broadness*

ences in job-finding rates.

### 1.3.1 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.

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 1.6 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

**Table 1.1:** *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.

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 (1.3): 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  $\Theta_o$  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.

$$f_{j,o,z,t} = \alpha m_{o,z} + B_1 X_j + \Lambda_{z,t} + \Theta_o + \epsilon_{j,o,z,t} \quad (1.3)$$

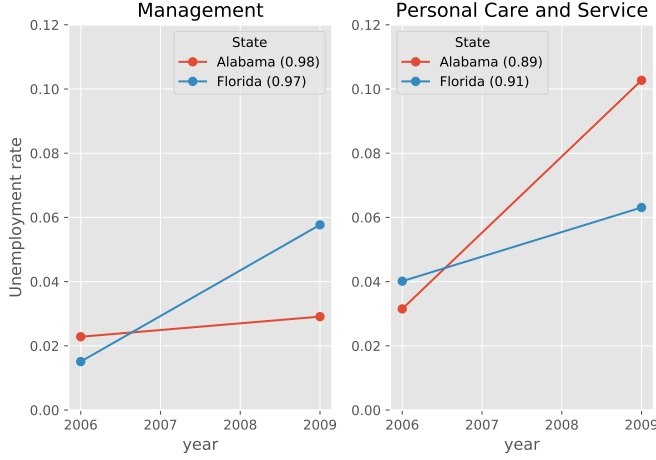
Table 1.1 shows the results. Columns (1)–(2) build the regression by adding controls and column (3) shows the main specification. The average monthly job-finding rate in that period for that sample amounted to 0.18. A one standard-

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  $\alpha$ , 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.

### 1.3.2 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 broad-

**Figure 1.7:** *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.

ness. 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 1.7. 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 (1.4).

$$u_{o,z,2010} - u_{o,z,2007} = \alpha m_{o,z} + \Lambda_z + \Theta_o + \epsilon_{o,z} \quad (1.4)$$

Figure 1.31 draws the regression line against all observations. Table 1.2 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 the unemployment. To put this into perspective, the mean increase in occupation-state specific unemployment rates between 2007 and 2010 weighted by occupation-by-state cell sizes was 0.034

(unweighted: 0.04), implying that a one standard deviation change in broadness explains a third of the increase in unemployment during that period.

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

Finally, I control for two types of heterogeneities across occupation-by-state bins. One type is individual-level characteristics which control for demographics that are potentially associated with a lower reemployment rate. Another type is the industry of last employment, interacted with state. Industry-by-state fixed-effects control for a differential exposure of industries to the recession, which is allowed to vary by state. I control for both heterogeneities by 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 1.2. 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 estimate for  $\alpha$ .

**Table 1.2:** *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

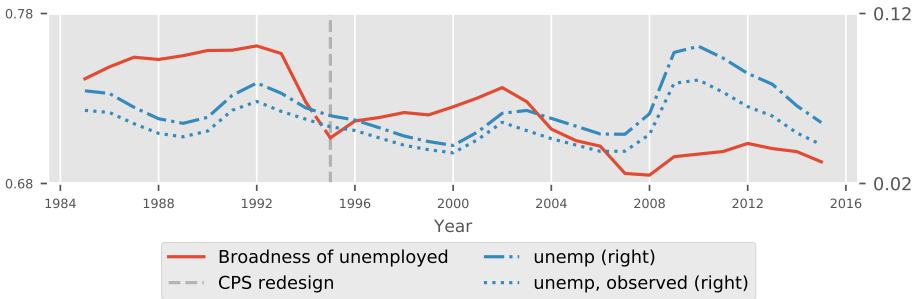
Observations weighted by the number of observations used to compute cell averages. Broadness standardized and computed using data before recession. Standard errors in parentheses and two-way clustered at state and occupation level. \*\*\* significant at 0.01, \*\* at 0.05, \* at 0.10.

## 1.4 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 1.8: 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 1.D for more information on the computation and robustness checks.

Figure 1.8 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 the those unemployed during the preceding 2002 recession.

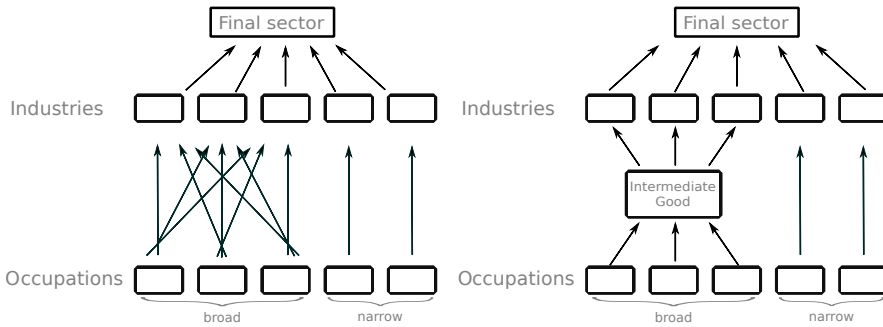
Şahin et al. (2014) empirically estimate that mismatch did not cause more

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 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 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  $\zeta$ . 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.

*Figure 1.9: The input-output structure between occupations and industries*

The production network of the economy. Notice that the two networks are isomorphic, as Section 1.4.3 shows.

**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  $\gamma$  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 (1.9). 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.

### 1.4.1 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  $\theta$ . The environment is dynamic. For ease of exposition, I ignore time indices until they are necessary.

$$Y = \left[ \int_{[0,1]} y(i)^{\frac{\theta-1}{\theta}} di \right]^{\frac{\theta}{\theta-1}} \quad (1.5)$$

$$p(i) = \left( \frac{Y}{y(i)} \right)^{\frac{1}{\theta}} \quad (1.6)$$

### 1.4.2 Specialist 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 (1.7), 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 (1.8)

$$y(i) = A(i)z(i) \quad (1.7)$$

$$p(i) = \frac{p_z(i)}{A(i)} \quad (1.8)$$

### 1.4.3 Broad industries

Firms in each broad industry  $i$  employ a CRS production function with elasticity of substitution  $\theta_b$ . 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 level of output (1.9).

$$\min_{\{z(i,o)\}_o} \int_{[0,\gamma]} p_z(o)z(i, o)do \quad (1.9)$$

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

The appendix shows that optimal input composition is given by (1.10), 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  $x(i)$ .

$$\frac{z(i, o)}{x(i)} = \left( \frac{P_x}{p_z(o)} \right)^{\theta_b}, \quad \forall i, o \quad (1.10)$$

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

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:

$$\begin{aligned}
x &\equiv \left[ A_x \int_{[0,\gamma]} z(o)^{\frac{\theta_b-1}{\theta_b}} do \right]^{\frac{\theta_b}{\theta_b-1}} \\
x &= \int_{[0,\gamma]} x(i) di
\end{aligned} \tag{1.11}$$

The question remains as to how  $x$  is distributed across industries. The appendix answers this question by using feasibility (1.11) and a rewritten firm's problem to compute equilibrium  $x(i)$  shares (1.12). 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  $\theta$ , as shown in (1.12).

$$\begin{aligned}
\frac{x(i)}{x} &= \left( \frac{A(i)}{A_b} \right)^{\theta-1} \\
A_b &= \left[ \int_{[0,\gamma]} A(i)^{\theta-1} di \right]^{\frac{1}{\theta-1}}
\end{aligned} \tag{1.12}$$

Finally, the appendix shows how one can use this result, together with prices implied by perfect competition (1.13), to compute  $P_x$  in closed-form as in (1.14).

$$p(i) = \frac{P_x}{A(i)} \tag{1.13}$$

$$P_x = A_x A_b \left( \frac{Y}{A_b x} \right)^{\frac{1}{\theta}} \tag{1.14}$$

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

**Definition 1.1.** A Static Broad Industry Partial Equilibrium is, given

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

a collection of

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

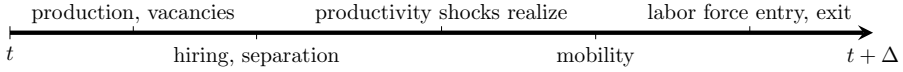
such that

1. Industry choice:  $z(i, o)/x(i)$  is optimal given prices  $\{p_z(o)\}_o, P_x, \forall i$  (1.10)
2. Industry choice: intermediate output consistent with zero profits,  $\forall i$  (1.13)
3. Feasibility:  $x(i)$  add up to  $x$  (1.11)

#### 1.4.4 Occupations

A DMP-style frictional labor market exists in each occupation. The timing is as in Figure 1.10. 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  $\zeta$  of workers exits the labor force, and is replaced by a new cohort.

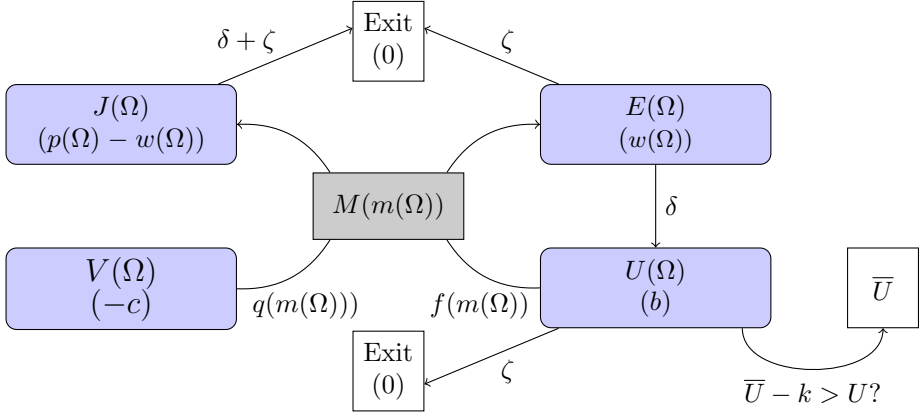
**Figure 1.10:** Timing of events within each period



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

Figure 1.11 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  $\Omega$  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

**Figure 1.11:** Dynamics within each occupation

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  $\delta$ . 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  $\Omega$ , all value functions and policy functions differ across broad and spe-



cialized 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  $\zeta$  with the terminal value 0. This implies that the effective discount rate  $\rho$  is a sum of both impatience and the exit rate:  $\rho = \tilde{\rho} + \zeta$ .

$$U^{\text{stay}}(\Omega) = b\Delta + e^{-\rho\Delta} \left[ \left(1 - e^{-f(m(\Omega))\Delta}\right) \mathbb{E}[E(\Omega')] + e^{-f(\Omega')\Delta} \mathbb{E}[U(\Omega)] \right] \quad (1.15)$$

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

$$E(\Omega) = w(\Omega)\Delta + e^{-(\tilde{\rho}+\zeta)\Delta} \mathbb{E} \left[ e^{-\delta\Delta} \mathbb{E}[E(\Omega')] + (1 - e^{-\delta\Delta}) \mathbb{E}[U(\Omega')] \right] \quad (1.16)$$

$$J(\Omega) = [p_s(\Omega) - w(\Omega)]\Delta + e^{-(\tilde{\rho}+\zeta+\delta)\Delta} \mathbb{E}[J(\Omega')] \quad (1.17)$$

$$V(\Omega) = -c\Delta + \left(1 - e^{-q(m(\Omega))\Delta}\right) e^{-\tilde{\rho}\Delta} \mathbb{E}[J(\Omega')] \quad (1.18)$$

In equilibrium, market tightness is governed by free-entry, (1.19), and wages are determined by Nash bargaining with workers' bargaining power  $\beta$ , (1.20).

$$V(\Omega) = 0 \quad (1.19)$$

$$\beta J(\Omega) = (1 - \beta) (E(\Omega) - U(\Omega)) \quad (1.20)$$

**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 (1.6), industry-level technology (1.7), and free-entry, (1.8), to compute  $p_s$  (1.21).  $p_s$  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  $\ell$  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  $\Omega_s = \{a, u, \ell\}$ .

$$p_s(a, u, \ell) = a \left( \frac{Y}{a(1 - u)\ell} \right)^{\frac{1}{\theta}} \quad (1.21)$$

$$p_b(u, \ell) = \left( \frac{x}{(1 - u)\ell} \right)^{\frac{1}{\theta_b}} \cdot P_x \quad (1.22)$$

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  $p_b$  (1.22). This price is composed 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 occu-

pations 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  $\Omega_b$  and  $\Omega_s$ . 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:

$$\begin{aligned} g_{u;s}(a, u, \ell, \ell') &= 1 - e^{-\zeta\Delta}(1 - \tilde{u}(a, u, \ell)) \frac{\ell}{\ell'} \\ \tilde{u}(a, u, \ell) &= (1 - e^{-\delta\Delta})(1 - u) + e^{-f(m(a, u, \ell))\Delta}u \end{aligned} \quad (1.23)$$

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.

$$\begin{aligned} \tilde{u}_b(u, \ell) &= (1 - e^{-\delta\Delta})(1 - u) + e^{-f(m_b(u, \ell))\Delta}u \\ g_{u;b}(u, \ell, \ell') &= 1 - e^{-\zeta\Delta}(1 - \tilde{u}_b(u, \ell)) \frac{\ell}{\ell'} \end{aligned} \quad (1.24)$$

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

**Definition 1.2.** 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 (1.15)-(1.17)
2. Given  $\{J_s, E_s, U_s^{stay}\}$ : wages satisfy Nash bargaining (1.20)
3. Given  $\{J_s\}$ :  $m$  satisfies free-entry (1.19)
4. Law of motion  $g_{u;s}$  is consistent with  $\{m\}$  (1.24)

**Definition 1.3.** 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  $\{J_b(\Omega_b), E_b(\Omega_b), U_b^{stay}(\Omega_b), U_b(\Omega_b)\}$ ,
- 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 (1.15)-(1.17)
2. Given  $\{J_b, E_b, U_b^{stay}\}$ : wages satisfy Nash bargaining (1.20)
3. Given  $\{J_b\}$ :  $m$  satisfies free-entry (1.19)
4. Law of motion  $g_{u;b}$  is consistent with  $\{m\}$  (1.25)

### 1.4.5 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  $U_s$ .

$$\begin{aligned}\bar{U}_b &= \max_{(u,\ell): g_b(u,\ell) > 0} U_b(u,\ell) \\ \bar{U}_s &= \max_{(a,u,\ell): g_s(a,u,\ell) > 0} U_s(a,u,\ell)\end{aligned}$$

where  $g_b$  and  $g_s$  denote the density of broad occupations over the  $(u, \ell)$  space, and specialist occupations over the  $(a, u, \ell)$  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  $\underline{U}$ .

$$\begin{aligned}\bar{U} &= \max\{\bar{U}_b, \bar{U}_s\} \\ \underline{U} &= \bar{U} - k\end{aligned}$$

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 (1.25).

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 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 (1.26) follows the same spirit.

$$\begin{aligned}
g_{\ell;b}(u, \ell) &= \begin{cases} e^{-\zeta\Delta\ell} & \text{if } U_b(g_{u;b}(u, \ell, e^{-\zeta\Delta\ell}), e^{-\zeta\Delta\ell}) \in (\underline{U}, \overline{U}) \\
x : U_b(g_{u;b}(u, \ell, \ell' = x), x) = \overline{U} & \text{if } U_b(g_{u;b}(u, \ell, e^{-\zeta\Delta\ell}), e^{-\zeta\Delta\ell}) \geq \overline{U} \\
(1 - \tilde{u}_b(u, \ell))e^{-\zeta\Delta\ell} & \text{if } U_b(g_{u;b}(u, \ell, e^{-\zeta\Delta\ell}), e^{-\zeta\Delta\ell}) < \underline{U} \\
x : U_b(g_{u;b}(u, \ell, \ell' = x), x) = \underline{U} & \text{otherwise} \end{cases} \quad (1.25)
\end{aligned}$$
  

$$\begin{aligned}
g_{\ell;s}(a', a, u, \ell) &= \begin{cases} e^{-\zeta\Delta\ell} & U(a', g_u(a, u, \ell, e^{-\zeta\Delta\ell}), e^{-\zeta\Delta\ell}) \in (\underline{U}, \tilde{U}) \\
x : U(a', g_u(a, u, \ell, \ell' = x), \ell' = x) = \tilde{U} & U(a', g_u(a, u, e^{-\zeta\Delta\ell}, e^{-\zeta\Delta\ell}), \ell) \geq \tilde{U} \\
(1 - \tilde{u}(a, u, \ell))e^{-\zeta\Delta\ell} & U(a', 0, e^{-\zeta\Delta}(1 - \tilde{u}(a, u, \ell)))\ell \leq \underline{U} \\
x : U(a', g_u(a, u, \ell, \ell' = x), \ell' = x) = \underline{U} & \text{else if } U(a', g_u(a, u, e^{-\zeta\Delta\ell}), e^{-\zeta\Delta\ell}) \leq \underline{U} \end{cases} \quad (1.26)
\end{aligned}$$

### 1.4.6 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.

### 1.4.7 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  $G_s(\tilde{a}, u, \ell)$ :

$$A(i) \sim \log \text{Normal}(\text{s.t. stationary AR (1)}) \quad \forall i \in [0, 1] \quad (1.27)$$

$$(u(i), \ell(i)) \sim G_s(a, u, \ell | a = A(i)) \quad \forall i \in (\gamma, 1] \quad (1.28)$$

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:

$$z(o) = (1 - u(o))\ell(o) \quad , \forall o \in [0, 1] \quad (1.29)$$

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



$$p_b(u, \ell) = \left( \frac{x}{\ell(1-u)} \right)^{\frac{1}{\theta_b}} P_x \quad (1.30)$$

$$p_s(a, u, \ell) = a \left( \frac{Y}{a(1-u)\ell} \right)^{\frac{1}{\theta}} \quad (1.31)$$

Feasibility in terms of labor is stated as follows:

$$\begin{aligned} L &= \gamma \int_{\mathcal{U} \times \mathcal{L}} \ell dG_b(u, \ell) + (1-\gamma) \int_{\mathcal{A} \times \mathcal{U} \times \mathcal{L}} \ell dG_s(a, u, \ell) \\ L &= L_b + (1-\gamma) \int_{\mathcal{A} \times \mathcal{U} \times \mathcal{L}} \ell dG_s(a, u, \ell) \end{aligned} \quad (1.32)$$

where  $L$  is a parameter.

**Definition 1.4.** 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 (1.5)
2.  $z(i)$  is consistent with occupation-level output (1.29)
3. Specialist industry states consistent with specialist occupation distribution (1.28)
4.  $\underline{U}$  is consistent with  $G_b, G_s$
5. Prices are consistent with industry-level demand and feasibility (1.30)-(1.31)

6. *Laws of motion for labor are consistent with  $\{\underline{U}, \overline{U}\}$  (1.25)-(1.26)*
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 (1.8)*
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  $\{L_b, p_b(u, \ell), \underline{U}, \overline{U}\}$ :  $\{J_b, E_b, U_b, m, u, g_{u;b}\}$  solve Recursive Broad Occupation PE*
12. *Feasibility w.r.t  $L$  (1.32)*

#### 1.4.8 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 productiv-

Table 1.3: Parameters of the model

Parameter	Value	Description	Source
<b>General</b>			
$\rho$	0.001	Discount rate	
$\Delta$	0.333	Length of period	
<b>Industries</b>			
$\sigma$	0.050	Productivity std	
$\rho_A$	0.800	Productivity autocorr	
$\theta$	4.500	Elasticity, Final sector	
<b>Network</b>			
$A_x$	4.322	Productivity ( $x$ )	Labor force distribution
$\gamma$	0.500	Measure of broad occupations	Illustration
$\bar{\theta}$	0.500	Elasticity, broad industries	High complementarity
<b>Occupations</b>			
$A$	1.355	Matching productivity	Literature
$\alpha$	0.510	Matching elasticity	Literature
$c$	0.127	Vacancy posting cost	Average unemployment rate
$b$	0.955	Home production	HM (2008)
$\beta$	0.052	Bargaining Power: Worker	HM (2008)
$\delta$	0.100	Monthly separation rate	Shimer (2005)
$\zeta$	0.006	Labor force entry/exit	Average working years
$k$	0.103	Moving cost	

All rates in quarterly units.

ity shock at the industry level yields higher equilibrium employment in linked occupations. By choosing high values for  $\sigma$  and  $\theta$ , 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  $\gamma$ , 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  $\gamma$  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.  $\alpha$  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 therefore I simply set  $A$  to the value in Shimer (2005). I calibrate  $c$  to match an average unemployment rate of  $u = 0.05$ .

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

Finally,  $k$  will govern the rate at which workers respond to shocks by changing occupations. Unfortunately, there is no causal evidence on 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 upwards-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 1.C 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 percentile.  $k$  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  $k$ .

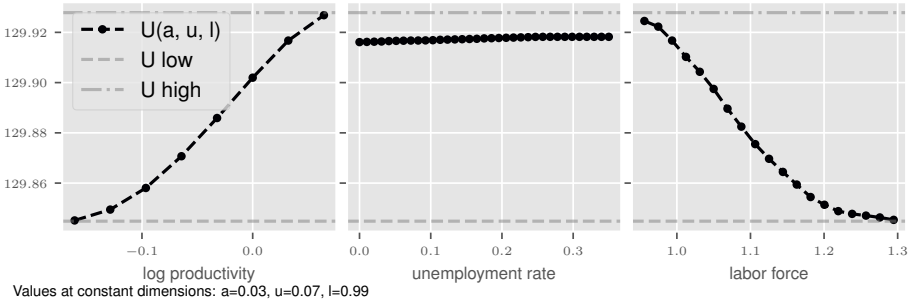
**Table 1.4:** Key statistics of the steady state

Moment	Value	Description
<b>Industries</b>		
$Y$	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
<b>Occupations</b>		
$v_b$	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

#### 1.4.9 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 1.4 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, 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.

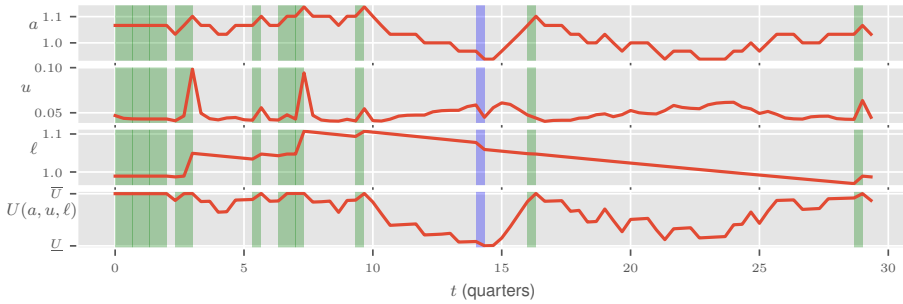
*Figure 1.12: Value function of the unemployed*

### Mobility and compensating differentials

We begin our steady state analysis by analyzing the behavior of individuals within a single given occupation. Figure 1.12 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.

A 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 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

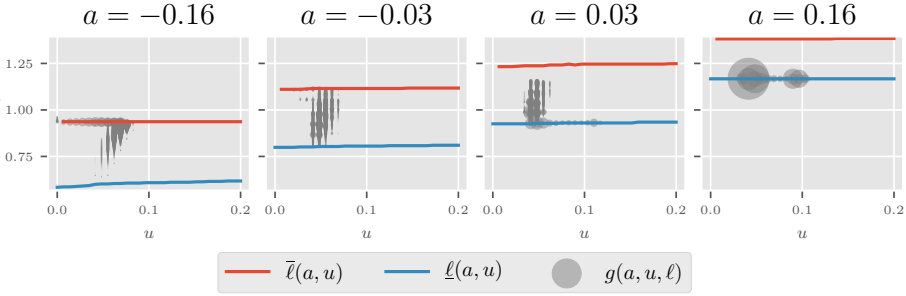
**Figure 1.13:** Dynamics of a simulated specialized occupation

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

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 1.13 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  $\ell$  are equilibrium outcomes. The fourth panel displays  $U(\Omega_s)$ , which is in equilibrium bound between  $\underline{U}$  and  $\overline{U}$ . Episodes where  $U_s$  is at its corner values are highlighted in green. Whenever a positive productivity shock would push  $U_s$  above  $\overline{U}$ ,  $\ell$  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, we observe a sharp decline in both labor force and unemployment rate.

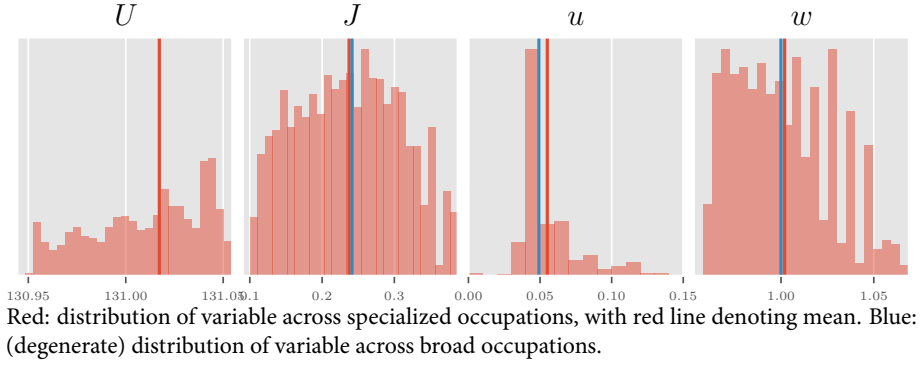


**Figure 1.14:** *Mobility*

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

Next, we analyze the stationary distribution that is implied by the dynamics of each occupation. Figure 1.14 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  $(u, \ell)$  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.

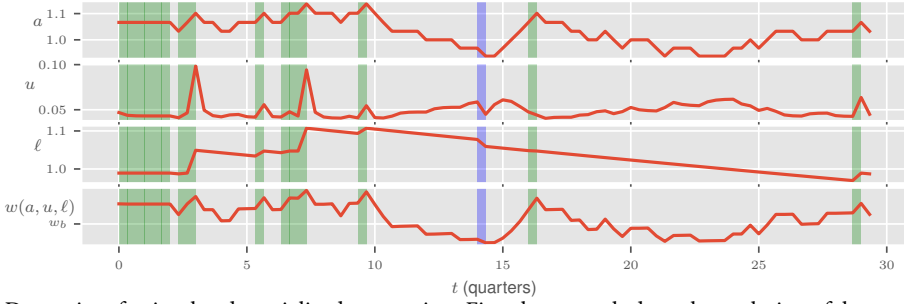
**Figure 1.15:** Key labor market variables in specialized and broad occupations

### Compensating differentials and wage profiles

Now we highlight wage formation in this model. Figure 1.15 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  $(u, \ell)$ , 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  $J_b > E[J_s]$ , 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 broader 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 1.16 again considers the simulated

**Figure 1.16:** *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 law panel depicts the evolution of wages.

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.

## 1.5 Aggregate shocks

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 fairing similarly in such a recession. Appendix 1.E.1 shows that this is not the case: broad occupations actually are 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 reduce 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 1.E.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.

$$\begin{aligned}
A(i, t) &= \begin{cases} A(t) + \tilde{A}(i, t) & \text{if } i \in \mathcal{I} \\ \tilde{A}(i, t) & \text{else} \end{cases} \quad (1.33) \\
\tilde{A}(i, t) &= \phi A(i, t-1) + \epsilon_t \\
A(t) &= \begin{cases} \mu & \text{if } t \leq T \\ 0 & \text{else} \end{cases}
\end{aligned}$$

Equation (1.33) 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  $\mu$ , 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.

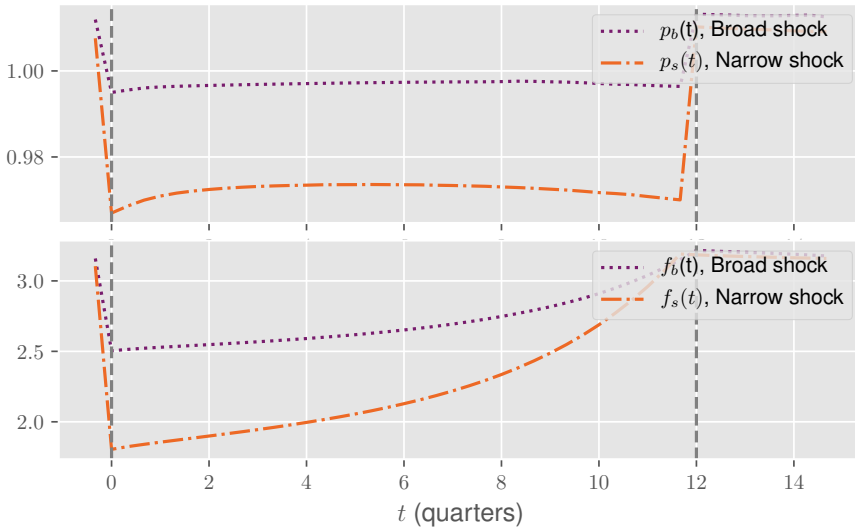
This recession is a unexpected by the agents. As soon as the initial shock hits, all agents have perfect foresight about the remaining evolution of the process. This type of zero-probability aggregate shocks are often referred to as “MIT shocks”<sup>2</sup>.

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 1.17 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

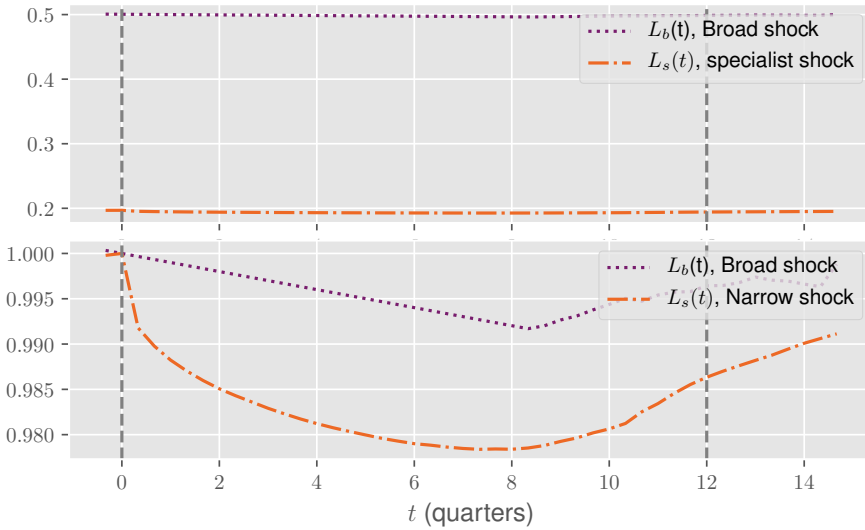
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<sup>2</sup>Studying the economy’s deterministic response to shocks that are ex-ante unexpected is useful to understand its response to recurring aggregate shocks, see Boppart, Krusell, and Mitman (2018)

**Figure 1.17:** Cross-sectional responses

recessions. As established earlier, workers in broader occupations are insured against industry-specific recessions as they can sell their good to unaffected sectors. This insurance manifests 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 is less responsive than that of specialized occupations.

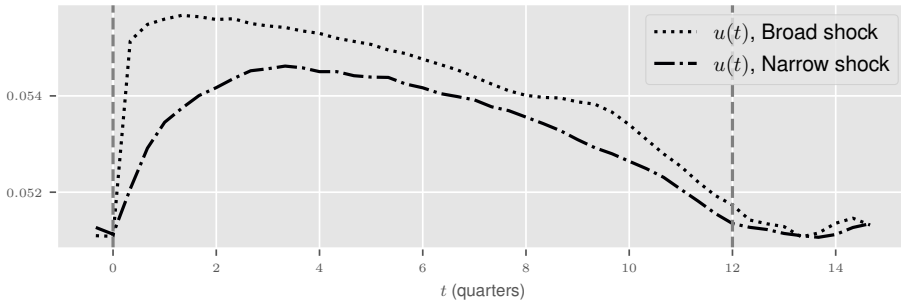
These are the implications of the direct effect. They qualitatively track what we measured in the empirical section. However, we have to take into account the size of the populations affected by each shock. The first panel in Figure 1.18 compares the relative labor forces that are directly affected by 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

**Figure 1.18:** Comparison compositions

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 1.18 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

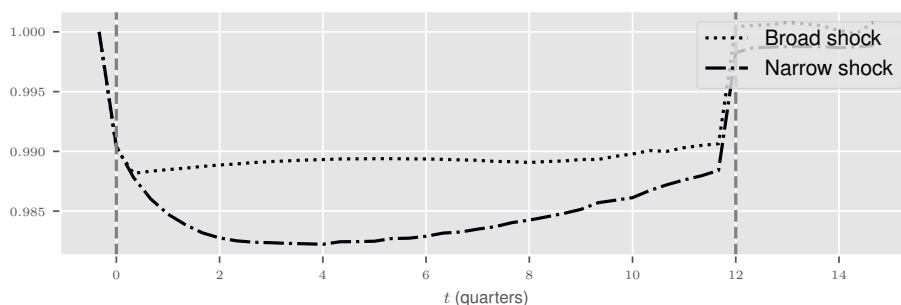
**Figure 1.19:** Aggregate unemployment response

market and therefore dampen the impact of the aggregate productivity shock onto 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 1.19 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 non-linearity is the aforementioned occupation-switching. A shock to specialized occupations leads to a 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.



*Figure 1.20: Aggregate output response*

Therefore, it is sufficient to show that the output losses are larger in the specialized recession than in the broad recession (Figure 1.20), 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.

## 1.6 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 unemployment 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.

A large 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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## 1.A Occupation-level unemployment during Great Recession

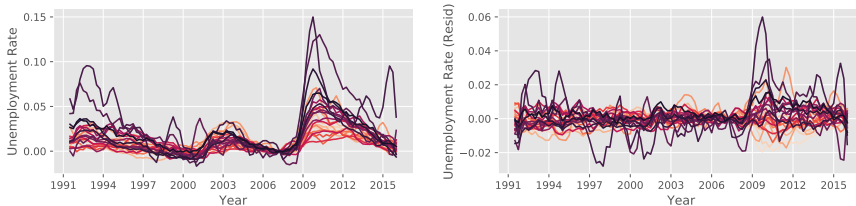
In the introduction, Figure 1.1 displays the standard deviation of occupation-level unemployment rates.

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

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

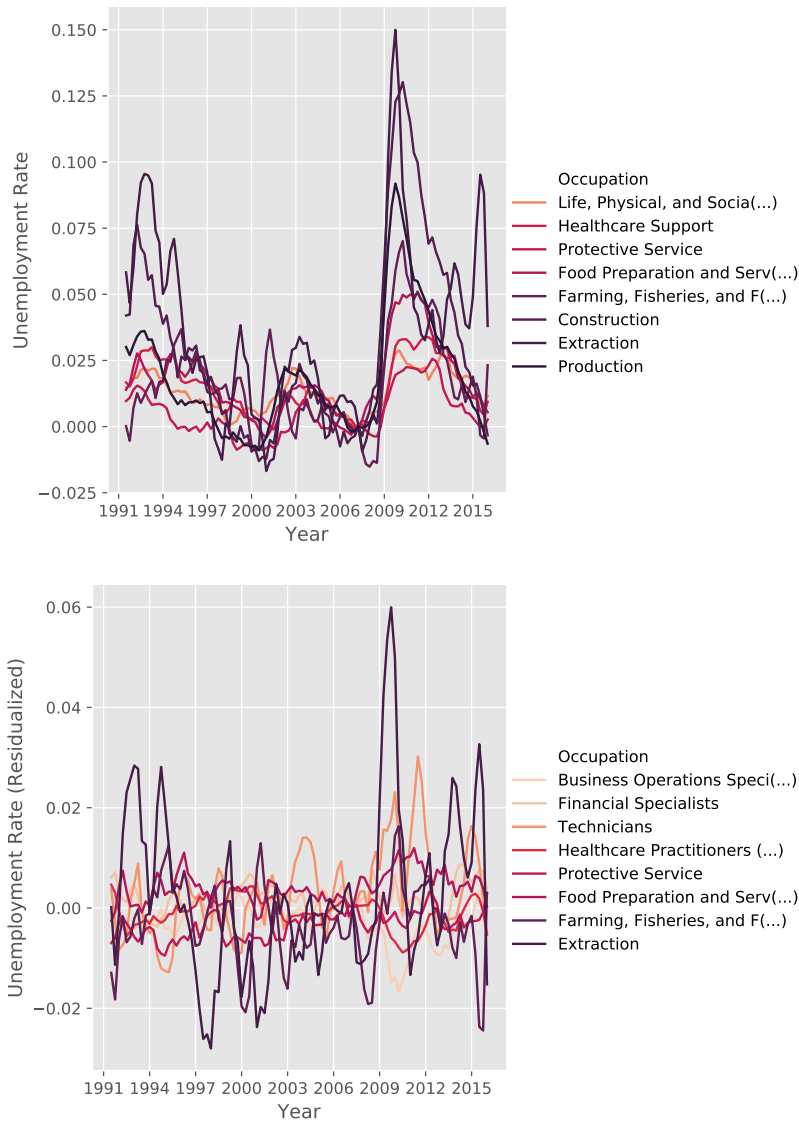
The resulting unemployment rates are displayed in Figure 1.21. To give a feeling of which occupations are affected most and least, I display the unemployment rates for the least and most affected occupations in Figure 1.22.

**Figure 1.21:** *Occupation-level unemployment rates during Great Recession*



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

Figure 1.22: Occupation-level unemployment rates for subset of occupations





## 1.B Classification

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

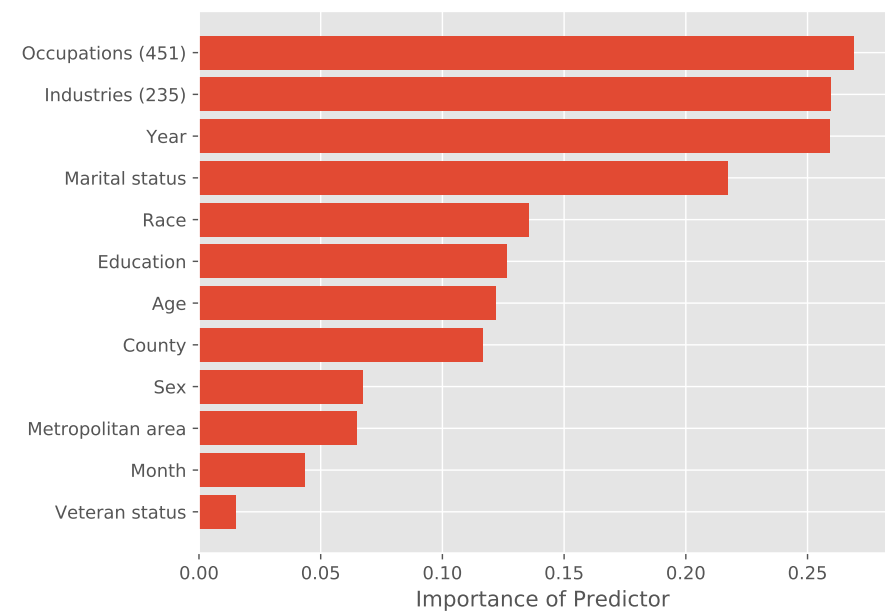
Shapley values constitute a solution concept in game theory: they uniquely distribute a surplus to a coalition of players. Shapley values are the unique distribution that satisfies the following four important characteristics for a given player set: they distribute the total surplus (“efficiency”), attribute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

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

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

Figure 1.23 plots average absolute Shapley Additive Explanations across all observations for each independent variable.

**Figure 1.23:** Occupations are an important predictor of individual-level unemployment status



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

## 1.C Measuring occupation and industry switching

In the CPS, respondents are asked about their typically performed tasks. After the interview, these are coded into occupation groups. The reported tasks may change from interview to interview even if the individual is still in the same occupation. This may be the case when two occupations have a large set of coinciding tasks, and the interviewee reports a different subset of tasks in each interview<sup>3</sup>.

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

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

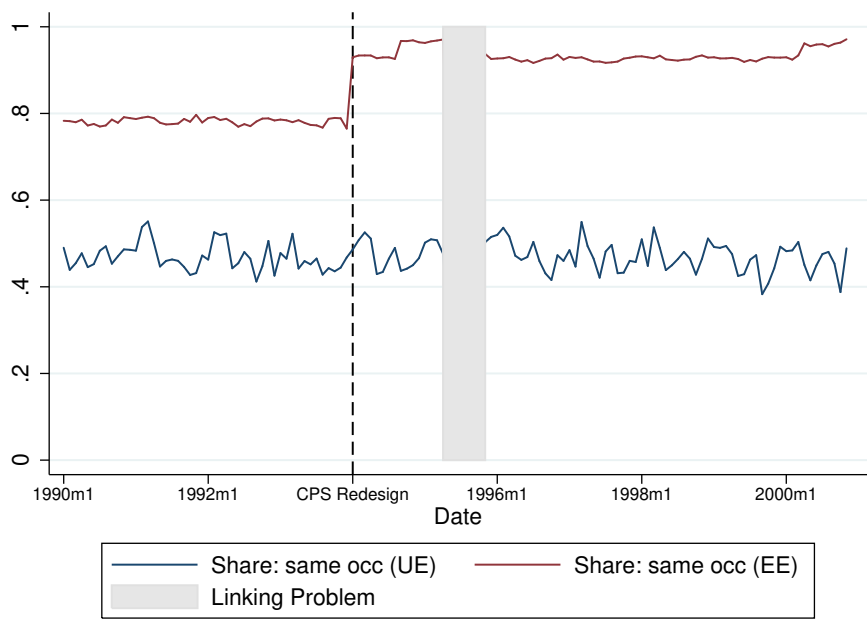
$$S_{x,i,t} = \begin{cases} 1 & \text{if } x_{i,t} = x_{i,t-1} \\ 0 & \text{else} \end{cases}$$

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

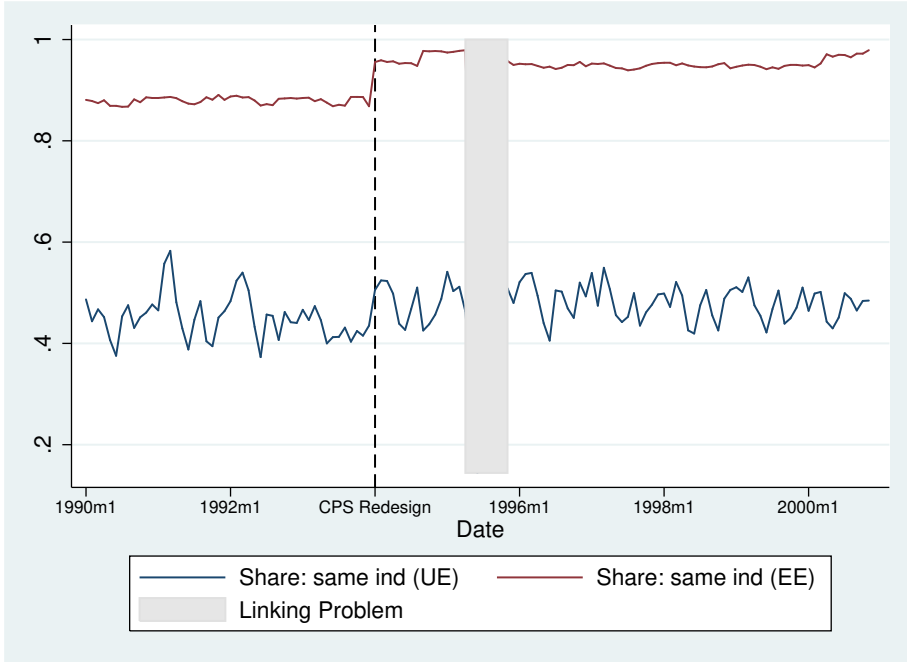
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<sup>3</sup>Another question is whether these similar tasks should be coded into different occupations, but out of the scope of this summary.

**Figure 1.24:** *Occupation stayers by employment status*



Occupations are grouped into 26 larger time-consistent groups.

**Figure 1.25:** Industry stayers by employment status

Industries are grouped into 29 larger time-consistent groups.

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

Figure 1.24 displays  $\bar{S}_{x,u,t}$  and  $S_{x,e,t}$  for the United States computed using the CPS, where  $t$  is measured in monthly frequency. Note that, on average,  $\bar{S}_{x,e,t} > \bar{S}_{x,u,t}$ . Additionally, the CPS redesign in 1994 introduced a sharp break in  $\bar{S}_{x,e,t}$ : dependent coding increased the share of identified occupation stayers. The same is not true for  $\bar{S}_{x,u,t}$ : as dependent coding was only introduced for the employed, estimated transitions for the unemployed are still very noisy.

In analogue, I can define  $x$  to instead hold industry status. Figure 1.25 displays industry stayers for the same sample. The similar patterns are clear here:

staying is more likely in EE than in UE transitions. Again, the CPS redesign increases the measured stayers for the employed, but not the unemployed.

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

## 1.D Broadness of the unemployed

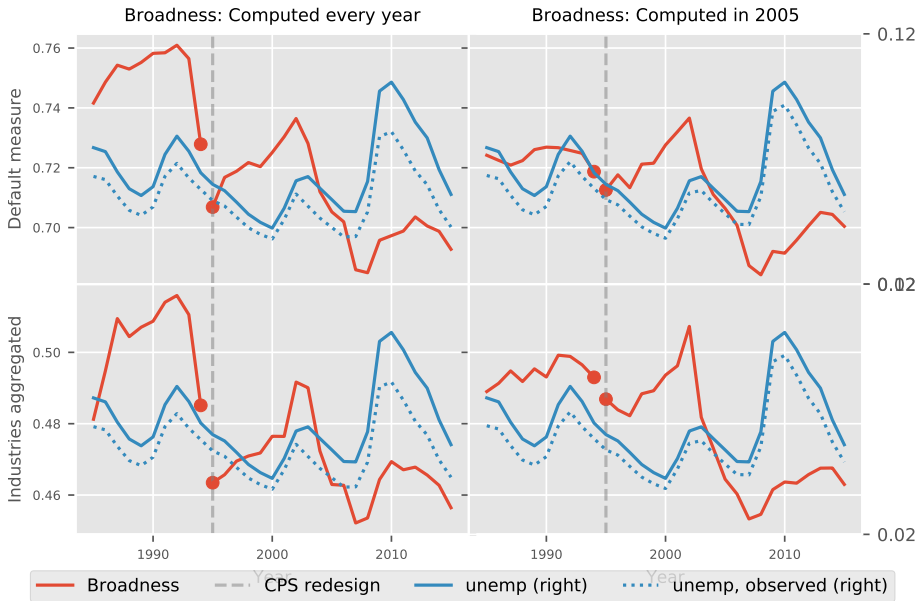
In Figure 1.8, I plot the time series of average broadness of the unemployed. This is done as follows: I compute  $m_{o,t}$  for each occupation, using a whole year to compute the shares  $s_{i,o,t}$  and the corresponding broadness. I then essentially compute the average broadness of the unemployed  $\bar{m}_t$  as

$$h_{o,t} = \frac{u_{o,t}}{\sum_o u_{o,t}}$$

$$\bar{m}_t = \sum_o h_{o,t} m_{o,t}$$

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

Figure 1.26 displays several robustness checks to that baseline computation. The top-left panel is identical to the figure in the main text. The top-right panel computes  $m_{o,t}$  in 2005 and holds it constant. The second row computes both

**Figure 1.26: Broadness of the unemployed**

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

versions for aggregated industry groups.

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

## 1.E Cross-sectional Experiments

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

equilibrium, there are two additional forces at play that will be the focus of this section.

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

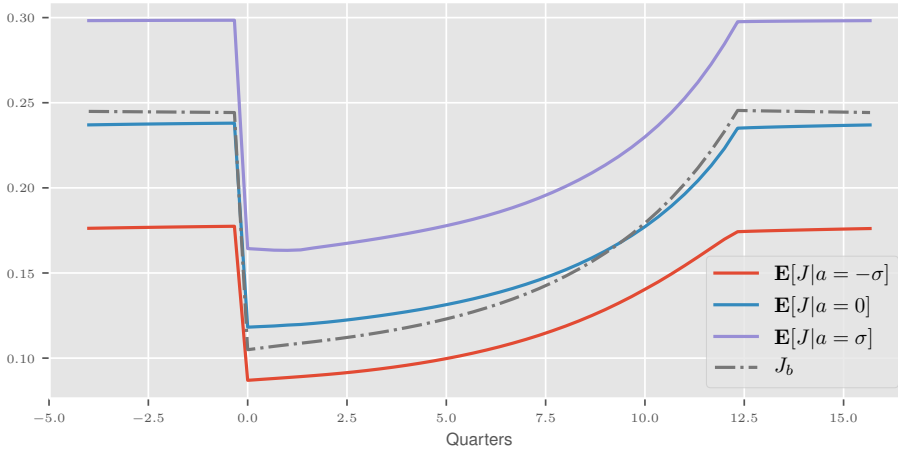
### 1.E.1 Indiscriminate shock

Here, we play through an experiment in which the productivity in each sector is reduced for a finite number of periods. I will now denote the industry-specific shock  $A(i, t)$  as a sum of an industry-specific AR(1) process  $\tilde{A}(i, t)$ , and an aggregate component  $A(t)$ . For clarity of exposition,  $A(t)$  will not dissolve geometrically. Instead, it will switch between any non-zero value during the periods of the experiment,  $t \in \mathcal{T}$ , and zero otherwise. The shock structure is summarized in (1.34).

$$\begin{aligned} A(i, t) &= A(t) + \tilde{A}(i, t) \\ \tilde{A}(i, t) &= \phi A(i, t-1) + \epsilon_t \\ A(t) &= \begin{cases} \mu & \text{if } t \in \mathcal{T} \\ 0 & \text{else} \end{cases} \end{aligned} \tag{1.34}$$

As it turns out, broad occupations fare *worse* than specialists throughout the episode. Figure 1.27 displays the impact of the aggregate shock on firm values at the occupation level. As the aggregate productivity enters multiplicatively with idiosyncratic productivity, firms with a high idiosyncratic productivity are affected more by the aggregate shock. This leads to a compression of firm values during the aggregate shock. Firms in broad occupations face no idiosyncratic shocks as they are diversified across industries. Prior to the aggregate shock, broad firms had the same value as the median productivity specialist firms. However, their values drop more during the recession. This is because of the interaction of idiosyncratic shocks with aggregate shocks: specialist firms' upside from a positive shock dominates the downside from a negative shock.



**Figure 1.27:** *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 riskiness of their output price has positive value, which is why broad firms (which lack this value) lose more on value during the recession than their specialist counterparts.

Figure 1.28 separates the effects into the three main layers of the model. As all industries are affected, relative productivity changes are equal in both broad and specialist industries. The shock hits at time 0. Notice that unemployment is frictional, and production is timed to happen before adjustments through hirings and separations can happen: the initial output response in  $Y(0)$  purely comes from the change in productivity. Labor market responses then result in a further reduction of output in subsequent periods.

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

The disadvantage of broad occupations is displayed among all margins of the

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

### 1.E.2 Lilien-type recession

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

I will denote the set of industries that are affected by the aggregate shock by  $\mathcal{I}$ . I adjust the previous shock structure as in (1.35).

$$A(i, t) = \begin{cases} A(t) + \tilde{A}(i, t) & \text{if } i \in \mathcal{I} \\ \tilde{A}(i, t) & \text{else} \end{cases} \quad (1.35)$$

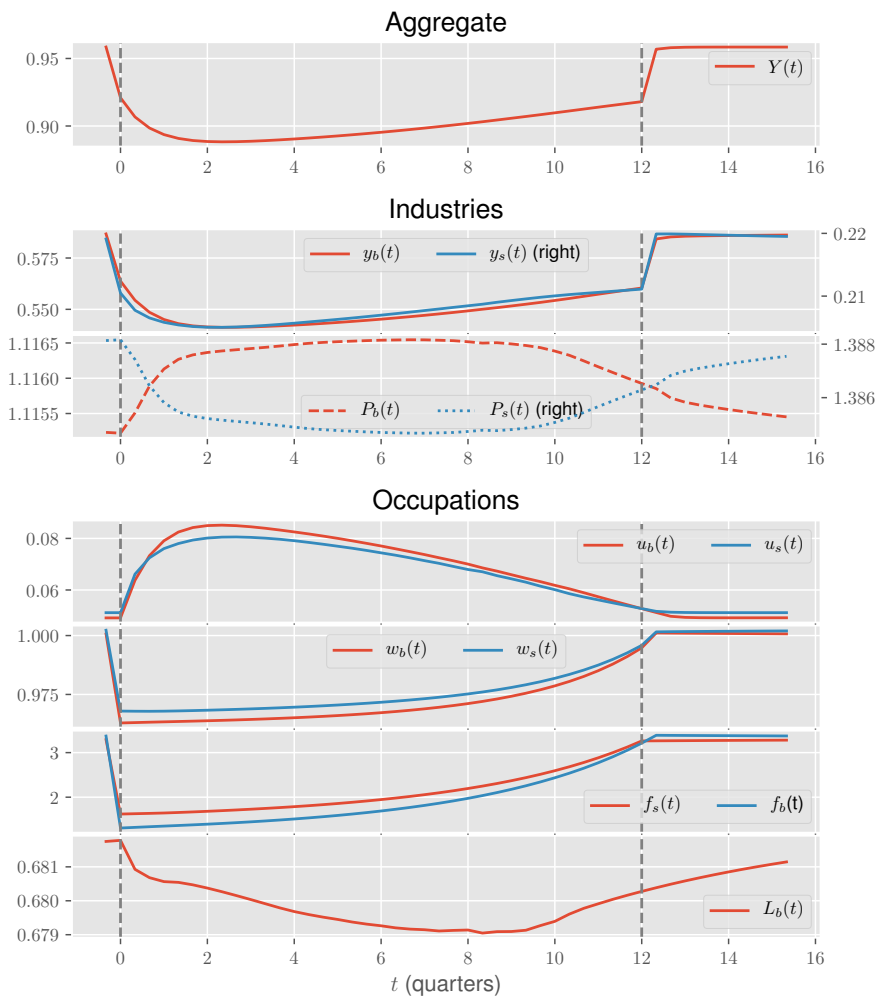
$$\tilde{A}(i, t) = \phi A(i, t-1) + \epsilon_t$$

$$A(t) = \begin{cases} \mu & \text{if } t \in \mathcal{T} \\ 0 & \text{else} \end{cases}$$

$\mathcal{I}$  consists of an equal measure of (randomly drawn) broad and specialist industries. Figure 1.29 summarizes the effects for level of aggregation.

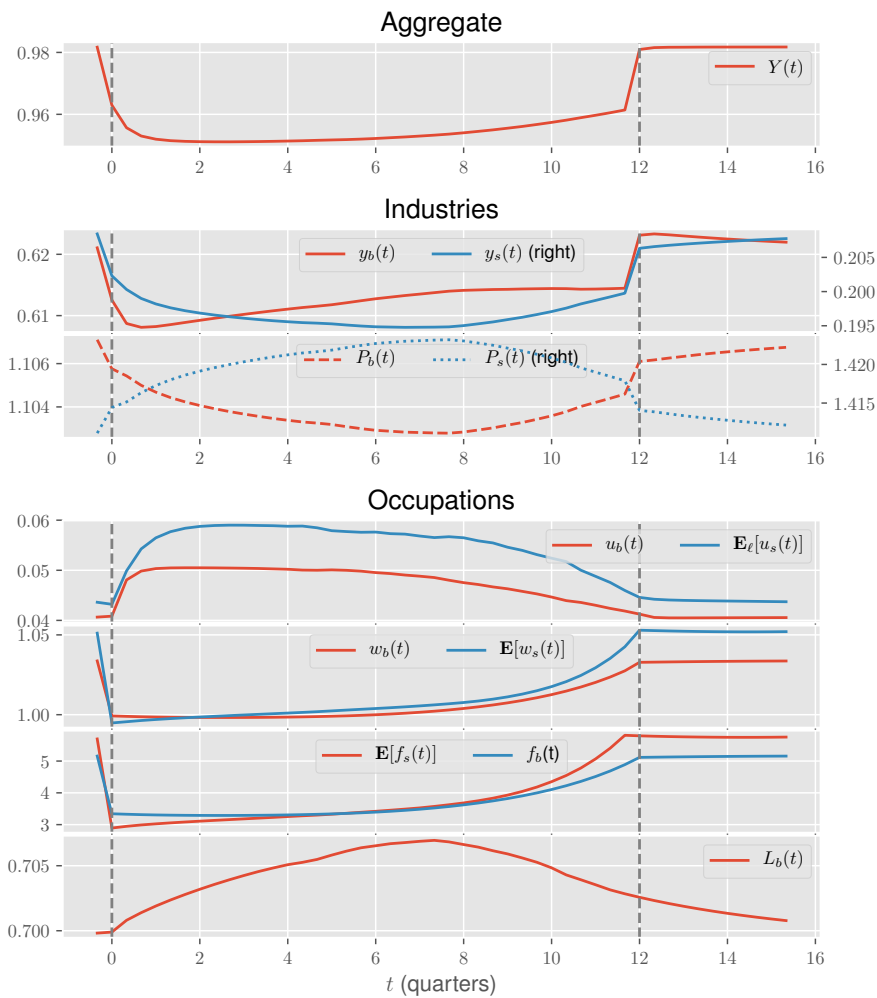
As before, one can distinguish the instantaneous drop in productivity from the changes from employment by comparing the output response in period 0 against those in subsequent periods. In a recession where not all industries are hit, specialist occupations fare substantially worse than broad occupations: the change in unemployment is doubled, and the relative wage cuts are higher. All

Figure 1.28: Response of the economy to an indiscriminate shock



these effects coexist with a larger response in labor force adjustments: 7 quarters into the experiments, an additional .5% of the labor force have now relocated in broad occupations. This additional labor force has been successfully integrated in the broad occupations in such a way that unemployment rates and wages are still performing better in that part of the labor market.

Figure 1.29: Response of the economy to a Lilien-type recession



## 1.F Computational appendix

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

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

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

### 1.F.1 Solving for $U_b$

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

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

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

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

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

### 1.F.2 Solving for $\bar{U}$ given $U_b$

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

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

### 1.F.3 Solving for mobility given $\bar{U}$

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

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

The main computational problem in this environment is exactly how to do the 4th step here: there is no contraction mapping at play here, or no other obvious updating process. Also, every time we have to compute value functions

in the 2nd step is very costly. Thus, a good method for updating  $(\underline{\ell}, \bar{\ell})$  is crucial. The following methodology is stable, and I will argue why that is the case.

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

Denote

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

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

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

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

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

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

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



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

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

### 1.F.4 Solving for specialized value functions

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

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

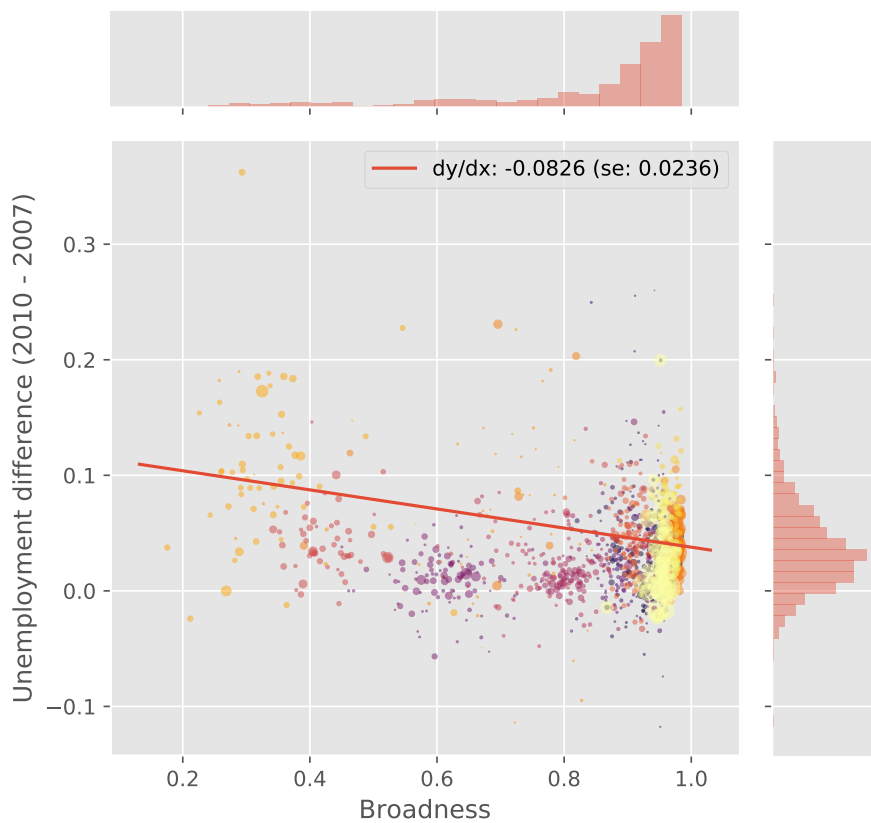
$$\begin{aligned} J &= J(f(m(J), T)) \\ T &= T(f(m(J), \underline{\ell}, \bar{\ell})) \\ U &= U(J, f(m(J), T, \underline{U})) \end{aligned}$$

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

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

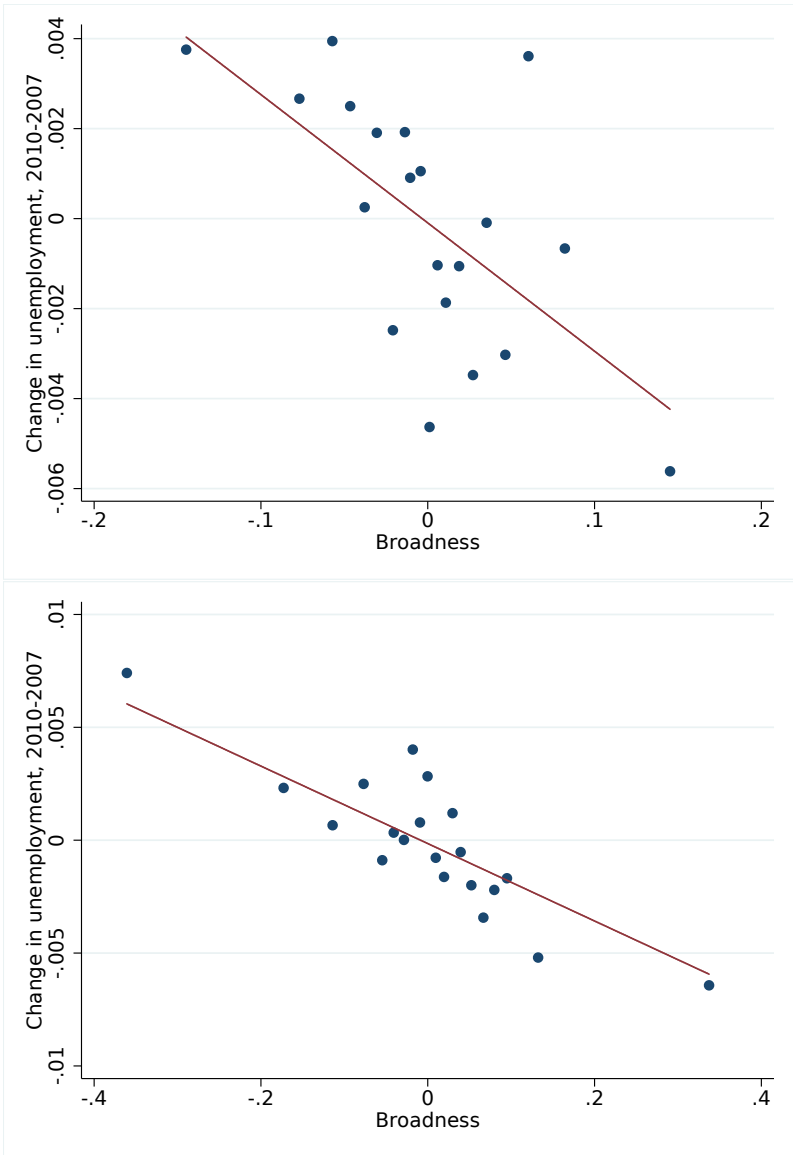
## 1.G Figures

**Figure 1.30:** *Broader occupation's unemployment responses were mitigated*



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

**Figure 1.31:** *Broader occupation’s unemployment responses were mitigated*



Occupation-specific unemployment responses during the great recession as a function of their broadness. Top panel: only controlling for occupation and state-fixed effects, corresponding to column (3) in table 1.2. Bottom panel: controlling for individual demographics, and state-year fixed effects – as in column (4).

## Chapter 2

# Consumer good search: theory and evidence

How are the vast surpluses from economic activity split between firms and consumers, and how does that affect macroeconomic outcomes? When consumers compare prices they put downward pressure on prices and gain a larger share of the surplus associated with the transaction. Firms acknowledge the importance of this mechanism by actively undermining it: in Germany, gas stations are required to publish their prices on the internet. Yet, they hinder price comparisons by changing their prices on average 3 times a day, leading to a quite dispersed price market (Martin, 2018). In a similar fashion, US retail stores engage in temporary price discrimination and complex price bundles (Kaplan, Menzio, et al., 2019) to complicate consumers' good search.

Not only is consumer good search an important aspect of an individual firm's profitability, but it also has the potential to affect the aggregate economy. For example, total search might vary with the business cycle, and affect the cyclicity of profits (Qiu and Ríos-Rull, 2019; Kaplan and Menzio, 2016). The exact modeling of the search decision affects the aggregate behavior of these models. One way of constraining this modeling choice is to micro-found it to be consistent with empirical observations. So far, the literature has not chosen this approach.

For example, Kaplan and Menzio (2016) assume that all households randomly draw either one or two prices. The probability of drawing two prices

is fixed, but is higher for unemployed than for employed households. In their model, firms' pricing strategy changes with the business cycle, thus leading to strongly pro-cyclical prices. In equilibrium, price dispersion also changes with the business cycle. Good search is fixed by assumption and does not respond to these changes in dispersion. This is difficult to square with an empirically observed decline in the aggregate search activity during the most recent recession in the United States.

In this paper, I provide one microfoundation for the search decision and test whether the mechanism underlying these macroeconomic models can explain empirically observed search behavior.

First, I set up a search-leisure tradeoff that can readily be integrated into macroeconomic theory. Households have preferences over consumption and leisure that are consistent with balanced growth. Good search costs leisure, but leads to a larger random draw of prices. The households buy at the lowest observed price, implying that consumption weakly increases in the search decision. I show that the households' search decision increases weakly in its time endowment. A household's search decision is independent of its income due to the additive separability of preferences in consumption and leisure.

On the other side of the market, the firms are modeled as in Burdett and Judd (1983): they take as given the search intensities of the households and decide what prices to set. Setting a higher price leads to a higher revenue per customer, but a smaller set of customers to whom to sell. This trade-off can lead to a non-degenerate price distribution.

The model always features an equilibrium without search. There are 0, 1, or 2 search equilibria in which firms are indifferent between a range of prices. After describing these equilibria in detail, I test the model's ability to predict the search behavior by employment status that is key to the mechanism in Kaplan and Menzio (2016). I measure the search intensities and the time constraints in the American Time Use Survey and show that the unemployed spend 18% more time searching than the employed. I calibrate the price distribution to empirical moments: in particular, I match that the unemployed pay on average 2% less than the employed for a comparable consumption bundle ((Kaplan and Menzio, 2016)). I then test whether I can replicate the empirically observed

differences in search behavior across the employed and the unemployed. In the model, unemployed households spend between 200% and 300% more time searching than the employed - far more than the targeted 18%.

I discuss the different assumptions leading up to this result, and the degree to which relaxing them could reconcile the model with the data. The most potent explanation is that unemployed and employed households are not sampling prices from the same distribution: firms may strategically set prices to discriminate between households with a high and low marginal evaluation of time. The unemployed spend 18% more time shopping than the employed and pay 2% less on the same consumption bundle. When assuming that the employed and the unemployed are drawing from the same price distribution, this can be used to discipline price dispersion and the returns to search. If firms can actually discriminate by employment status, such a calibration strategy would be misguided. Discrimination by employment status may be implemented with time-varying prices (Klenow and Malin, 2010; Kaplan and Menzio, 2015): firms might vary prices hourly or daily to prevent the employed - who on average are more constrained in their times of shopping - from finding the same prices as the unemployed.

Alternative extensions to match the data involve different preferences or technology assumptions. Ultimately, which extension one chooses to fit the model to the data will affect the aggregate behavior of the model. For example, if stores are indeed able to discriminate by employment type, changes in the composition of searchers by employment status will not affect the price distribution, and the strong amplification mechanism in Kaplan and Menzio (2016) becomes moot. I conclude that at this stage, consumer good search is not ready to be integrated into macroeconomic analysis: realigning the model with the data in a credible way is key for this literature to make progress.

## 2.1 Model

The model is static and describes a single market. On the one side, we have households with fixed time and income endowments. Households take as given a distribution of prices from which they search. They decide how much time

to spend searching for prices and draw random prices out of that distribution. They draw multiple prices out of that distribution and will - with perfect recall - purchase consumption goods at the lowest price that they drew. On the other side of the market, we have firms that each take as given the search intensity of the households and the prices set by other firms. Firms choose their price so as to maximize profits. I will first analyze each side of the market in detail. Then, I introduce the notion of equilibrium as two partial equilibria that are consistent with each other.

### 2.1.1 Households

Households have standard macroeconomic preferences over leisure  $\ell$  and consumption  $c$  as in (2.1). Households have a total time endowment of  $T$  available to spend on both leisure and goods search. In this economy, households cannot directly consume their income  $y$ . They first have to transform it into consumption goods at a given price  $p$ . In this static economy, households will spend their entire income and purchase  $y/p$  units of consumption. Therefore, we can write the households' utility function for any time spent searching  $t$  and price  $p$  as  $U(p, t; y, T)$  given their time and income endowments as in (2.2).

$$\frac{1}{1-\sigma} [c^\gamma \cdot \ell^{1-\gamma}]^{1-\sigma} \quad (2.1)$$

$$U(p, t) = \frac{1}{1-\sigma} \left[ \left( \frac{y}{p} \right)^\gamma (T-t)^{1-\gamma} \right]^{1-\sigma} \quad (2.2)$$

At the core of the model is the transformation between time spent searching and the resulting price draws. Following Burdett and Judd (1983), I assume non-sequential search. Here, households commit time to be spent searching for prices, and receive a Poisson draw of prices out of the distribution  $F(p)$ . For any time  $t$ , the number of prices drawn will be Poisson distributed with mean  $\lambda(t)$ . I denote the probability of  $s$  draws given the arrival rate  $\lambda$  as  $P(s, \lambda)$ . We assume  $\lambda(t) = aSt$ , where  $S$  is the measure of firms operating in the economy and  $a$  is a search-efficiency parameter. Appendix 2.B provides a micro-foundation for this arrival rate.

$$K(t) = P(0; \lambda(t))U(r, t; y, T) + \sum_{s=1}^{\infty} P(s; \lambda(t)) \int U(p, t; y, T) h(p, s, F) dp$$

$$H(p; s) = \text{Prob}(\min \leq p) = 1 - \prod_{x=1}^s (1 - F(p)) \quad (2.3)$$

$$h(p; s) \equiv \frac{\partial H(p; s)}{\partial p} = s(1 - F(p))^{s-1} F'(p) \quad (2.4)$$

The household's objective is to trade off leisure against consumption by choosing the amount of search that maximizes its objective function. Households always have the option of transforming their income to consumption at the reservation price  $r$ . The objective function given choice  $t$ , endowments  $y, T$  and the exogenous distribution  $F$  is denoted as  $K(t)$ : with probability  $P(0; \lambda(t))$  households receive zero price draws. In that case, they transform at the reservation rate  $r$ . Otherwise, they receive  $s > 0$  draws and purchase at the lowest price - where  $h(p; s)$  denotes the density of the minimum of  $s$  price draws. To derive it, I first compute  $H(p; s)$ , the CDF of the minimum price, as the complement to the probability of all  $s$  prices being above  $p$  as in (2.3). Equation (2.4) computes the corresponding density.

**Lemma 2.1.** *The objective function has the following compact representation:*

$$K(t) = e^{-\lambda(t)} \frac{1}{1-\sigma} \left[ \left( \frac{y}{r} \right)^y (T-t)^{1-y} \right]^{1-\sigma} \quad (2.5)$$

$$+ \lambda(t) \int e^{-\lambda(t)F(p)} f(p) \frac{1}{1-\sigma} \left[ \left( \frac{y}{p} \right)^y (T-t)^{1-y} \right]^{1-\sigma} dp$$

*Proof.* In the appendix. □

The household chooses  $t$  so as to maximize the objective function (2.6), and I denote the policy function as  $g(y, t, F)$ .

$$g(y, T, F) = \arg \max_t K(t; y, T, F) \quad (2.6)$$



How does the solution vary with the individual's endowments and the given distribution?

**Proposition 1.** *Search is independent of income:*

$$g_y(y, T, F(p, t')) = 0$$

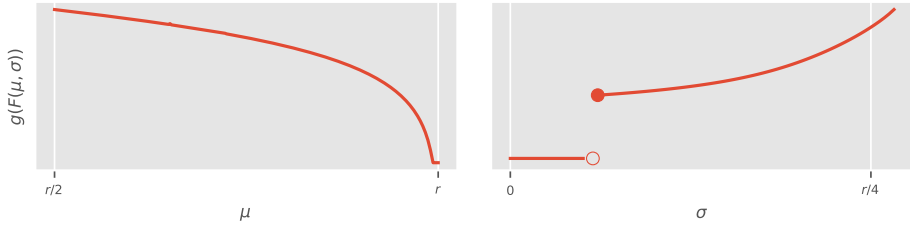
*Proof.* Note that  $K(t; y, T, F) = y^{1-\sigma} \cdot K(t; 1, T, F)$ . Income only scales the objective function and hence does not affect the optimal search intensity.  $\square$

Household income does not affect the search decision. Under the given preferences, this result holds also when including a labor choice: households' work and search decisions are independent of their wage rate. With respect to the second endowment,  $T$ , households' search decisions appear to be weakly increasing in the amount of time that they have available: households that are at a corner solution and spend no time searching might not respond to an increase in  $T$ , but those that are spending some time shopping will increase their search intensity when provided with more time.

Finally, we look at how  $g(y, T, F)$  varies with the distribution  $F$ . It is difficult to make general statements: we focus on a case where prices stem from the truncated normal distribution with mean  $\mu$  and variance  $\sigma$  and observe how optimal search varies with mean and variance. We use the normal distribution since it is a well-known distribution without excess kurtosis or skewness that allows us to vary both the mean and the variance.

Figure 2.1 displays how  $g$  varies with  $\mu$  and  $\sigma$ . In the left-hand panel, the standard deviation is tiny and constant: all draws from the distribution will be very similar. Here, the main motivation for search is to have at least one draw from  $F$ , and the value of additional draws is negligible. As  $\mu \rightarrow r$ , the gains from search decrease, and optimal search decreases. Since search is random and costly, households already exert zero effort when  $\mu$  is close - but not equal - to  $r$ .

In the right-hand panel, we fix  $\mu = r$ : the expected value of each price drawn is equal to the outside option. Now, the primary motivation from search comes from the dispersion of prices: the distribution  $F$  has a positive support for prices below  $r$ , and the household searches to find those. A higher variance also entails

**Figure 2.1:** Optimal search decreases in mean and increases in variance

Optimal search under normally distributed prices with mean  $\mu$  and standard deviation  $\sigma$ . The left-hand panel varies  $\mu$ , holds  $\sigma = 0.001$  constant. The right-hand panel fixes  $\mu = r$ , and varies  $\sigma$ .

prices with a positive support above  $r$ , but since the household cares about the minimum price drawn and can always fall back to its outside option, a higher variance is always beneficial to it.

Due to the positive variance, there is a value in additional searches – and the higher the variance, the higher the value of searching more: the households want to search more when the variance is higher.

Notice that there is a discontinuity when varying  $\sigma$ , but not when varying  $\mu$ . When the distribution is degenerate, a single draw is always sufficient, and effectively  $t$  is chosen to trade-off the probability of 0 vs 1 draw. In the right-hand panel, the motivation for search is variance: the distribution warrants no searches at all when the variance is small. When the variance is large enough for the household to search, it immediately wants multiple draws. Therefore, the household either chooses a search intensity consistent with zero price draws or one that likely leads to multiple price draws, thus generating a discontinuous search profile.

### 2.1.2 Firms

There is a fixed measure  $S$  of stores in the economy. These make profits by selling to a measure  $H$  of households. Households that draw multiple prices purchase at the store that offers them the lowest price. Out of the customers that arrive at a particular store, the store will only sell to those that have not drawn a lower price elsewhere. I will refer to these customers as “captured”. For any price  $p$ , the probability of capturing a customer conditional on contact is denoted

as  $\eta(p; \lambda, F)$ . Captured customers spend their total income on consumption and will hence buy  $y/p$  units of consumption. Stores produce the consumption good at unit cost  $c$  and hence make per-unit profits of  $p - c$ . Chaining these components allows us to compute the profits  $\pi(p; \lambda, F)$  as in (2.7). The appendix shows that  $\eta(p)$  permits the compact formulation as in (2.8).

$$\pi(p; F, \lambda) = \underbrace{\frac{H\lambda}{S}}_{\# \text{ contacts}} \cdot \underbrace{\eta(p; \lambda, S)}_{\text{Share captured}} \cdot \underbrace{\frac{y}{p}}_{\# \text{ goods sold}} \cdot \underbrace{(p - c)}_{\text{profit per sale}} \quad (2.7)$$

I denote the lowest and the highest price observed in  $F(p)$  as  $\underline{p}, \bar{p}$ :

$$\underline{p} \equiv \min\{p : f(p) > 0\}$$

$$\bar{p} \equiv \max\{p : f(p) > 0\}$$

**Lemma 2.2.** *The capturing probability  $\eta(p; \lambda, F)$  is given by*

$$\eta(p; \lambda, F) = \frac{e^{-\lambda}}{1 - e^{-\lambda}} \frac{1}{1 - F(p)} \left[ e^{\lambda(1-F(p))} - 1 \right] \quad (2.8)$$

*It satisfies*

$$\eta(\underline{p}; \lambda, F) = 1$$

$$\eta(\bar{p}; \lambda, F) = \frac{\lambda e^{-\lambda}}{1 - e^{-\lambda}}$$

*Proof.* In the appendix. □

Naturally, the firms that offer the lowest price in the economy capture all customers that contact them. The firms that offer the highest price only capture the customers that have a single price draw. The probability of meeting such customers - conditional on capture - is given by  $\lambda e^{-\lambda}/(1 - e^{-\lambda})$ .

We can now state a definition of a partial equilibrium. Informally, a partial equilibrium is such that any observed price maximizes the profits.

**Definition 2.1** (Partial firm equilibrium). *For any  $\lambda \geq 0$ , a partial firm-side equilibrium is given by a density of prices  $\{f(p; \lambda)\}$  such that*

$$\pi(p; F, \lambda) \geq \pi(p'; F, \lambda) \quad \forall p : f(p; \lambda) > 0, \forall p'$$

**Lemma 2.3.** *In any equilibrium with a strictly positive search, profits are strictly positive. The price distribution  $F(p)$  is continuous and connected. It satisfies  $c < \underline{p} \leq r$  and  $\bar{p} = r$ .*

*Proof.* In the appendix. □

**Proposition 2** (Equilibrium price distribution). *Under positive search, the unique price distribution consistent with these characteristics is given by (2.9).*

$$F(p; \lambda) = \frac{1}{\lambda} (z + \text{Lambert}W(-ze^{-z})) + 1 \quad (2.9)$$

$$z = \frac{r}{p} \frac{p - c}{r - c}$$

*The lower bound of the distribution satisfies*

$$\underline{p}(\lambda) = \frac{rc}{r - \lambda \frac{e^{-\lambda}}{1 - e^{-\lambda}} (r - c)}$$

*Proof.* In the appendix. □

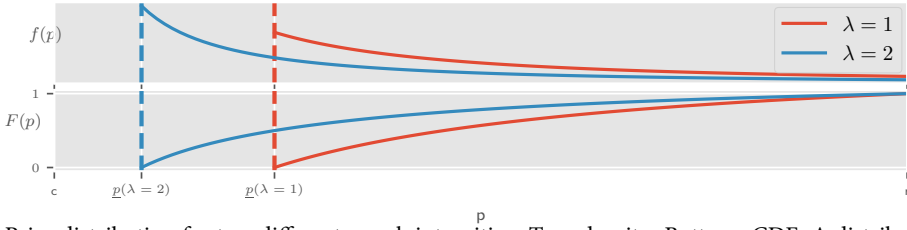
Next, we discuss how the price distribution responds to changes in search intensity.

**Proposition 3** (Price distribution and search intensity). *Distributions consistent with a lower  $\lambda$  first-order stochastically dominate those with a higher  $\lambda$ :*

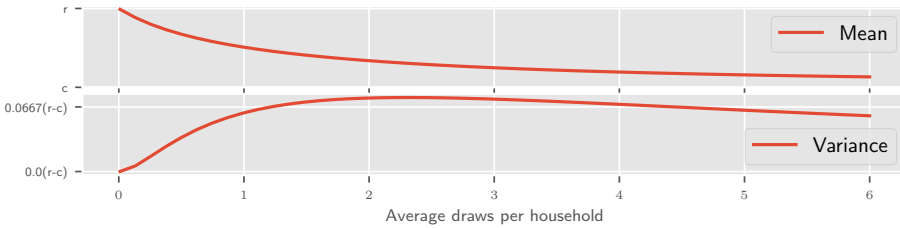
$$F(p; \lambda) \geq F(p; \lambda') \quad \forall \lambda > \lambda', \forall p$$

$$F(p; \lambda) > F(p; \lambda') \quad \forall \lambda > \lambda', \forall p \in [\underline{p}(\lambda'), r)$$

$$\underline{p}'(\lambda) = \frac{e^\lambda(1 - \lambda) - 1}{(e^\lambda - 1)^2} \frac{r - c}{rc} \underline{p}(\lambda)^2 < 0$$

**Figure 2.2:** Price distribution and varying  $\lambda$ 

Price distribution for two different search intensities. Top: density. Bottom: CDF. A distribution consistent with a lower  $\lambda$  first-order dominates the higher- $\lambda$  distribution and has a smaller support.

**Figure 2.3:** Mean and variance under varying  $\lambda$ 

*Proof.* In the Appendix. □

Figure 2.2 draws the price distribution for varying search intensities to demonstrate this point. A corollary of Proposition 3 is that distributions consistent with a lower  $\lambda$  have higher mean prices.

The relationship between  $\lambda$  and the variance of the distribution is ambiguous. When  $\lambda$  is low, the distribution has most of its mass close to  $r$ : an increase in  $\lambda$  now increases the dispersion. As the distribution spreads out, the lower bound of its support converges to  $c$ . An increase in  $\lambda$  leads to even more prices close to  $c$ : when  $\lambda$  is high, an increase in  $\lambda$  leads to a concentration of prices around  $\underline{p}(\lambda)$  and a decrease in dispersion. Figure 2.3 demonstrates this by plotting the mean and variance of  $F(p)$  against  $\lambda$ .

### 2.1.3 Equilibrium

We can now define an equilibrium for this economy. We will not consider firm entry and treat the measure of firms  $S$  as an exogenous parameter.

**Definition 2.2** (Equilibrium). *Given measures  $\{S, H\}$  and endowments  $\{y, T\}$ , an equilibrium is described by a tuple  $\{F, t\}$  such that*

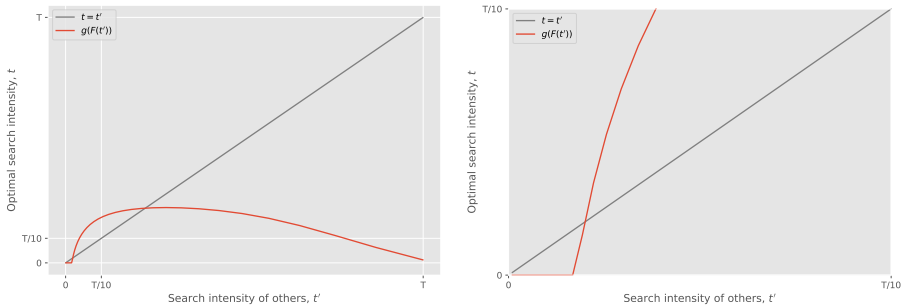
1.  $t = g(y, T, F)$  is optimal given  $F$  (2.6)
2.  $F$  is consistent with  $t$  (2.9)

Figure 2.4 displays the best response of an individual household to the aggregate search behavior of all other households. Aggregate search behavior affects the search distribution and thereby the individual household, which summarizes the fixed-point problem that characterizes the equilibrium.

Many distributions  $F$  are consistent with zero search, for example a degenerate distribution with support only on  $r$ . This distribution would induce zero search and demonstrates that an equilibrium without search always exists.

When aggregate search  $t'$  is very low, most of the mass of the price distribution will still be near  $r$ , inducing a very little search: both the mean and the variance of  $F$  are such that search is not optimal. Following Proposition 3, a higher  $\lambda$  leads to distributions that are preferred by the agent. This induces additional search to draw from that distribution:  $dg/dt > 0$ . As  $t$  increases, the dispersion in  $F$  eventually starts decreasing, such that additional searches do not improve much on a first price draw. Since the variance motivation of search decreases, households reduce their search:  $dg/dt < 0$ .

**Figure 2.4:** Equilibrium as a fixed-point problem



On the x-axis, we vary the aggregate search intensity which affects the price distribution. Against that, we plot the search intensity which is optimal given the price distribution. The right-hand panel zooms into the lower-left quadrant of the left-hand panel.

In conclusion,  $g(F(t'))$  always first increases and then decreases. What

does this mean for the number of potential search equilibria?

This particular example in Figure 2.4 features two search equilibria. Figure 2.5 changes the search-efficiency parameter  $a$  which linearly scales  $\lambda'(t)$ . When search is very inefficient, no search equilibrium exists. An increase in the search effectiveness shifts  $g(F)$  upwards, and eventually leads to the two familiar equilibria. There exists an intermediate value of  $a$  such that  $g(F)$  would be tangential to  $t' = t$ , implying that there was only a single equilibrium.

Which of these equilibria are more likely to be observed in the real world? To answer this question, and select an equilibrium to which to calibrate, I focus on a particular type of trembling-hand mistake where *all* agents tremble at the same time. I call an equilibrium stable if a sequence of best responses to any tremble in the neighborhood around that equilibrium will converge to the equilibrium.

**Definition 2.3** (Stable equilibrium). *A stable equilibrium  $\{t, F\}$  is one such that the sequence of best responses to any  $\tilde{t}$  in a neighborhood around  $t$  converges to  $\{t, F\}$ . Denote  $t^i = g(F(\lambda(t^{i-1})))$ . Then, a stable equilibrium  $\{t, F\}$  satisfies*

$$\lim_{x \rightarrow \infty} \tilde{t}^x \rightarrow t \quad \forall \tilde{t} \in (t - \epsilon, t + \epsilon) \quad , \epsilon > 0$$

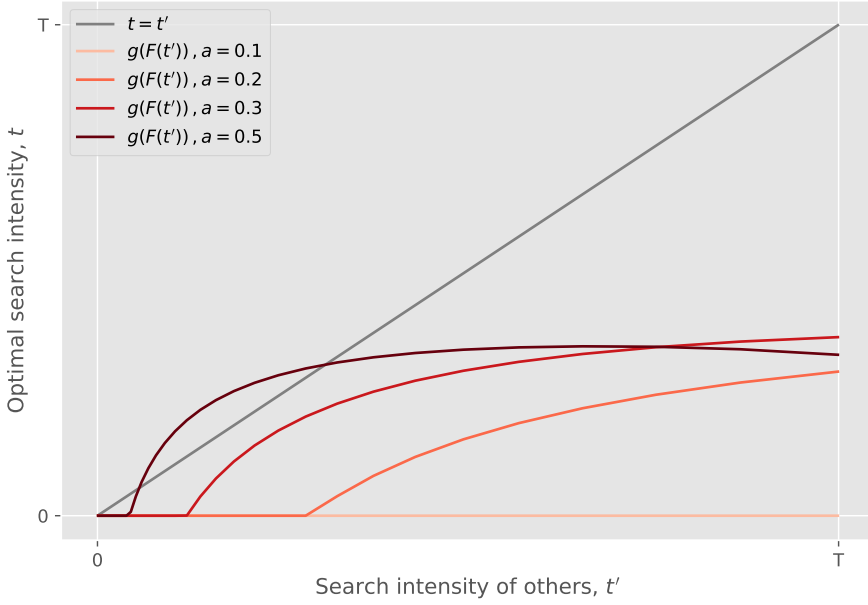
From inspecting Figure 2.5 it is clear that in the two equilibria scenarios, only the latter is stable. When there is a single equilibrium, it is stable.

### 2.1.4 Normalizations

To inform the calibration, it is useful to analyze the impact of  $c$  and  $r$  on the price distribution. Increasing either of these will tilt the distribution to the right. However, a proportional scaling of  $c$  and  $r$  shifts and scales the price distribution proportionally, as claimed by Lemma 2.4.

**Lemma 2.4.** *A proportional increase in both  $r$  and  $c$  by a scaling factor  $\psi > 0$  proportionally scales  $F(p)$ .*

$$\begin{aligned} \underline{p}(\lambda, \psi r, \psi c) &= \psi \underline{p}(\lambda, r, c) \\ F(\psi p; \lambda, \psi r, \psi c) &= F(p; \lambda, r, c) \end{aligned}$$

**Figure 2.5:** Visualization of equilibria

On the x-axis, we vary the aggregate search intensity which affects the price distribution. Against that, we plot the search intensity which is optimal given the price distribution.

*Proof.* In the appendix. □

**Lemma 2.5.** *Household income  $y$  does not affect the outcomes.*

*Proof.* The two endogenous outcomes in the economy are  $t$  and  $F$ .  $y$  does not affect income, as shown in Proposition 1. Moreover,  $y$  does not appear in the expression for  $F$ . □

**Lemma 2.6.** *For any  $\{H, S, a\} \exists a'$  such that the equilibrium outcomes under  $\{H, S, a\}$  and  $\{1, 1, a'\}$  are identical.*

*Proof.*  $H$  and  $S$  do not directly affect either  $F$  or  $t$ . The affected variable is  $\lambda = atS$ , and rescaling  $a' = aS$  will allow us to normalize  $S = 1$  and keep  $\lambda$  at its previous level. □



## 2.2 Goods search by employment status

I want to test how good the model is at capturing the essential properties of the consumer goods market. There are many dimensions along which we could test the model. Some studies that have integrated consumer goods search into macroeconomics rely on heterogeneity across employed and unemployed households in search intensity, and we will validate the model by its ability to match the search behavior of employed and unemployed individuals. We will find that the calibrated model cannot match the data: it vastly overestimates how many additional hours the unemployed want to search, compared to the employed.

Before detailing the measurement of the search data and the calibration procedure, I need to extend the model to allow for both employed and unemployed households.

### 2.2.1 Model with employment status

Most of the model is very similar to the earlier homogeneous household framework. I will keep it in the static partial equilibrium and fix the unemployment rate to  $u$ . As argued before, I can normalize  $H = 1$  and  $S = 1$ . The employed households have wage income  $w$ , while the unemployed worker's income is denoted as  $b$ . They have different time endowments available that I denote  $T^e$  and  $T^u$ . Following Kaplan and Menzio (2016), firms are not able to discriminate between their employed and unemployed customers: both the employed and the unemployed draw from the same price distribution  $F$ . For any given price distribution  $F$ , I denote the optimal search choice of the employed and the unemployed as  $g(w, T^e, F)$  and  $g(b, T^u, F)$ .

The main difference as compared to the previous framework is that firms now have to consider the two different types of customers when setting their prices. Conditional on contact, the probability of meeting an agent of type  $i$  is denoted as  $\xi^i$  and is a function of both arrival rates and the relative shares. These probabilities naturally satisfy  $\xi^e + \xi^u = 1$ . The probability of capturing  $\eta$  is now type-dependent and denoted as  $\eta^i$ .

$$\begin{aligned}\xi^e &= \frac{(1-u)\lambda^u}{(1-u)\lambda^e + u\lambda^e} \\ \xi^u &= \frac{u\lambda^u}{(1-u)\lambda^e + u\lambda^e} \\ \eta^i &= \frac{e^{-\lambda^i}}{1 - e^{-\lambda^i}} \frac{1}{1 - F(p)} \left[ e^{\lambda^i(1-F(p))} - 1 \right]\end{aligned}$$

$$\pi(p; \lambda^e, \lambda^u, u, F) = \lambda \cdot \left[ \xi^e(\lambda^e, \lambda^u, u) \eta^e(p, F, \lambda^e) \frac{w}{p} + \xi^u(\lambda^e, \lambda^u, u) \eta^u(p, F, \lambda^u) \frac{b}{p} \right] (p - c)$$

An equilibrium is now characterized by  $\{t^e, t^u, F\}$  where  $t^e = g(y, T^e, F)$ ,  $t^u = g(b, T^u, F)$  and  $F$  has positive support for any price that maximizes  $\pi(p, \lambda^e, \lambda^u)$ .  $F$  can no longer be expressed in closed-form. However, there does exist a closed-form solution for  $\underline{p}$ , the lower bound of the support for the price distribution.

$$\underline{p} = \frac{\left[ \xi^e w + (1 - \xi^e) b \right] cr}{\left[ \xi^e w + (1 - \xi^e) b \right] r - \left[ \xi^e \eta^e(r, F, \lambda^e) w + (1 - \xi^e) \eta^u(r, F, \lambda^u) b \right] (r - c)} \quad (2.10)$$

As in the simple model, the absolute levels of income do not affect  $F$ . Here, this implies a proportional scaling of  $\{w, b\}$ . Proportional increases in  $\{c, r\}$  linearly scale  $\underline{p}$  and  $F$ .

### 2.2.2 Measurement

I use the American Time Use Survey (ATUS) to measure the search intensity of the employed and the unemployed. Each individual that is interviewed for the ATUS provides a detailed record of all activities for a particular random day. I weight each individual by her ATUS record weight, and use all years between

*Table 2.1: Time use by employment status*

	Employed	Unemployed
Leisure	5.147	7.744
Shopping	0.544	0.642
Personal care	10.439	11.327
Home production	1.405	2.267
Work	5.495	0.862
Education	0.154	0.381

Source: American Time Use Survey. Measured in hours per day. Unassigned time: ca 40 minutes.

2003 and 2017. I aggregate the reported activities into major groups and exclude some ambiguous activities that amount to a total of on average 40 minutes per day. The resulting aggregated time use categories are summarized in Table 2.1.

Personal care includes sleep and it is the largest category for both types. The model allows individuals to distribute time-at-hand into either leisure or search, and cannot speak to other margins of time use: I calibrate total time-at-hand  $T$  to the sum of leisure and shopping.

### 2.2.3 Calibration

I want to test whether the empirically observed search choices of employed and unemployed households are one equilibrium outcome of the model. I test whether these time allocations can be a fixed-point by employing the following calibration strategy. I fix a number of preference and technology parameters. Importantly, I also fix  $t^e$  and  $t^u$ , the optimal search intensity of employed and unemployed households, to their empirical counterparts. Given these values, I calibrate the price distribution to match the empirical counterparts. Then, I test whether - given the calibrated distribution - I can recover  $t^e$  and  $t^u$  as solutions to the households' problem.

I assume the period length to be one week. Table 2.2 lists the chosen parameters. Time at hand  $T^i$  is calibrated to the sum of the household's leisure and shopping time, as sourced in Table 2.1. For unemployed and employed households, this amounts to 8.38 and 5.68 hours, respectively. The model is

*Table 2.2: Selected parameters*

Moment	Value	Description
$T^e$	0.679	Time endowment (employed)
$T^u$	1.000	Time endowment (unemployed)
$\sigma$	0.500	Curvature of utility
$b$	0.085	Expenditure of unemployed
$t^e$	0.022	Search (employed)
$t^u$	0.028	Search (unemployed)
$u$	0.050	Unemployment rate

Sources detailed in text.

isomorphic in the absolute value of time endowments. Therefore, I normalize  $T^u = 1$  and set  $T^e = 5.68/8.38 = 0.68$ . I set the risk-aversion parameter  $\sigma$  to 0.5 but will conduct robustness later. As argued before, price distributions are invariant to a proportional scaling of  $b$  and  $w$ . Moreover, search decisions are independent of incomes. Therefore, I normalize  $w = 1$ , and follow Kaplan and Menzio (2016) by setting  $b = 0.85$  to match the relative expenditures of the unemployed and the employed. I fix the share of unemployed households to 0.05.

Two parameters that are related to the price distribution are calibrated to match moments in the data. First,  $a$  governs the translation of time spent searching into average price draws. For any fixed search intensities  $t^u, t^e$ , we can choose the difference in the average number of draws by selecting  $a$  appropriately. A direct implication of the difference in the average number of draws is the expected difference in average prices: a higher  $a$  will lead to a larger difference in the average expected prices between the employed and the unemployed. Following Kaplan and Menzio (2016), I calibrate  $a$  to match the fact that the unemployed spend on average 2% less on a comparable consumption basket. Second, the households' outside-option price  $r$  is calibrated to match the max-to-min ratio of the empirical price distribution. From (2.10) it is clear that  $\underline{p}$  responds less than one-for-one to a change in  $r$ . Therefore, one can target  $r/\underline{p}$  through the calibration of  $r$ . I follow Kaplan and Menzio (2016) by targeting a max-to-min ratio of 1.7. Table 2.3 displays the implied values for  $r$  and  $a$ .

**Table 2.3:** *Calibrated parameters*

Moment	Target	Value	Parameter
$r/p$	1.70	1.700	$r$
$E[\bar{p}^u]/E[p^e]$	0.98	0.980	$a$

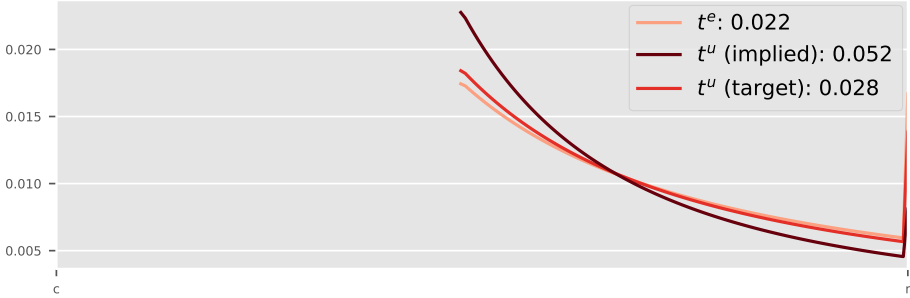
**Table 2.4:** *Endogenous search intensities*

Variable	Target	Value	Description
$t^e$	0.022	0.022	Search intensity, employed
$t^u$	0.028	0.052	Search intensity, unemployed

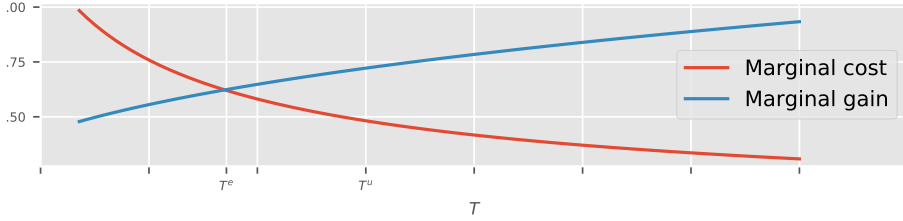
Next, I want to test whether the model can produce the so-far fixed search choices  $t^e$  and  $t^u$  as optimal choices under the calibrated price distribution. The last free parameter is  $\gamma$ . It governs the relative importance of leisure in preferences. I calibrate  $\gamma$  to match  $t^e$  and test how close the implied  $t^u$  is from its empirical counterpart. Table 2.4 documents the result:  $\gamma$  manages to pin-point  $t^e$  exactly at its target, but  $t^u$  is twice as large as its empirical counterpart.

#### 2.2.4 Mechanism

Why do the unemployed spend more time shopping in the model than in the data? Households that have a higher time endowment want to spend it on all available margins – leisure and search. Qualitatively the result makes sense: households with more time available want to spend more time on search. Quantitatively, the large extent to which an unemployed individual's time is devoted to search is not in line with the data. The reason is that - in the model - the gains from additional search are relatively high. Figure 2.6 displays the distribution of the minimum price of  $F$  for different search intensities  $t^i$ . It is clear that the effective price distributions for the targeted employed and unemployed households look very similar. In particular, both have a high rate of making zero draws leading to the high minimum price  $r$ . However, the  $t^u$  that is implied by optimal choice leads to a distribution that has a much larger mass at the lower end of the distribution, and a much lower weight on the maximum price. The

**Figure 2.6:** Minimum-price distributions by search intensity

Density of the minimum-price distribution under the (fixed) equilibrium price distribution. Returns to search are partly driven by a reduction in the probability of paying  $r$ .

**Figure 2.7:** Variation of marginal cost and gains with  $T$ 

gains associated with additional search appear high.

Why does the model predict large differences in optimal search by employment status? The employed and the unemployed both differ in their time and their income endowment. We know that in the model, the household's choice does not vary with income: the variation is purely caused by the time endowment. To analyze the relevance of the time endowment, we can decompose the objective function into the product of a leisure component and a consumption component - I refer to the latter as  $A(t, y)$ .

$$K(t, T, y) = \frac{(T - t)^{(1-\gamma)(1-\sigma)}}{1 - \sigma} A(t, y)$$

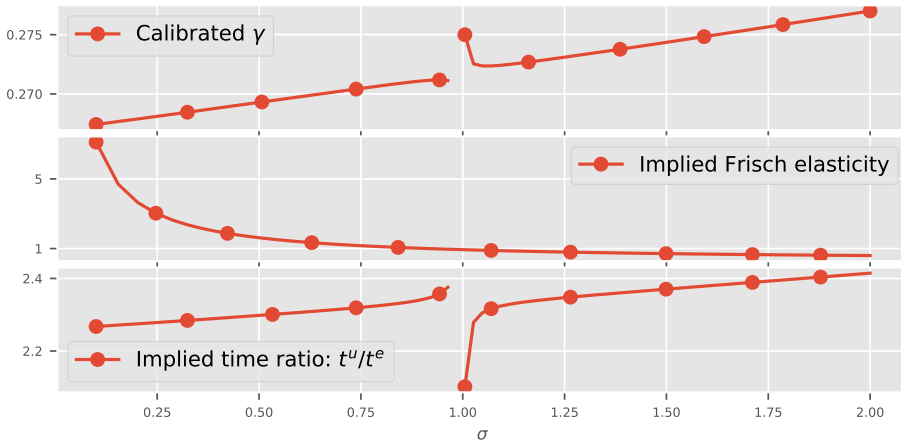
$$A(t, y) \equiv e^{-\lambda(t)} \left( \frac{y}{r} \right)^{\gamma(1-\sigma)} + \lambda(t) \int \left( \frac{y}{p} \right)^{\gamma(1-\sigma)} f(p) e^{-\lambda(t)F(p)} dp$$

An interior solution requires that  $K_t = 0$ : the marginal cost in terms of leisure is equal to the marginal gains in terms of consumption. Equation (2.11) computes this derivative. The first term denotes the marginal cost associated with searching more, and the second term the corresponding consumption gain. Figure 2.7 displays these marginal costs and the marginal gains as we vary the time endowment  $T$  and hold the solution  $t = t^e$  fixed. An increase in the time endowment naturally decreases the marginal cost of search. That the marginal gains vary with  $T$  is more surprising since  $T$  does not directly appear in  $A_t(t, y)$ . For a fixed  $t$ , a larger  $T$  does increase the utility derived from leisure and it complements the gains from consumption. Both the decreased costs and the increased gains lead to the choice of a high  $t^u$  as implied by the calibration.

$$K_t(t, T, y) = -\frac{(1-\gamma)(1-\sigma)}{T-t}K(t, T, y) + \frac{(T-t)^{(1-\gamma)(1-\sigma)}}{1-\sigma}A_t(t, y) \quad (2.11)$$

$$A_t(t, y) = \left[ -e^{\lambda(t)} \left( \frac{y}{r} \right)^{\gamma(1-\sigma)} + \int \left( \frac{y}{p} \right)^{\gamma(1-\sigma)} f(p) e^{-\lambda(t)F(p)} [1 - \lambda(t)F(p)] dp \right] \lambda'(t)$$

The only arbitrarily set parameter in the calibration strategy was the degree of risk aversion,  $\sigma$ . We want to ensure that the riskiness of receiving zero draws together with the chosen degree of risk aversion is not the main driver behind the results. Therefore, I redo the calibration for a range of values for risk aversion. Figure 2.8 displays the results of this exercise. The top panel shows that the calibrated  $\gamma$  slightly increases in  $\sigma$  almost everywhere. The discontinuity of preferences at  $\sigma = 1$  is also visible in the calibrated  $\gamma$ . To provide another testable prediction of the model, I compute the Frisch elasticity for each calibrated  $\gamma$ - $\sigma$  combination. For very low degrees of risk aversion, the implied Frisch elasticity is high. For the more reasonable values of  $\sigma$ , the Frisch elasticity is around 1, in-between its typical micro estimations and macro calibrations. The last panel displays the implied ratio of  $t^u/t^e$ . The model generates ratios around 2.2 for all  $\sigma$  values – far off the empirical ratio of 118%.

*Figure 2.8: Optimal allocation of leisure with varying  $\sigma$* 

## 2.3 Discussion

The attempt to validate the model by targeting different search intensities by employment status fails. In the data, the unemployed spend 18% more time shopping than the employed, and on average spend 2% less on a similar consumption basket. When targeting the implied price distribution, the model generates ratios of search intensities that are around a factor of 2: under reasonable calibrations and independently of the chosen degree of risk aversion, the model generates search intensities of the unemployed that are far beyond those measured empirically. Which key assumption(s) of the model are causing the disconnect?

First, households have perfect information about the distribution of prices, but no information about the actual prices at any given store. To the extent that prices are not completely unpredictable on a weekly basis, households could use information from previous periods to reduce the required search intensity – a feature missing in this static framework. However, it is unclear why the introduction of additional information would reduce the search gap between the unemployed and the employed.



### 2.3.1 Heterogeneous goods

In this model, households search to find low prices for a single representative good. In the data, unemployed households spend 15% less on nondurable consumption than the employed. If the model featured multiple varieties of consumption goods, and search was required for each of these, the observed small search gap could potentially be rationalized. For example, suppose households have non-homothetic preferences over two goods, “food” and “other”. Unemployed households purchase food only, while employed households use their higher disposable income to purchase both types of goods. To phrase the solution in terms of Figure 2.7, if both types choose the same search intensity, the marginal cost of time will still be lower for unemployed households. However, their marginal gains from additional search will also be lower, since they only spend that additional search on a single good. Employed households spend their time on two goods: when they search as much as the unemployed, they effectively draw fewer prices for each good. The difference in total varieties purchased across the employed and the unemployed could be used to discipline the consumption good aggregator in the preferences.

### 2.3.2 Time does not equal search

A second approach involves the fact that price draws are probably not linear in the time spent searching. In the micro-foundation for the Poisson draws, we assumed that households spend  $t$  traveling at constant speed on a unit circle, and contact stores randomly. This implied that the average number of prices drawn linearly increases in the time spent searching  $\lambda(t) = atS$ . Alternatively, the search process might involve a fixed sunk cost  $\underline{t}$ :

$$\lambda(t) = a(t - \underline{t})S \quad (2.12)$$

This additional technology parameter would indeed allow the model to fit any search gap  $t^u - t^e$ . One micro-foundation involves the fact that stores are not randomly spread on a unit circle. Instead, several stores are located in the

vicinity of a parking space. Households have to first spend  $\underline{t}$  to reach that parking space, but can then access many stores at a high rate.

### 2.3.3 Discrimination by employment status

The model assumes that the stores cannot discriminate prices by employment status: both the employed and the unemployed are drawing from the same distribution  $F$ . There is some suggestive evidence that firms are indeed able to discriminate. For example, employed households are typically constrained by the times of the day at which they can search for prices. Consistent with that type of discrimination, Kaplan and Menzio (2015) show that some prices vary within the same good and store over time. If such a mechanism were true, the employed and the unemployed would be searching from different distributions. This could explain why the unemployed only spend 18% more time shopping: the distribution of prices is very compressed both for the employed and the unemployed, which reduces the incentives for additional price draws.

In this model, even if  $F^e$  and  $F^u$  were both calibrated to the same technology parameters  $r$  and  $a$  they would look different. To see this, assume by contradiction that both distributions were identical. In that case, the unemployed would search more, since they have the same marginal gains, but a smaller marginal cost of searching. By Proposition 3,  $F^e$  would then stochastically dominate  $F^u$ , which is a contradiction. Note that  $F$  is independent of income  $y$ , and different expenditures by the employed and the unemployed would not play any role here.

The question left to answer is whether the differences between  $F^u$  and  $F^e$  are such that they reduce the gap in search intensity between the two types. Recall that a household's search intensity decreases in the expected price of the distribution, and increases in its dispersion.  $F^e$  first-order stochastically dominates  $F^u$ , and so the difference in average prices would even increase the search gap. The dispersion could potentially offset this: if  $F^u$  has a smaller dispersion than  $F^e$ , the returns to additional price draws are smaller for the unemployed, which might overall shrink the gap in search between the employed and the unemployed.

## 2.4 Conclusion

In this paper, I provide a micro-foundation for the household's search decision that can be readily integrated into macroeconomic analysis. However, I caution against doing exactly that because the model - taken at face value - cannot make any sense of the empirically observed search behavior. More precisely, the model predicts a much larger ratio of search time between the unemployed and the employed than what is observed in the data.

I discuss several potential mechanisms that can reduce this search gap. I argue that a model could make sense of the data if searching households have to sink a fixed-cost of time prior to receiving price draws. A second approach would be to incorporate non-homothetic preferences. Finally, I argue that a model that allows firms to discriminate by employment status could potentially rationalize the empirical findings.

Given the limited empirical data available, it is difficult to distinguish which of these mechanisms are at play. However, different implementations of the search environment in a macroeconomic model will likely lead to different aggregate behavior of the model.

For example, a model that follows the fixed-cost approach would understand the rise in internet shopping as a decrease in the fixed-cost component and predict that the search gap increased in recent year – not entirely in line with empirical observations. Also, Kaplan and Menzio (2016) emphasize a business cycle mechanism where the search behavior of the unemployed affects the revenue that the firms receive from employed shoppers. If firms are indeed able to discriminate by employment status, that mechanism is moot and the model's dynamics become very similar to those of a simpler version that does not include consumer good search (Pissarides, 1979). Therefore, it is important to understand which of these mechanisms is actually the most critical for bringing the model's micro-foundation closer to the observed search behavior. So far, our understanding of these mechanisms is minimal: little is known about stores' ability to discriminate across their customers, or how additional time spent searching transforms to lower effective prices. This paper emphasizes the value of additional empirical work on that front to ensure that the resulting models are less

susceptible to the Lucas (1976) critique.



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## 2.A Proofs

### 2.A.1 Proof of Lemma 2.1

After inserting the Poisson probabilities, we get

$$\begin{aligned}
 K(t; y, T, F) &= e^{-\lambda(t)} U(r, t; y, T) + \sum_{s=1}^{\infty} e^{-\lambda(t)} \frac{\lambda^s}{s!} \int U(p, t; y, T) s(1 - F(p))^{s-1} f(p) dp \\
 &= e^{-\lambda(t)} U(r, t; y, T) + e^{-\lambda(t)} \int U(p, t; y, T) \lambda(t) \sum_{s=1}^{\infty} \frac{\lambda(t)^{s-1}}{(s-1)!} (1 - F(p))^{s-1} f(p) dp \\
 &= e^{-\lambda(t)} U(r, t; y, T) + e^{-\lambda(t)} \int U(r, t; y, T) \lambda(t) e^{\lambda(t)(1-F(p))} f(p) dp \\
 &= e^{-\lambda(t)} U(r, t; y, T) + \int U(r, t; y, T) \lambda(t) e^{-\lambda(t)F(p)} f(p) dp
 \end{aligned}$$

where the third line used one definition of the exponential. Replacing again  $U(r, t; y, T)$  yields the expression in the Lemma.

### 2.A.2 Proof of Lemma 2.2

To compute  $\eta$ , we expand  $P(\text{p is lowest} \mid \text{contact})$  using the law of total probability:

$$\begin{aligned}
 \eta(p; \lambda, F) &= \sum_{s=0}^{\infty} P(\text{p is lowest} \mid \text{draws} = s) \cdot P(\text{draws} = s \mid \text{contact}) \\
 &= \sum_{s=1}^{\infty} P(\text{p is lowest} \mid \text{draws} = s) \cdot P(\text{draws} = s) \\
 &= \sum_{s=1}^{\infty} (1 - F(p))^{s-1} \cdot e^{-\lambda} \frac{\lambda^s}{s!} \\
 &= e^{-\lambda} \sum_{s=1}^{\infty} \frac{[\lambda(1 - F(p))]^s}{s!} \frac{1}{1 - F(p)} \\
 &= \frac{e^{-\lambda}}{1 - e^{-\lambda}} \frac{1}{1 - F(p)} \left[ e^{\lambda(1-F(p))} - 1 \right]
 \end{aligned}$$

The second line uses the fact that contacted customers cannot have zero draws. The final line uses the definition of the exponent.

Notice that  $F \rightarrow 0$  as  $p \rightarrow \underline{p}$ . In that case, the expression simplifies to 1. As  $p \rightarrow r$ ,  $F \rightarrow 1$ . The application of L'Hospital's Rule:

$$\frac{e^{-\lambda}}{1 - e^{-\lambda}} \cdot \frac{\lim_{F \rightarrow 1} -\lambda e^{\lambda(1-F)}}{\lim_{F \rightarrow 1} -1} = \frac{\lambda e^{-\lambda}}{1 - e^{-\lambda}} = \frac{\text{Poisson}(1)}{1 - \text{Poisson}(0)}$$

The latter expression is the probability of the customer having exactly one draw, conditional on having at least one.

### 2.A.3 Proof of Lemma 2.3

The price distribution  $F$  is consistent with the firm's optimal pricing strategy only if

$$\begin{aligned} \pi(p; F, \lambda) &= \pi^* \forall p : f(p; \lambda) > 0 \\ \pi^* &\equiv \max p \pi(p; F, \lambda) \end{aligned}$$

**Profits are strictly positive.** Profits at the reservation price are given by

$$\pi(r, F, \lambda) = \frac{H\lambda}{S} \frac{\lambda e^{-\lambda}}{1 - e^{-\lambda}} \frac{y}{p} (r - c)$$

With  $\lambda > 0$ , these are strictly positive since  $r > c$ . Therefore,  $\pi^* > 0$ .

**The distribution is continuous.** Intuitively, there is no price with a positive mass of sellers. If there existed a price  $p_0$  with a positive mass of sellers, firms setting  $p = p_0 - \epsilon$  for some small  $\epsilon$  should make a second-order loss on the price per sold unit, but a first-order gain from the share of consumers captured. Proofs of this point are available for similar environments in the literature and we omit a detailed proof here. In preparing the chapter for publication, a full proof will be added.



**Upper bound satisfies  $\bar{p} = r$ .** Suppose that  $\bar{p} < r$ . At  $\bar{p}$ , we have  $F = 1$  and the profits are given by

$$\pi(\bar{p}, F, \lambda) = \frac{H\lambda}{S} \frac{\lambda e^{-\lambda}}{1 - e^{-\lambda}} \frac{y}{r} (\bar{p} - c)$$

If a firm was to sell at price  $r$ , it would make profits of

$$\pi(r, F, \lambda) = \frac{H\lambda}{S} \frac{\lambda e^{-\lambda}}{1 - e^{-\lambda}} \frac{y}{r} (r - c)$$

Clearly,  $\pi(\bar{p}, F, \lambda) < \pi(r, F, \lambda) \leq \pi^*$ , contradicting the fact that  $F$  is consistent with profit maximization.

Now suppose that  $\bar{p} > r$ . In that case, firms that set  $p = \bar{p}$  make zero profits, since households will not be buying. Again,  $\pi(\bar{p}, F, \lambda) = 0 < \pi^*$ , which is a contradiction.

**The lower bound satisfies  $\underline{p} \in (c, r)$ .** We know that  $\underline{p} \leq \bar{p} = r$ . If  $\underline{p} = r$ , the distribution would have a positive mass at  $r$ , a contradiction. If  $\underline{p} \leq c$ , we have  $\pi(\underline{p}, F, \lambda) < 0 < \pi^*$ , inconsistent with profit maximization. The only remaining possibility is  $\underline{p} \in (c, r)$ .

**The support is connected.** Suppose that the support of  $F$  is not connected. Then, there exists  $p_0 < p_1$  such that  $F(p_0) = F(p_1)$ . In that case, we have

$$\begin{aligned} \pi(p_0, F, \lambda) &= \frac{H\lambda}{S} \eta(p_0; \lambda, F) \frac{y}{p_0} (p_0 - c) \\ &< \frac{H\lambda}{S} \eta(p_0; \lambda, F) \frac{y}{p_1} (p_1 - c) = \pi(p_1, F, \lambda) \leq \pi^* \end{aligned}$$

This is a contradiction: no firm that sets  $p_0$  can be maximizing profits under this  $F$ .

### 2.A.4 Proof of Proposition 2

Lemma 2.3 has established that  $\pi(r; F, \lambda) = \pi^*$ . Because the support is connected, we have that  $\pi(p; F, \lambda) = \pi^* \forall p \in [\underline{p}, r]$ . Therefore,  $\pi(p; F, \lambda) = \pi(r; F, \lambda) \forall p \in [\underline{p}, r]$ . Solving that identity delivers:

$$\begin{aligned} \frac{H\lambda}{S} \eta(p; \lambda, F) \frac{y}{p}(p - c) &= \frac{H\lambda}{S} \eta(r; \lambda, F) \frac{y}{r}(r - c) \\ \frac{1}{1 - F(p)} \left[ e^{\lambda(1 - F(p))} - 1 \right] \frac{y}{p}(p - c) &= \lambda \frac{y}{r}(r - c) \end{aligned}$$

This provides an indirect representation of  $F(p; \lambda)$ . An explicit form of  $F$  is given by (2.9).

**Lower bound  $\underline{p}(\lambda)$**  We solve for  $\underline{p}$  using the fact that  $\pi(\underline{p}; F, \lambda) = \pi(r; F, \lambda)$ :

$$\begin{aligned} \frac{H\lambda}{S} \eta(\underline{p}; \lambda, F) \frac{y}{\underline{p}}(\underline{p} - c) &= \frac{H\lambda}{S} \eta(r; \lambda, F) \frac{y}{r}(r - c) \\ \frac{y}{\underline{p}}(\underline{p} - c) &= \lambda \frac{e^{-\lambda}}{1 - e^{-\lambda}} \frac{y}{r}(r - c) \\ r(\underline{p} - c) &= \lambda \frac{e^{-\lambda}}{1 - e^{-\lambda}} (r - c) \underline{p} \\ \underline{p} &= \frac{rc}{r - \lambda \frac{e^{-\lambda}}{1 - e^{-\lambda}} (r - c)} \end{aligned}$$

### 2.A.5 Proof of Lemma 3

To see the first part, note that  $F_\lambda(p; \lambda) < 0 \forall p$ . For the second part, we need to show that  $p'(\lambda)$ . Before computing the derivative, note that

$$\begin{aligned}
\frac{\partial \lambda e^{-\lambda} 1 - e^{-\lambda}}{\partial \lambda} &= \frac{(e^{-\lambda} - \lambda e^{-\lambda})(1 - e^{-\lambda}) - (e^{-\lambda}(\lambda e^{-\lambda}))}{(1 - e^{-\lambda})^2} \\
&= \frac{e^{-\lambda}(1 - e^{-\lambda}) - \lambda e^{-\lambda}(1 - e^{-\lambda}) - e^{-\lambda} \lambda e^{-\lambda}}{(1 - e^{-\lambda})^2} \\
&= \frac{e^{-\lambda}(1 - e^{-\lambda} - \lambda)}{(1 - e^{-\lambda})^2} \\
&= \frac{e^{\lambda}(1 - \lambda) - 1}{(e^{\lambda} - 1)^2}
\end{aligned}$$

Using this, we can compute the derivative as

$$\begin{aligned}
\underline{p}'(\lambda) &= \frac{0 - \left(\frac{e^{\lambda}(1-\lambda)-1}{(e^{\lambda}-1)^2}\right)(r-c)rc}{\left(r - \lambda \frac{1}{e^{\lambda}-1}(r-c)\right)^2} \\
&= \frac{[1 - e^{\lambda}(1 - \lambda)](r - c)rc}{(e^{\lambda} - 1)^2 \left(r - \lambda \frac{1}{e^{\lambda}-1}(r - c)\right)^2} \\
&= \frac{e^{\lambda}(1 - \lambda) - 1}{(e^{\lambda} - 1)^2} \frac{r - c}{rc} \underline{p}(\lambda)^2
\end{aligned}$$

To sign this expression, note that the denominator is always positive. As for the numerator,

$$\frac{\partial e^{\lambda}(1 - \lambda) - 1}{\partial \lambda} = e^{\lambda} \lambda$$

The numerator has a single maximum/minimum at  $\lambda = 0$ . Notice that

$$e^{\lambda}(1 - \lambda) - 1|_{\lambda=1} = -1 < 0$$

This implies that  $\lambda = 0$  is a maximum, and the derivative  $p'(\lambda)$  is negative everywhere else.

### 2.A.6 Proof of Lemma 2.4

For the first part, note that

$$\begin{aligned}\underline{p}(\lambda, \psi r, \psi c) &= \frac{\psi c}{1 - \lambda \frac{e^{-\lambda}}{1 - e^{-\lambda}} \frac{r - c}{r}} \\ &= \psi \frac{c}{1 - \lambda \frac{e^{-\lambda}}{1 - e^{-\lambda}} \frac{r - c}{r}}\end{aligned}$$

For the second part, recall that  $F$  is given by

$$\begin{aligned}F(p; \lambda, r, c) &= \frac{1}{\lambda} (z + \text{LambertW}(-ze^{-z})) + 1 \\ z(p; r, c) &= \frac{r}{p} \frac{p - c}{r - c}\end{aligned}\tag{2.13}$$

It is sufficient to see that  $z(\psi p; \psi r, \psi c) = z(p, r, c) \Rightarrow F(\psi p; \lambda, \psi r, \psi c) = F(p; \lambda, r, c)$ .

## 2.B Microfoundation of matching

Let  $S$  be the (integer) number of stores uniformly distributed on a unit circle. Before the start of the period, households commit to search for time duration  $t$ . During that time, they start at a random location on the unit circle and walk at speed  $a$  - distance/time - in a random direction.

We divide  $t$  into  $N$  subperiods of length  $\Delta_N = t/N$ . The number of stores met during that subperiod are binomially distributed: the probability of meeting  $x$  stores is given by

$$\tilde{p}_N(x) = \binom{S}{x} p^x (1 - p)^{S-x}$$

What is the probability of any arbitrary store being contacted within  $\Delta_N$ ? Stores are uniformly distributed over the unit circle, and within  $\Delta_N$  we travel  $at/N$ . Hence

$$p = at/N$$

**Claim:** as  $\Delta \rightarrow 0$ , the expected number of multiple-draws of stores within same  $\Delta$  vanishes .

*Proof.* We have  $N$  subperiods. For  $x > 1$ , the expected number of multiple draws is given by

$$\lim_{N \rightarrow \infty} N \cdot \binom{S}{x} (at/N)^x (1 - at/N)^{S-x} = \lim_{N \rightarrow \infty} N^{1-x} \binom{S}{x} (at)^x (1 - at/N)^{S-x} \rightarrow 0$$

where the  $N^{1-x}$  term vanishes, and the remainder remains constant.  $\square$

Intuitively, since  $S$  are uniformly distributed, there is a measure 0 of stores at exactly the same physical location. Therefore, for any ex-post distribution of  $S$  over the unit circle, we can pick large enough  $N$  s.t. the probability of 2 or more stores on length  $\Delta_N$  is negligible.

We will hence focus on computing the probability of contacting 1 store in a subinterval  $\Delta_N$ . Define

$$\begin{aligned} \lambda_N &\equiv N p_N(1) = NS(at/N)^1 (1 - (at/N)^{S-1}) \\ \lambda &\equiv \lim_{N \rightarrow \infty} \lambda_N = atS \end{aligned}$$

With the machinery in place, we can compute the probability of meeting  $s$  stores during the total search time  $t$ . Given that each subperiod has a binary outcome - meeting a store with probability  $p_N(1)$ , or none, the total number of stores met is also binomially distributed with the total number of draws  $N$ .

$$\begin{aligned} P(s) &= \frac{N!}{(N-s)!s!} p_N(1)^s (1 - p_N)^{S-s} \\ &= \frac{\mu_N^s}{s!} \frac{N!}{(N-s)!N^s} \left(1 - \frac{\mu_N}{N}\right)^S \left(1 - \frac{\mu_N}{N}\right)^{-s} \end{aligned}$$

where the rearrangement allows me to study the limits for each component:

$$\begin{aligned}\lim_{N \rightarrow 0} \frac{N!}{(N-s)!N^s} &= 1 \\ \lim_{N \rightarrow 0} \left(1 - \frac{\mu_N}{N}\right)^s &= e^{-\lambda} \\ \lim_{N \rightarrow 0} \left(1 - \frac{\mu_N}{N}\right)^{-s} &= 1\end{aligned}$$

Assembling the parts yields that the total number of stores contacted is Poisson distributed:

$$\begin{aligned}P(s) &= e^{-\lambda(t)} \frac{\lambda(t)^s}{s!} \\ \lambda(t) &= atS\end{aligned}$$



## Chapter 3

# Worker protection and heterogeneous match quality<sup>\*</sup>

### 3.1 Introduction

In 2008, many countries were affected by the so-called Great Recession when a financial crisis and a collapse in housing prices led to a global productive slowdown and a worsening of the labor markets. Among them, southern European countries were hit particularly hard. While it is true that they were particularly exposed to the initial triggers of the recession, their labor markets are also highly regulated (Karamessini, 2008; Hassel, 2014), and some have faulted these rigid labor markets for the slow recoveries.

Since the seminal work of Lazear (1990), an extensive literature has analyzed the theoretical and empirical links between employment protection and the functioning of labor markets. In this paper, we revisit the impact of worker protection on aggregate output and unemployment in the presence of worker-firm pairs

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<sup>\*</sup> Parts of this work has been previously published as two separate chapters in Gustaf Lundgren's thesis "Essays on job market screening, in-group bias and school competition". The first of these chapters is entitled "A search model with multiple applications" and considers the impact of heterogeneous match quality. The second chapter is entitled "Ranking, unemployment duration and unemployment volatility" and considers the interaction between screening and business cycle fluctuations. We are indebted to advice from Per Krusell, Lars Ljungqvist, Kurt Mitman, Oskar Nordström Skans and seminar participants at the Stockholm School of Economics, Stockholm University, and the Oslo-Bi-NHH Workshop in Macroeconomics.



that differ in their match productivities. Workers and firms are both risk-neutral. Given our assumptions, aggregate consumption is an appropriate measure of steady-state welfare. The model uncovers a potential mean-volatility trade-off of protecting employment: in our simulation, the policy will improve aggregate consumption but render the economy more volatile to aggregate shocks.

Worker protection has some bite whenever it is not undone by Coasean transfers (Lazear, 1990) and layoffs are desired by the firm either in equilibrium, or as an off-equilibrium threat. To satisfy the second requirement, most of the literature focuses on shocks to a firm's profitability. For example, worker protection tampers with a firm's ability to respond to a recession by reducing size. Instead, we analyze the extent to which worker protection interferes with the screening potential of layoffs. Specifically, firm-worker matches differ in productivity: "good" matches are more productive than "bad" matches. Moreover, workers persistently differ in the probability of drawing a good match: workers of the "high" type are more likely to have a good draw than the "low" type. Wage contracts are constrained: they cannot discriminate by match-specific productivity. Here, wages do not offset the differences in productivity, and bad matches are not profitable for the firm. Firms observe match quality in the hiring stage only if they engage in the costly screening. After hiring, the match productivity is revealed instantly. Without employment protection, firms could forego costly screening of candidates and instead fire them once their match quality is revealed. Therefore, we analyze worker protection in a novel context where it interacts with an average match quality. After the introduction of employment protection, firms that hire without screening their applicant pool can no longer fire workers with a bad match quality. This affects aggregate consumption through two main channels. First, some firms will still hire without screening. Consequently, the average match quality in the economy decreases as non-screening firms employ workers but can no longer disengage from bad matches. Second, the policy decreases the value of a match. Consequently, the hiring intensity falls initially when the policy is introduced. Under our benchmark calibration, the welfare gains associated with such a policy are still positive: aggregate consumption is higher at the new steady state and during the transition thereto.

Next, we compare the economy's response to productivity shocks in the

steady states with and without worker protection. Importantly, the ability to lay off workers puts a floor on the value of randomly hiring. The employment protection removes that floor and increases the pro-cyclicality of the value of hiring. Consequently, aggregate unemployment and consumption fall more in recessions when firms' ability to fire workers is reduced. In the recession, fewer firms hire without screening. Over the course of the recession, low-type workers have a relatively harder time when becoming unemployed, and the quality of the pool of unemployed workers deteriorates. When aggregate productivity recovers, the quality of the applicant pool is persistently lower, thus inducing a lower hiring rate: the recession leads to a jobless recovery.

**Literature** This paper builds on and is motivated by a large microeconomic literature that analyzes statistical discrimination and screening in the hiring process. Kroft, Lange, and Notowidigdo (2013) and Ghayad (2013) show that employers use unemployment duration to screen for persistent ability. Motivated by these empirical findings, Jarosch and Pilossoph (2019) argue that discrimination at the interview stage is irrelevant if it only arises for candidates that would ultimately not have been hired anyway. In our model, these candidates would have been laid off right after employment. Masters (2014) finds that statistical discrimination in the screening process can be self-fulfilling: discrimination against a group can worsen their unemployment pool and thereby solidify that discrimination. Josephson and Shapiro (2016) analyze the impact of screening in an environment where individuals have private information on their own type.

When placed in the context of aggregate fluctuations, Bertola (1999) argues that employment protection reduces layoffs but also hirings, with an ambiguous effect on total unemployment. Another theoretical prediction is that such protections will dampen the layoffs in recessions, but also employment in booms. In line with our model, Lindbeck (1993) argues that employment protections can increase the volatility of the value associated with hiring: in a recession, increased uncertainty could induce firms to choose not to hire at all, thus leading to long-lasting recessions. Lindbeck and Snower (2001) argue that worker protections strengthen the position of insiders within the firm and thus lead

to wage gains at the cost of outsiders. O. Blanchard and Landier (2002) and Cahuc and Postel-Vinay (2002) analyze the impact of weakening temporary employment. Autor, Kerr, and Kugler (2007) measure the impact of employment protection on productivity in the context of the “wrongful discharge protection” in the United States. Dal Bianco, Bruno, and Signorelli (2015) estimate the role of labor market institutions in the European unemployment response.

Modeling-wise, our theory has the potential to generate large and persistent unemployment responses to a TFP shock. Here, we contribute to a large literature which has studied the volatility of unemployment since Merz (1995), Andolfatto (1996), and Shimer (2005), often referring to it as the “unemployment-volatility puzzle”. The persistence of unemployment has received new attention since the so-called Great Recession of 2008, when the recovery did not coincide with a proportional reduction in unemployment. With respect to explaining jobless recoveries, Acharya and Wee (2019) performs a similar exercise where he shows that increased screening in a recession leads to large and persistent unemployment responses. The two papers vary in their source for additional screening: in our model, it stems from the number of applicants and a convex return to screening, while their model centers around rational inattention.

The remainder of this paper is as follows. Section 2 introduces our model. We analyze the introduction of employment protection in section 3, where we observe the economy’s transition to a new steady state. In section 4, we compare the aggregate shocks in both steady states. Section 5 concludes the paper.

## 3.2 Model

In the model, time is continuous. The economy is populated by workers, firms, and vacancies. Firms post vacancies and collect applications from unemployed workers. These unemployed workers differ in the value they provide to the firm. Firms can employ costly screening for a vacancy to find out the value of all applicants to the firm. It can then decide to hire at most one of them. In the remainder of this section, we will lay out these parts in detail.

### 3.2.1 Matching

Vacancies on the labor market are opened subsequently and these remain open for a fixed duration  $\tau$ . Each unemployed worker sends out  $a$  applications in each time window of length  $\tau$ . Each application randomly arrives at one vacancy that is open during the time of submission. When a vacancy closes, it inspects all applications it received during the opening window of the vacancy of length  $\tau$ . The appendix shows that the number of applications at each vacancy is Poisson distributed with mean  $\lambda \equiv \frac{au}{v}$ , where  $u$  is the mass of unemployed workers, and  $v$  the mass of vacancies. If  $u$  and  $v$  do not change during the window of length  $\tau$ , the distribution of applications over vacancies is exact. This will be true in a steady state. We use this expression to approximate the distribution also outside of steady states.

### 3.2.2 Match-specific productivity

The canonical urn-ball model described so far can only match empirical job-finding rates when the unemployed workers apply to vacancies at a very low rate. That low application rate then implies that the vacancies receive very few applications, which limits the scope of screening and discrimination in the hiring process. From the view point of the vacancy: an empirically measured *monthly* vacancy filling rate around 0.6 – 0.8 in a model with homogeneous vacancies and urn-ball matching implies that a sizable fraction of vacancies receives no applicant. The applicants are Poisson-distributed over the vacancies: a sizable fraction of vacancies not matching with an applicant is only possible if vacancies on average receive around one applicant.

This small number of applications per vacancy is not only inconsistent with the empirical estimates, but also affects the incentives for firms to screen and discriminate. For example, O. J. Blanchard and Diamond (1994) discuss the implications of discrimination by unemployment duration for wage dispersion and job-finding rates. In their calibration, the average number of applicants per vacancy is small. Moreover, business-cycle changes in market tightness lead to small variations in the number of applications per vacancy. They compare an economy in normal times with an unemployment rate of 5% to a recession with

an unemployment rate of 10%. Despite calibrating to such a strong recession, their model only generates an increase in the average applications per vacancy from 0.7 to 1.22: the resulting impact of screening and discrimination does not vary a great deal with the business cycle.

We extend the urn-ball matching model to address this calibration dilemma. We envision the productivity of a worker at a firm to be a component of a multitude of factors, one of which is specific to the worker-firm pair. Such a catch-all productivity-term could contain different amenities at the firm, and how important they are for the worker: some components could be flexible time vs fixed schedules, private offices vs. shared office space, strong top-down management vs. horizontal structures, or whether the worker and the manager match on a personal level. We think about the match-specific productivity as a continuous random variable. For modeling purposes, we will approximate that distribution with two values, good and bad:  $A_g > A_b$ . In this paper, we consider calibrations where hiring an employee with a bad match value is not profitable for the firm. The calibrated model can then match many applications per vacancy if a large share of the applications draws a low match-specific productivity that potentially does not lead to employment.

We nest this match-specific productivity with a worker-specific component: some workers have a higher probability of drawing a good match-specific productivity than others. We will call these workers of the “high type”. This feature of the model matches the fact that in reality, some workers are quite adaptable to many environments: they could be productive in a multitude of settings, they are very socially skilled or contain more general human capital. These factors enable them to be more likely to be a good match at any particular firm. Denote by  $\mathcal{P}_i$  the probability of a worker of type  $i$  to draw a *low* match-specific probability. Consequently, the high types are less likely to draw a low match value:  $\mathcal{P}_h < \mathcal{P}_\ell$ . We normalize the size of the labor force to 1, and denote the (fixed) mass of low-type workers as  $L_\ell$ . The endogenous share of low-type workers among the unemployed will be denoted by  $P_u$ .

### 3.2.3 Wages

If the vacancy decides to hire an unemployed individual, the two form a one-worker firm. Total productivity in each match is a composite of the match-specific productivity  $A_i$  and an aggregate component  $A(t)$ .

Key in the model is that the heterogeneity in match-specific productivity is not offset by wages: firms pay the workers in good or bad matches the same. Such fixed task-specific wage schedules could be motivated by unions that prevent heterogeneous compensation within occupation-firm. We assume that the wages for all workers are given by

$$w(t) = \beta A_g A(t) + (1 - \beta)b \quad (3.1)$$

where  $b$  denotes the consumption of the unemployed workers. This wage schedule can be rationalized for workers in good matches using Nash bargaining with workers' bargaining power  $\beta$ , where in case of (off-equilibrium) disagreement, both sides make a pause in the negotiation instead of disbanding the match. During that pause, the worker receives home production  $b$ , and the firm receives 0.

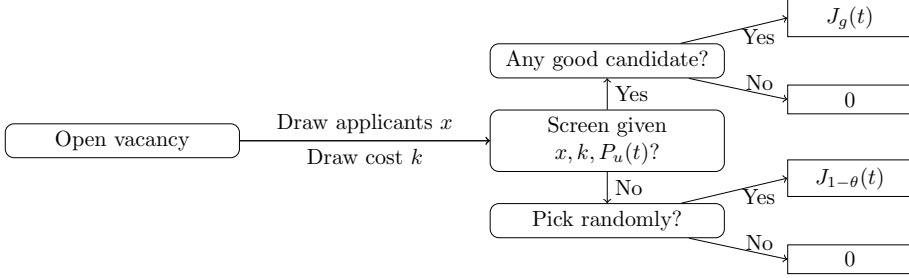
The worker-firm matches separate at an exogenous rate  $\delta$ . The firms discount the future at rate  $\rho$ . We denote by  $J_i$  the value of a firm that has match-specific productivity  $i$ :

$$\rho J_i(t) = A_i A(t) - w(t) - \delta J_i(t) + \dot{J}_i(t) \quad (3.2)$$

As emphasized before, the cutoff  $A_b$  ensures that bad matches are not profitable to the firm.

**Assumption 3.1.** *Match productivities are such that bad matches are not profitable.*

$$A_b A - \beta A_g A - (1 - \beta)b \leq 0$$

**Figure 3.1:** Payouts of the screening decision

We will hereinafter work with Assumption 3.1, which ensures that  $J_b \leq 0$ . There are many ways of approximating the productivity distribution such that  $J_b$  is negative. In the benchmark calibration, we will select  $A_b$  such that firms make exactly zero profits.

### 3.2.4 Job openings and screening

Now we present the details of the vacancy's problem. After having received  $x$  applications, the vacancy has to decide whether to screen the applications. Here, the cost of screening amounts to a fixed cost  $k$ .<sup>1</sup> After paying  $k$ , the vacancy learns about the match-specific productivity of every applicant. If one of the applicants is a good match, the firm will hire that person. If none of the applicants are a good match, the firm will refrain from hiring since bad matches are not profitable. If the firm posting the vacancy decides not to screen, it can either hire one applicant at random - the value of which we denote as  $J_{1-\phi}$  - or not hire all. Figure 3.1 provides an overview over these choices and the associated outcomes. This model will contrast two policy regimes which differ in whether firms can lay off workers at will or not.  $\mathcal{L}$  is a binary variable that takes the value of 1 whenever firms can lay off workers. Before setting up the vacancy's problem, it will be useful to establish two auxiliary variables.  $J_{1-\theta}(t)$  denotes the value of

<sup>1</sup>An earlier version of this paper incorporated a variable cost on top of the fixed cost. Variable costs add a great deal of complexity to the problem, but the results remain qualitatively similar.

hiring at random in time  $t$ . With probability  $\tilde{P}(t)$ , the random draw has a low match value. When firms can fire at will, the downside risk of such a draw is limited to 0.

$$J_{1-\phi}(t) = \tilde{P}(t) [\mathcal{L} \cdot 0 + (1 - \mathcal{L})J_b(t)] + (1 - \tilde{P}(t))J_g(t)$$

$$\tilde{P}(t) = P_u(t)\mathcal{P}_\ell + (1 - P_u(t))\mathcal{P}_h$$

With these in place, equations (3.3)-(3.5) compute the value of a vacancy with screening decision  $\phi$ ,  $x$ -number of applications and the screening cost  $k$ . If the vacancy decides to screen, it will hire if at least one application is of a good match quality. The probability of that happening is the complement to all of  $x$  applications being a bad match - which arises with probability  $\tilde{P}^x$ . If the vacancy does not screen, it can decide to either hire an unemployed individual at random - yielding  $J_{1-\phi}(t)$  - or not hire at all, yielding 0. Figure 3.1 provides an overview of these choices and the associated outcomes.

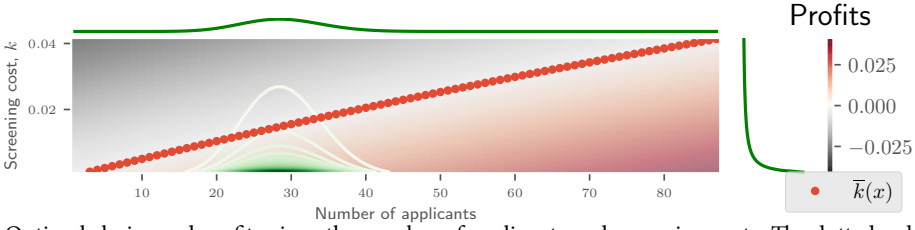
$$\tilde{\pi}(\phi, x, k, t) = \phi [(1 - \tilde{P}(t)^x)J_g(t) - k] + (1 - \phi) \max\{J_{1-\phi}(t), 0\} \quad (3.3)$$

$$\phi(x, k, t) = \arg \max_{\phi \in [0,1]} \tilde{\pi}(\phi, x, k, t) \quad (3.4)$$

$$\pi(x, k, t) = \max_{\phi \in [0,1]} \tilde{\pi}(\phi, x, k, t) \quad (3.5)$$

The probability of finding at least one good match increases in the number of applications, while the cost of screening is invariant to the number of applications. Therefore, a vacancy with a given cost  $k$  will always screen if it receives a sufficiently large number of applications. Vacancies have heterogeneous screening costs: when opening a vacancy, the firm first pays a fixed vacancy cost  $c$ , and then draws the screening cost from a distribution with CDF  $G^k$ . The number of applications that each vacancy receives is a random draw with density  $g^x$ . This allows us to write the expected value of opening a vacancy  $V$  as in (3.6).



**Figure 3.2:** Optimal screening choice and maximum profits

Optimal choice and profits given the number of applicants and screening costs. The dotted red line displays the curve where firms are indifferent between screening and not screening. Green contour lines display the joint-density of the distribution of firms across fixed-costs and applicants, with partial distributions displayed on the margins.

$$V(t) = -c + \int \sum_{x=1}^{\infty} \pi(x, k, t) g^x(x) dG^k(k) \quad (3.6)$$

It will be useful to define by  $\bar{k}(x, t)$  the screening cost that makes firms indifferent between screening or not screening:

$$\bar{k}(x, t) \equiv \{k : \pi(0, x, k, t) = \pi(1, x, k, t)\}$$

It satisfies  $\bar{k}(x, t) > 0 \quad \forall x > 0$ . It is computed in (3.7) by collecting the  $\phi$  terms in (3.3).

$$\bar{k}(x, t) = (1 - \tilde{P}(t)^x) - J_{1-\theta}(t) \quad (3.7)$$

We assume that the screening costs  $k$  are Gamma distributed with shape and scale parameters  $\mu_k$  and  $\sigma_k$ . The number of applications are Poisson-distributed. The appendix uses this to show that we can write the value of a vacancy  $V$  as in (3.8).

$$\begin{aligned}
V(t) &= -c + (1 - e^{-\lambda(t)})J_{1-\theta}(t) \\
&\quad + \sum_{x=1}^{\infty} [J_h(t)(1 - \tilde{P}^x) - J_{1-\theta}(t)] g^x(x) G^k(\bar{k}(x, t)) - \mathcal{K}(t) \quad (3.8) \\
\mathcal{K}(t) &= \sum_{x=1}^{\infty} g^x(x) \frac{\beta}{\Gamma(\alpha)} [\Gamma(1 + \alpha, 0) - \Gamma(1 + \alpha, \frac{\bar{k}(x, t)}{\beta})]
\end{aligned}$$

Every vacancy has to pay the fixed entering cost  $c$ , and receives the value of a random draw  $J_{1-\theta}$  if it draws more than zero applicants. Given  $x$  applications, screening yields the net value of  $J_h(t)(1 - \tilde{P}^x) - J_{1-\theta}$  on top of that. The third term adds up this additional value, weighting it by the probability of drawing  $x$  applications  $g^x$ , and the probability of drawing a screening cost  $k$  that is below  $\bar{k}(x, t)$ . Finally,  $\mathcal{K}(t)$  computes the expected screening cost for the outcomes under which the firm posting the vacancy optimally decides to screen.

### 3.2.5 Flows

Now we will compute the job-finding rates for both high and low types of unemployed workers. We start by computing the probability that a firm posting a vacancy hires an unemployed individual of type  $i$ , denoted  $o_i(t)$ . If that firm screens, it finds a good match with probability  $1 - \tilde{P}^x$ , and  $\psi_h$  denotes the conditional probability of that hire being high type. The offer probability from a non-screening vacancy varies under the two policy regimes. A firm with a non-screening vacancy selects a high type with probability  $1 - P_u$ . If layoffs are not permitted, it will then hire that applicant if the value of randomly hiring is positive. If layoffs are permitted, the firm posting the vacancy will hire that applicant and keep him if he turns out to be a good match with probability  $\mathcal{P}_h$ . For individuals from the low-type pool, the offer probability is analogous.

$$\begin{aligned}
o_h(t) &= \int \sum_{x=1}^{\infty} g(x) \left[ \phi(x, k, t)(1 - \tilde{P}(t)^x) \psi_h(t) \right. \\
&\quad \left. + (1 - \phi(x, k, t))(1 - P_u(t)) \cdot \left[ (1 - \mathcal{L})\mathbf{1}_{J_{1-\phi}(t) \geq 0} + \mathcal{L}(1 - \mathcal{P}_h) \right] dG^k(k) \right] \\
o_\ell(t) &= \int \sum_{x=1}^{\infty} g(x) \left[ \phi(x, k, t)(1 - \tilde{P}(t)^x) \psi_\ell(t) \right. \\
&\quad \left. + (1 - \phi(x, k, t))P_u(t) \cdot \left[ (1 - \mathcal{L})\mathbf{1}_{J_{1-\phi}(t) \geq 0} + \mathcal{L}(1 - \mathcal{P}_\ell) \right] dG^k(k) \right] \\
\psi_h(t) &= \frac{(1 - \mathcal{P}_h)(1 - P_u(t))}{1 - \tilde{P}(t)} \\
\psi_\ell(t) &= \frac{(1 - \mathcal{P}_\ell)P_u(t)}{1 - \tilde{P}(t)}
\end{aligned}$$

We use these offer probabilities to compute the probability that any individual application of a type- $i$  unemployed worker results in a job offer, which we denote  $\mu_i$ . This is accomplished by employing an accounting identity of the matching function: the number of filled vacancies has to equal the number of hired unemployed workers.

$$\begin{aligned}
v(t)o_\ell(t) &= a\mu_\ell(t)u(t)P_u(t) \\
v(t)o_h(t) &= a\mu_h(t)u(t)(1 - P_u(t))
\end{aligned}$$

Once we know the success probability of any individual application, we can compute the job-finding rates within each application cycle as the complement to all applications failing. We scale these rates up by  $\tau$  to transform the job-finding rates from application-cycle length to period length.

$$f_i(t) = \tau(1 - (1 - \mu_i(t))^a)$$

The laws of motion for the unemployment rates can then be written as follows, where  $\delta$  denotes the exogenous separation rates  $\delta$ .

$$\begin{aligned} \dot{u}_h(t) &= \delta e_h(t) - u_h(t)f_h(t) \\ \dot{u}_\ell(t) &= \delta e_\ell(t) - u_\ell(t)f_\ell(t) \end{aligned}$$

### 3.2.6 Equilibrium

Given regime status  $\mathcal{L}$ , initial  $\{u_\ell(0), u_h(0)\}$ , we can describe an equilibrium as a path

$\{u_\ell(t), u_h(t)\}_{t>0}, \{J_i(t)\}_{i \in \{\ell, h\}}, v(t)\}_{t \geq 0}$  such that

1.  $J_i(t)$  satisfies the Bellman equation (3.2) for all  $t \geq 0$
2. Screening decisions solve the vacancy's problem for all  $x, k, t$  given  $\mathcal{L}$ ,  $\{u_\ell(t), u_h(t), J_i(t)\}_{t>0}$
3. Free-entry:  $v(t)$  is such that  $V(t) = 0$  in all periods, given  $\{J_i(t), u_i(t)\}_{t \geq 0}$
4.  $u_i(t)$  is consistent with the screening decisions and  $v(t)$  for  $i \in \{b, g\}$ ,  $t > 0$

A steady state is an equilibrium where the unemployment rates, the vacancy value and the Bellman equation  $\{u_\ell, u_h, v, J\}$  are all time-independent.

### 3.2.7 Parameter selection

Table 3.1 lists the chosen parameters. This paper lays down theory ahead of measurement: many of the moments in the model lack empirical counterparts, but we hope that the theory put forward motivates future empirical work. When the empirical counterparts are unclear, we choose parameter values that are either conservative estimates, or ease the illustration of the mechanisms at play. We will perform robustness checks for these parameters. We include job-to-job transitions when computing firms' effective discount rates  $\rho$ . The separation rates are taken from Bjelland et al. (2011). The values of home production  $b$  and bargaining power  $\beta$  are taken from Hagedorn and Manovskii (2008). We will discuss the importance of this calibration for the results and estimate alternative specifications for  $b$ .

Table 3.1: Parameter selection

Parameter	Value	Description	Source
<b>General</b>			
$\rho$	0.112	Discount rate	Includes J2J transitions
$\delta$	0.039	Separation rate	Fallick and Fleischman (2016)
$b$	0.955	Home production	Hagedorn and Manovskii (2008)
$\beta$	0.520	Bargaining power	Hagedorn and Manovskii (2008)
<b>Vacancies and matching</b>			
$c$	0.015	Vacancy opening cost	Vacancy measure of 0.025
$a$	15.957	Average # applications per cycle	Benchmark
$\mu_k$	0.014	Screening cost: Shape parameter	Screening share of 95%
$\sigma_k$	1.000	Screening cost: Scale parameter	Benchmark
$\tau$	10.870	Inverse of vacancy duration	Vacancy duration of one week
<b>Worker heterogeneity</b>			
$L_\ell$	0.500	Share of low types in labor force	Benchmark
$\mathcal{P}_\ell$	0.999	Probability of low match (low type)	$\Delta \mathcal{P} = 10$
$\mathcal{P}_h$	0.985	Probability of low match (high type)	Unemployment rate of 0.04
$A_b$	0.978	Productivity of low match	Bad matches have zero value
$A_g$	1.000	Productivity of high match	Normalization

Chosen parameter values and targets. All rates are quarterly.

The vacancy cost  $c$  targets an empirical average vacancy rate of 0.025. We calibrate  $a$  such that vacancies on average have 30 applications. We calibrate one screening cost parameter,  $\mu_k$ , such that 95% of the vacancies are screening their applicant pool. The scale parameter of the screening cost distribution  $\sigma_k$  is chosen to be 1: this pins down the dispersion and skewness of the fixed-costs. For the chosen value of  $\sigma_k$ , the distribution of screening costs has a fat left tail, and many vacancies will draw zero or negligible screening costs. We will later test the robustness of the results under less skewed distributions  $G^k$ .

To ease the exposition, we pick half of the labor force to be of the low type.  $\mathcal{P}_\ell$  and  $\mathcal{P}_h$  jointly satisfy an unemployment rate of 4%, and a chosen differential in success rates between the two types  $\Delta_{\mathcal{P}} \equiv \frac{1-\mathcal{P}_h}{1-\mathcal{P}_\ell}$ .  $A_g$  is normalized to one.  $A_b$  is set such that low types have zero value for the firm.

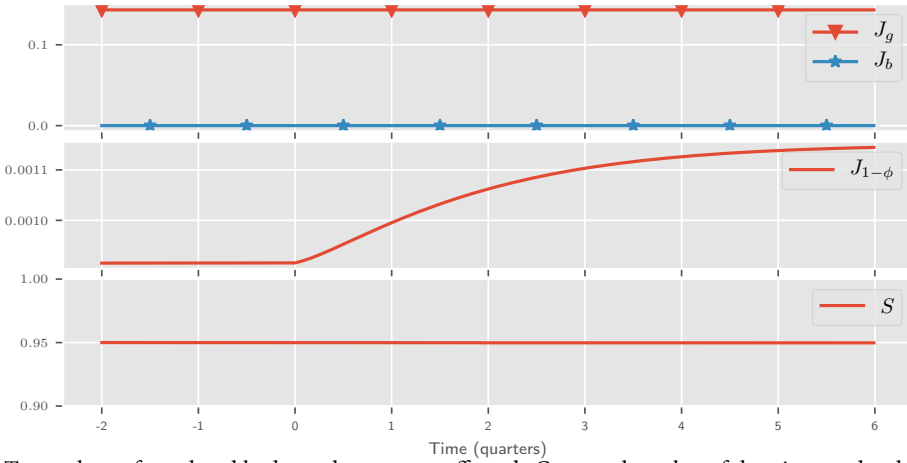
### 3.3 Introducing worker protection

We use the model to understand the impact of the firing restrictions on the aggregate economy in steady state and over the business cycle. To that end, we have calibrated the economy to a historic long-run steady state in which firings are not regulated ( $\mathcal{R}^F = 0$ ). Then, we introduce the policy change ( $\mathcal{R}^F = 1$ ) and observe the transition to a new steady state. We observe that regulating firings actually improves welfare, since firms were previously destroying matches that were generating a surplus, but were not beneficial to the firm.

The economy is at a steady state with  $\mathcal{R}^F(0) = 0$ , and at period 0 we introduce  $\mathcal{R}^F(t) = 1, t \geq 0$ . This policy change was unexpected to the agents up to  $t = 0$ , but the whole forward sequence of  $\mathcal{R}^F$  from then onward is known to them.

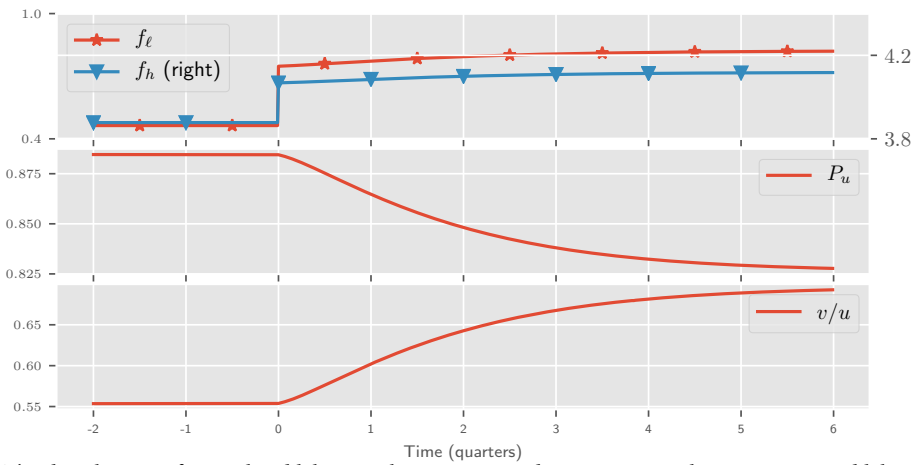
Figure 3.3 shows that the change of policy does not directly affect the value of good and bad matches,  $J_g$  and  $J_b$ . Forbidding firms to fire badly matched workers does not directly affect the value of randomly hiring,  $J_{1-\phi}$ . Over time, we observe that  $J_{1-\phi}$  improves together with the pool quality  $P_u$ . As  $J_{1-\theta}$  remains positive, firms with non-screening vacancies still hire. However, now they cannot separate from bad matches: this improves the effective job-finding rate of both low and high type unemployed workers.

**Figure 3.3:** Job values and screening



Top: values of good and bad matches are not affected. Center: the value of drawing randomly improves slightly with pool quality. Bottom: the share of screening vacancies is unaffected.

**Figure 3.4:** The rise in job-finding rates improves pool quality and raises market tightness



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

Figure 3.4 plots these job-finding rates on the same scale: the low-type unemployed worker's job-finding rate appreciates more as a response to the policy change. Consequently, the quality of the pool of the unemployed,  $P_u$ , appreciates, which makes vacancies more profitable. Market tightness increases as a response.

Table 3.2 summarizes the two steady states in more detail. One key finding is that the improved job-finding rates lead to a reduction of unemployment. This reduction of unemployment reduces the number of total vacancies. To evaluate welfare, we measure output. The reform affects output via two channels. First, a reduction in unemployment mechanically increases the number of firms and hence output. However, a positive share of these pairs is now low quality matches that produce less output than a high quality match. The table shows that the latter effect is not dominating: total output is higher in the new steady state. In this model with homogeneous and risk-neutral households, total consumption is an appropriate measure of welfare. To compute consumption, we subtract recruitment costs from aggregate output. A lower vacancy rate in the new steady state together with a constant screening share imply that the total recruitment costs actually decreased over the period. Reducing unemployment here leads to small consumption gains as the unemployed consume a high amount of home production under the Hagedorn and Manovskii (2008) calibration. Instead of representing home production,  $b$  could represent unemployment benefits, financed with lump-sum taxation. In that interpretation, the correct consumption measure is net of unemployment benefits, which we display in the last column. When taking into account the transition to the new steady state, the present-discounted value of the consumption gain associated with the reform amounts to 1.7%.

In the appendix, table 3.3 provides an overview of many alternative model specifications. The productivity of the bad matches,  $A_b$ , deserves special attention as it has the largest potential impact on the welfare effects. In the benchmark calibration, we assumed that bad matches still generate a positive surplus: workers in bad matches are more productive than at home. One of the parameters varied in table 3.2 is  $A_b$ . First, we calibrate  $A_b = b$  - which implies that bad matches generate zero surplus. In that scenario, the extent to which unemployment is



Table 3.2: The regulation increases output

Moment	$P_u$	$u$	$\nu$	SS	$Y$	Vac c	Scr c	C	Consumption, net
$\mathcal{L} = 1$	0.885	0.044	0.024	0.95	0.9980	0.0006	$8.2 \times 10^{-6}$	0.9975	0.9555
$\mathcal{L} = 0$	0.832	0.029	0.019	0.95	0.9987	0.0004	$6.5 \times 10^{-6}$	0.9983	0.9710

Comparison of the steady state where firings are allowed ( $\mathcal{L} = 1$ ) with the steady state where firings are forbidden ( $\mathcal{L} = 0$ ). C: total consumption. CN: consumption, excluding home production of the unemployed. SS: share of screening vacancies, Vac c: total vacancy cost, Scr c: total screening cost.

affected by worker protection is negligible, but still positive. Unemployment drops much more because  $J_{1-\phi}$  - the value of randomly hiring - is now rendered negative by the policy: non-screening vacancies do no longer hire. In this case, the consumption gains are also positive, but negligible: the introduction of the policy is still welfare-improving in the steady state. As an extreme case, we calibrate workers to be completely unproductive in bad matches. The table shows that the welfare gains associated with worker protection are now negative, but also negligible. Notice that at  $A_b = 0$ , all firms are screening and only hiring good matches: lowering  $A_b$  below 0 is not going to have any additional effect. We conclude that under our preferred calibration where bad matches have a positive surplus, the policy improves aggregate consumption by around one percentage point – and a negative but negligible consumption loss is a reasonable lower bound for the introduction of such a policy.

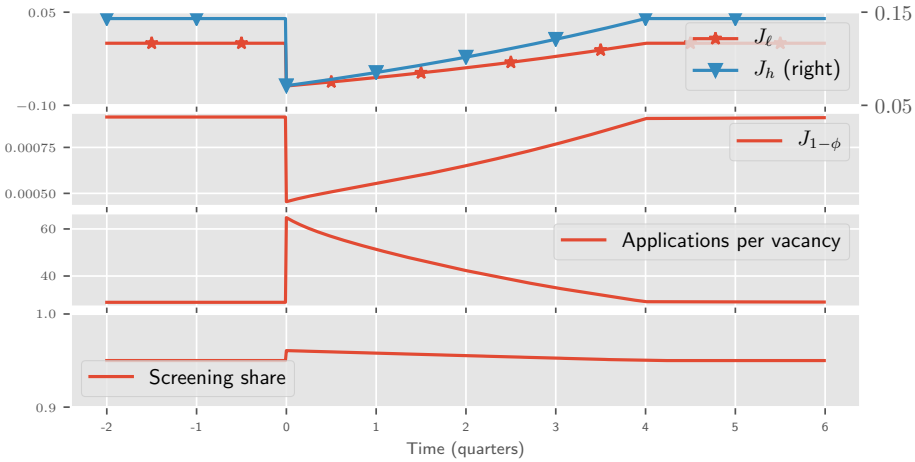
### 3.4 Business cycle fluctuations

Judging by the transition to the new steady state, the reform was a success: output has been increased and recruitment expenditure has been reduced. We now emphasize that this comes at a significant cost: the introduced policy renders the aggregate economy more volatile.

To be specific, we analyze the impact of an unexpected aggregate productivity shock in both steady states with and without the layoff constraint. In the simulations, we decrease  $A(t)$  by 10% for 4 quarters in period 0. The shock is unexpected prior to period 0. From that period onward, the whole forward path of  $A(t)$  is known by the agents.

#### 3.4.1 Unconstrained equilibrium

First, we will analyze the impact of the shock when layoffs are unconstrained. As Figure 3.5 shows, the initial productivity shock reduces the value of both  $J_g$  and  $J_b$ . The value of random hiring,  $J_{1-\theta}$ , drops by half. The loss of job values leads to a drop in vacancies: the average number of applications received for vacancies doubles and it becomes profitable for more vacancies to screen their

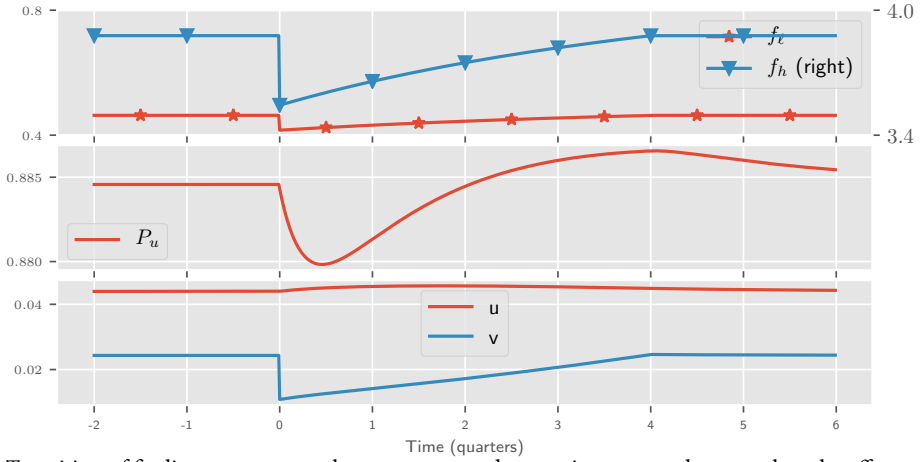
**Figure 3.5:** TFP shock in unregulated environment, screening

Job values, probabilities and resulting screening strategies on the transition to steady state

applicants.

Figure 3.6 displays the impact of this change in policy on the unemployed's job-finding and unemployment rates. A sharp drop of vacancies at period 0 results in a drop in the job-finding rates for both types. The axes in the top panel have the same scale: the job-finding rates drop slightly more for the high type than for the low type. This is because the drop in  $v$  leads to a proportional drop in job-finding rates, and the high-type unemployed had a higher initial job-finding rate. Consequently, the share of low types among the unemployed,  $P_u$ , starts to drop slightly at the onset of the productivity shock. However, these changes in  $P_u$  and the increase in the unemployment rate are of negligible size.

Here, reasonable fluctuations in the vacancy rate do not generate any measurable changes in the aggregate unemployment rate. The model's failure to generate empirically measured unemployment fluctuations can be reproduced in the most basic version of the urn-ball model. Essentially, the Poisson distribution of the unemployed over vacancies implies that when the measure of vacancies drops, the remainder of the vacancies are much more likely to match with unemployed workers that they will then hire. This increased vacancy filling rate then offsets much of the impact of the vacancy rate on the job-finding rates.

**Figure 3.6:** TFP shock in unregulated environment, flows

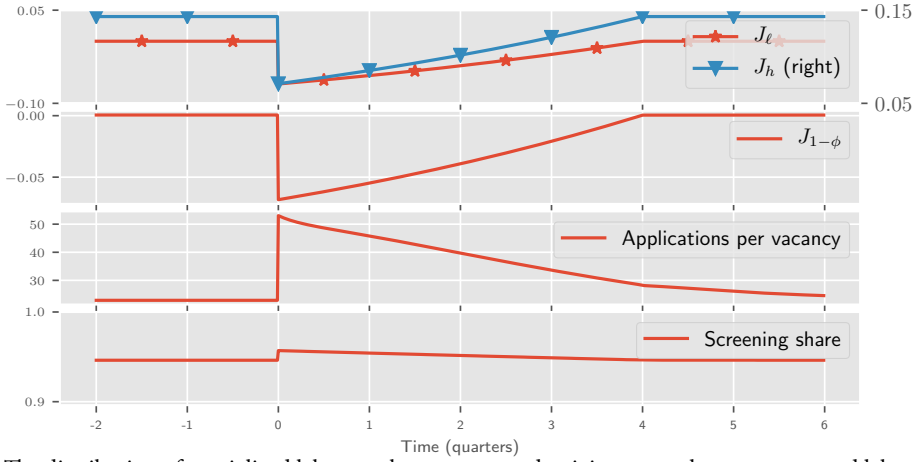
Transition of finding-rates, unemployment rates and vacancies to a steady state where layoffs are regulated.

### 3.4.2 Constrained equilibrium

We introduce the same aggregate productivity shock in the steady state where layoffs are constrained, and observe that - unlike before - a TFP shock leads to a strong increase in the unemployment response.

Figure 3.7 shows that the impact of the shock on job-values  $\{J_g, J_b\}$  is the same as before. Yet, the value of random firing,  $J_{1-\phi}$  is much more affected under the new regime: firms have to keep bad matches, and the downside risk of randomly hiring is no longer floored at zero. Therefore, the productivity shock implies a much larger drop in  $J_{1-\phi}$ . In fact, the value of randomly hiring workers becomes negative, and firms with vacancies that decide not to screen their applicants will completely cease hiring. The drop in the vacancy rate and the increased share of screening vacancies are comparable to the previously analyzed recession.

Figure 3.8 shows that the unwillingness of non-screener to hire leads to a sharp drop in the job-finding rates for both types, as they will no longer be hired if matched with a non-screening vacancy. Since low types are more dependent on non-screening vacancies, their job-finding rates drop relatively more: the unemployment rate increases for both low and high types, but more so for low

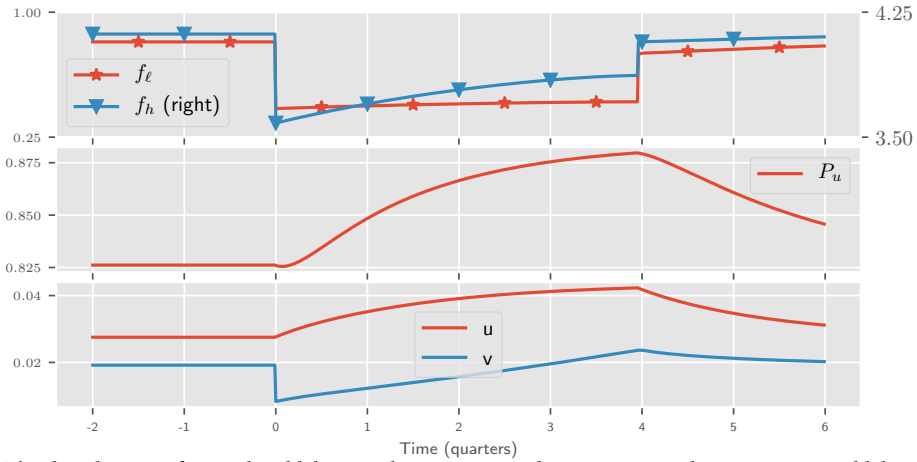
**Figure 3.7: Mobility**

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

types:  $P_u$  increases in response to the productivity shock. The job-finding rates start to recover slightly as market tightness returns. However, the continuous recovery of the job-finding rate is much smaller than the discrete jumps of the job-finding rate at the beginning and end of the recession, when firms with non-screening vacancies stop and restart hiring at random. These large changes in the job-finding rate translate into a much larger increase in the unemployment rate: under the new policy regime, the unemployment rate increases by 2 percentage points. After 4 quarters, the aggregate productivity shock recedes. The pool quality  $P_u$  is persistent and remains lower for several additional quarters, which disincentivizes hiring. As a consequence, the economy suffers from a “jobless recovery”, where the average job-finding rate in the recovery is persistently lower than prior to the recession.

Quantitatively, the unemployment response is smaller than empirically observed. The goal of this model was to emphasize the mechanisms underlying the relationship between worker protection and unemployment: many features that would increase the fluctuations in the unemployment rate are missing here. The key take-away is that the introduction of worker protection increases the sensitivity of aggregate consumption to TFP shocks. In what follows, we will

Figure 3.8: Mobility



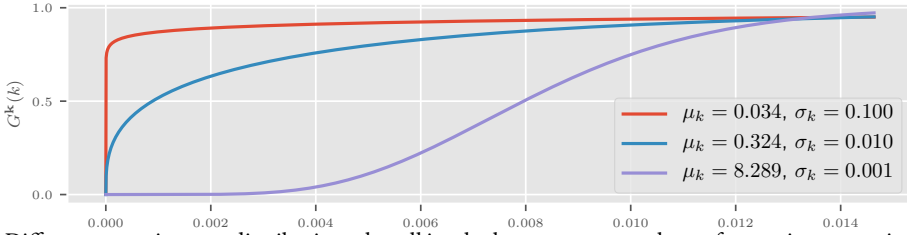
The distribution of specialized labor markets across productivity, unemployment rates and labor force, for four selected productivity states. Dots are proportional to mass.

shed some light on the mechanisms that lead to this response.

### Screening and unemployment fluctuations: a tale of three mechanisms

In this model, the unemployment response comes from three channels: a direct effect of productivity on vacancy values, a screening externality, and a reduction in random hiring.

**The direct effect** The first effect is standard in the literature: a decrease in productivity directly reduces the value of all matches and disincentivizes vacancy opening and hiring. In urn-ball models, this direct effect will not lead to a large decrease in the job-finding rates since the effect of losing vacancies is to a large extent offset by a higher share of vacancies that are now receiving more applications, good applicants, and thereby increase their hiring rate. One way of showing this is by varying  $b$ : in the context of Cobb-Douglas matching functions, Hagedorn and Manovskii (2008) show that this direct effect is stronger when  $b$  is calibrated to a higher value, as this will reduce the firm's surplus and increase its sensitivity to any fundamental. Table 3.4 shows that variations in the calibration of  $b$  do not significantly change the unemployment response to the TFP shock.

**Figure 3.9:** *Distribution of screening costs*

Different screening cost distributions that all imply the same average share of screening vacancies. Distributions with a higher  $\sigma_k$  have a larger mass around 0 and fewer vacancies

Therefore, we argue that the direct effect does not play an important role in explaining the observed changes in the unemployment rate.

**The screening externality** The new mechanisms both involve the screening decision. First, an increase in the share of screening vacancies in the recession reduces the share of high-type applicants. An increase in  $P_u$  then increases the likelihood that none of the applicants for a vacancy will be of a high match, and the vacancy will close without hiring. In equilibrium, this lower quality pool reduces the incentives to open vacancies and leads to an even higher number of applications per vacancy, increases screening and hence reinforces this mechanism.

The strength of this channel depends on two factors: (i) how many marginal vacancies that start screening in the recession, and (ii) the difference in the high-match likelihood between good and bad type.

The first factor depends on the shape of the fixed-cost distribution. The Gamma distribution has two parameters, and we have targeted one moment of that distribution: screening costs are distributed such that 95% of the vacancies are subject to screening in equilibrium. This leaves one parameter free that controls the variance and the skewness. Figure 3.9 plots different screening cost distributions which all lead to the same share of screening vacancies. In our baseline simulation, we fix  $\sigma_k = 1$  which implies a left-skewed distribution of vacancies over fixed costs, and only few marginal vacancies that respond to a change in applications per vacancy. Increasing the mass of marginal vacancies

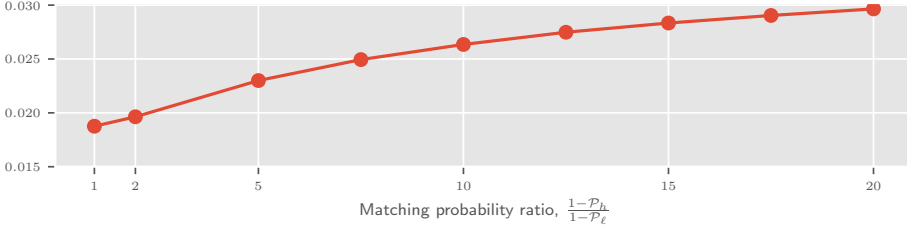
increases  $P_u$  between 0.059 and 0.065 but does not significantly affect the unemployment response.

The second factor depends on our choice of  $\mathcal{P}_\ell$  and  $\mathcal{P}_h$ . Figure 3.10 varies the calibrated differences in the probabilities. The pool composition  $P_u$  has a stronger impact on  $u$  when the difference in these likelihoods is higher: as we increase the difference in these likelihoods, the unemployment response increases. Note that  $\frac{1-\mathcal{P}_h}{1-\mathcal{P}_\ell} = 1$  implies that there is no difference in the high-match likelihood across types, and the screening externality is without effect. In the benchmark calibration, the unemployment response from the other two mechanisms adds up to about 1.9 percentage points.

**Reduced hiring for non-screeners** The last mechanism involves the share of vacancies that do not screen. In this model, some vacancies do not screen because the combination of the fixed-cost draw and the number of applications does not justify screening. In the recession, the quality pool of the unemployed drops and thereby affects the value of randomly hiring a worker. When layoffs are forbidden, the value of randomly hiring -  $J_{1-\theta}$  becomes negative under sufficiently negative productivity shocks. That is the case here and the firms posting non-screening vacancies stop hiring. The appendix performs a comprehensive robustness exercise. Table 3.4 shows that the unemployment response roughly doubles when we double the calibrated (steady state) share of non-screening vacancies from 5% to 10%.

This channel is very strong because all vacancies have the same decision threshold: whenever the value of  $J_{1-\theta}(t)$  crosses 0, all hiring decisions concerning non-screening vacancies change. In the real world, these thresholds probably vary by firm. For example, firms could be heterogeneous in the extent to which match-specific productivity matters in their production. This might be because some jobs - such as being a cashier - are very well regulated and standardized, and the extent to which match-specific productivity might affect firm profits would be limited. To capture that heterogeneity, job values could be modeled as follows:



**Figure 3.10:** Unemployment response increases in pool heterogeneity

$$\rho J_{i,\gamma}(t) = A_i^\gamma A(t) - w(t) - \delta J_{i,\gamma}(t) + \dot{J}_{i,\gamma}(t)$$

where  $\gamma \geq 0$  controls the extent to which the job depends on match-specific productivity. In an extension of this model, vacancies draw both  $k$  and  $\gamma$  when opened, and screening cost thresholds are now a function of both the number of applications  $x$  and  $\gamma$ :  $\bar{k} = \bar{k}(x, \gamma)$ . Such an extension would complicate the exposition of the model at little gain and is therefore not demonstrated here.

The remaining variations in Table 3.4 concern the share of low types in the economy,  $L_\ell$ , and the average number of applications per vacancy,  $au/\nu$ . Neither parameter has a sizable impact on the unemployment response.

### 3.5 Conclusion

We have built a model that adds to the literature on worker protection by analyzing its impact on firms' screening decision in an environment with heterogeneous match productivity. The model uncovers a new trade-off: the introduction of worker protections potentially increases aggregate consumption in the new steady state, and the transition thereto. However, this comes at the cost of higher volatility, as it renders the economy more susceptible to business cycle fluctuations. The presented model is very stylized and we do not provide a complete welfare assessment.

The model is a cautionary tale for welfare analysis: it is not always sufficient

to evaluate a policy along the transition to the steady state, as it may affect other dynamics of the model.

The consumption gains in the steady state primarily stem from the inefficient wage schedule: firms make losses from bad matches that actually generate positive surpluses. When layoffs are outlawed, firms with bad matches have to keep these individuals and thereby contribute to aggregate consumption. Worker protection reduces the economy's resilience to negative productivity shocks as they increase the risk of hiring without screening. Without layoffs as a safeguard, hiring unscreened applicants becomes a very risky proposal, and recruitment becomes more sensitive to the business cycle. This takes place through two channels. First, firms for which screening is too costly decide to completely withdraw from the market. Second, some firms intensify their screening efforts to prevent the risk of bad matches. Through their more discriminatory hiring practices, they worsen the pool of applicants and thereby magnify the impact of the original productivity shock.



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## 3.A Tables

**Table 3.3:** Robustness: transition to new steady state

change	Moment value	$P_u$	$u$	$v$	SS	C	CN
baseline		-0.05	-0.015	-0.005	-0.0003	0.0008	0.015
$L_\ell$	0.25	-0.13	-0.017	-0.005	-0.0003	0.0009	0.017
	0.4	-0.08	-0.016	-0.005	-0.0002	0.0008	0.016
	0.6	-0.03	-0.014	-0.005	-0.0002	0.0008	0.014
	0.75	-0.02	-0.013	-0.005	-0.0001	0.0007	0.013
$\sigma_k$	0.1	-0.05	-0.015	-0.005	-0.0006	0.0008	0.016
	0.01	-0.05	-0.016	-0.005	-0.0028	0.0008	0.016
	0.001	-0.07	-0.019	-0.006	-0.0205	0.0010	0.019
$b$	0.3	-0.05	-0.015	-0.005	-0.0007	0.0125	0.017
	0.5	-0.05	-0.015	-0.005	-0.0006	0.0089	0.017
	0.8	-0.05	-0.015	-0.005	-0.0004	0.0036	0.016
$\frac{1-\mathcal{P}_h}{1-\mathcal{P}_\ell}$	1	0.00	-0.010	-0.006	0.0000	0.0006	0.010
	2	-0.03	-0.011	-0.005	-0.0000	0.0006	0.011
	10	-0.05	-0.015	-0.005	-0.0003	0.0008	0.015
$au/v$	10	-0.05	-0.016	-0.005	-0.0018	0.0008	0.016
	50	-0.05	-0.015	-0.005	-0.0002	0.0008	0.015
SS	0.9	-0.11	-0.024	-0.008	-0.0010	0.0013	0.025
	0.925	-0.08	-0.021	-0.007	-0.0005	0.0011	0.021
	0.975	-0.02	-0.009	-0.003	-0.0001	0.0004	0.009
$A_b$	b	-0.00	-0.001	-0.002	0.0292	0.0000	0.001
	o	-0.00	0.000	-0.010	0.0499	-0.0000	-0.000

Change in moments (new steady state minus old steady state) under different robustness checks. SS: Share of screening vacancies. C: total consumption. CN: consumption, excluding home production of the unemployed. ss: steady state value. *max*: maximum value in transition. *change*: difference between maximum deviation and steady state.

Table 3.4: Robustness: Impact of negative TFP shock

change	value	$u$ (diff)	$\theta$ (diff)	$P_u$ (ss)	$P_u$ (diff)	SS (max)	Y (% diff)	C (loss)	CN (loss)
baseline		0.026	-0.308	0.807	0.059	0.960	-0.006	-0.353	-8.352
$L_\ell$	0.25	0.025	-0.306	0.506	0.105	0.960	-0.004	-0.347	-8.179
	0.4	0.027	-0.309	0.714	0.082	0.960	-0.005	-0.367	-8.683
	0.6	0.025	-0.306	0.872	0.040	0.960	-0.006	-0.329	-7.788
	0.75	0.023	-0.302	0.937	0.019	0.960	-0.007	-0.290	-6.848
$\sigma_k$	0.1	0.026	-0.313	0.807	0.059	0.971	-0.006	-0.348	-8.229
	0.01	0.025	-0.305	0.807	0.060	0.993	-0.006	-0.346	-8.161
	0.001	0.026	-0.303	0.804	0.064	1.000	-0.006	-0.387	-9.029
$b$	0.3	0.022	-0.097	0.807	0.050	0.951	-0.094	-4.622	-6.539
	0.5	0.024	-0.106	0.807	0.056	0.951	-0.066	-3.935	-7.748
	0.8	0.026	-0.111	0.807	0.058	0.953	-0.026	-1.653	-8.140
$au/\nu$	10	0.027	-0.308	0.808	0.059	0.961	-0.006	-0.358	-8.458
	50	0.026	-0.308	0.807	0.059	0.960	-0.006	-0.353	-8.346
Target SS	0.9	0.063	-0.319	0.649	0.112	0.919	-0.009	-0.819	-18.545
	0.925	0.043	-0.311	0.735	0.095	0.940	-0.008	-0.591	-13.510
	0.975	0.012	-0.306	0.855	0.027	0.980	-0.003	-0.141	-3.898
$A_b$	b	0.001	-0.242	0.887	-0.003	0.953	-0.019	0.026	-0.502
	0.5	0.001	-0.198	0.887	-0.003	0.951	-0.195	0.036	-0.484

Comparison of moments under different robustness checks. SS: share of screening vacancies. C: total consumption. CN: consumption, excluding home production of the unemployed. ss: steady state value. max: maximum value in transition. diff: difference between maximum deviation and steady state.





# Sammanfattning

En företagare tänker sig att skapa ett lönsamt företag genom att producera och sälja en vara. För att göra detta behöver han arbetstagare som har speciella färdigheter, men som även matchar företagarens arbetsmiljö. Efter att ha anställt dessa arbetstagare och producerat behöver han sälja sin produkt. Företagets lönsamhet beror på hur stark konkurrensen är och till vilket pris han kan sälja varan. De fristående uppsatserna i denna avhandling relaterar till dessa tre stadier av ekonomisk aktivitet och deras förhållande till arbetslöshet.

**Occupation-industry mismatch in the cross-section and the aggregate (Dålig matchning av yrke-bransch i tvärsnitt och aggregat).** Först fokuserar jag på yrke-bransch-nätverkens roll vid anställning. Jag observerar att olika yrken inte anställs lika mycket i alla branscher. Vissa yrken är specialiserade till väldigt få branscher medan andra är vad jag syftar på som ”breda”. De är anställningsbara i många branscher. Det är svårt för individer att byta yrke. När branscher som anställer inom specialiserade yrken råkar ut för negativa chocker halkar arbetslösa arbetstagare inom dessa yrken efter och kan inte anpassa sig till en förändring i branschstrukturen. Jag analyserar implikationerna av denna dåliga matchning mellan efterfrågan på arbetskraft i branschen och utbudet på arbetskraft inom yrken för arbetslöshetsrisken mellan olika arbetstagare och olika recessioner. Jag testar teorin empiriskt genom att använda data från den stora recessionen 2008. Jag visar att i USA hittade arbetstagare med bredare yrken arbete snabbare. Arbetslösheten var speciellt hög för arbetstagare i specialiserade yrken såsom elektriker som hade det svårt att anpassa sig till implosionen av byggsektorn under recessionen. I

ett andra steg tittar jag på flera recessioner. Jag jämför den stora recessionen som speciellt drabbade specialiserade yrken, när dot.com-bubblan sprack 2002, vilket drabbade breda yrken som programmerare och chefer. I modellen leder båda recessionerna till en jämförbar arbetslöshet men olika gensvar i form av utfall. Den stora recessionen påverkade specialiserade yrken som inte enkelt kunde flyttas över till mer produktiva sektorer. Sålunda är snedfördelningen av arbetskraft högre i den recessionen, vilket leder till den nämnda större produktionsförlusten.

**Consumer good search: theory and evidence(Sökande efter konsumtionsvaror: teori och bevis ).** Jag utvecklar en teori med hushåll som använder en del av sin fritid för att leta efter låga priser på varor och köper dem till lägsta tillgängliga pris – en process som normalt hänvisas till som ”shopping”. På senare år har många ekonomer integrerat sökteori tillämpad på konsumtionsvaror i sina modeller och gjort nya förutsägelser om beteendet i makroekonomin. Uppsatsen varnar för modellering på reducerad form av shoppingbeteendet genom att i detalj analysera kostnads-nyttanalysen av sökteori tillämpad på konsumtionsvaror. Jag använder teorin för att göra shoppingvalen begripliga i sysselsatta och arbetslösa hushåll. Empiriskt så har arbetslösa hushåll betydligt mer fritid än sysselsatta hushåll. Modellen förutspår att de arbetslösa skulle tillbringa mer tid med att shoppa än vad vi ser i data. Jag drar slutsatsen att sökandet efter konsumtionsvaror inte är redo för makroekonomisk analys. Jag föreslår flera sätt att omstrukturera teorin med bevisen. Emellertid så ska man noga överväga på vilket av dessa sätt man ska gå tillväga. De skiljer sig avsevärt i sina implikationer för makroekonomiska utfall.

**Worker protection and heterogeneous match quality (Skydd för arbetstagaren och heterogen matchningskvalitet).** I den förra uppsatsen (tillsammans med Gustaf Lundgren) studerar jag arbetsmiljöns relevans för anställningsbeslutet. Vår teori börjar med det grundläggande antagandet att företag har olika arbetsmiljöer och att arbetstagare har olika krav på sin arbetsmiljö. Ett slumpartat arbetstagar-företagspar kommer att vara synnerligen produktivt om miljön och kraven är förenliga och annars

ickeproduktivt. I vår teori kan – och kommer – företagen att ådra sig kostnader för att finna potentiellt bra matchningar bland sina sökande. I en värld utan anställningsskydd så är ett alternativt tillvägagångssätt att anställa arbetstagare, upptäcka kvaliteten på matchningen under anställningen och avskeda arbetstagaren om matchningen visar sig vara dålig. I detta sammanhang studerar vi införandet av en lagstiftning som syftar till att skydda arbetstagare. Vi visar att denna förändring förbättrar utvecklingstrenden i samhället, men ökar volatiliteten när det gäller arbetslöshet. Anställningsskydd gör samhället betydligt mer känsligt för aggrererade chocker.



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**Worker protection and heterogeneous match quality** investigates the impact of worker protection policies when firms hire applicants to learn about their quality.



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