What explains low-skilled unemployment? A new approach using occupational hiring and laying off probabilities*

Péter Hudomiet
University of Michigan

JEL codes: J24, J64
PRELIMINARY AND INCOMPLETE. PLEASE DO NOT CITE.

May 5, 2014

Abstract
The large difference in the unemployment rates of high and low skilled workers is an important yet poorly understood phenomenon. This paper proposes a novel method to help distinguish between competing explanations of this difference: I compute monthly job loss and job finding probabilities in detailed occupations between 1978 and 2012 and I formally compute their contribution to the cross-sectional variation in occupational unemployment. I find a surprising asymmetry: Even though hiring probabilities are strongly procyclical (it is harder to find jobs in recessions), the cross occupational differences in hiring rates are very small. In fact, occupational differences in layoff - rather than hiring - probabilities entirely explain the large cross sectional heterogeneity in occupational unemployment. Then, using a calibrated search and matching model I investigate what exogenous parameters can account for the observed occupational turnover differences: a mismatch between firms' demand and workers' supply of skills; UI benefits; skill specific productivity shocks, bargaining power and various adjustment cost differences across skill groups. Most parameters predict occupational differences in hiring that are too large to match the data. Most importantly, skill mismatch and the level of UI benefits are unlikely to have a large contribution to occupational unemployment. Three parameters, however, predict occupational turnover probabilities that are roughly in line with those in the data: 1) the amount of firm specific skills; 2) layoff cost of experienced workers; and 3) the variance of idiosyncratic productivity shocks. The contribution of these parameters to cross occupational unemployment differences, however, is not identified from the turnover data.

*I would like to thank Robert Willis, John Bound, Jeffrey Smith, Matthew Shapiro and Gábor Kézdi for continued feedback and support. I am also indebted to Hedvig Horváth, Cynthia Doniger, Daniel Hamermesh, László Sándor, Lasse Brune, Breno Braga, Mihály Fazekas, Reid Dorsey-Palmateer, Michael Gideon and Pawel Krolikowski for insightful comments and suggestions on earlier versions of this paper. Seminar participants at the Society of Labor Economists Annual Meetings and at various seminars at the University of Michigan also provided helpful comments. All remaining errors are mine. Please send comments or questions to hudomiet@umich.edu.

1 Introduction

Unemployment rates vary by demographic groups both in the observed cross section and over time[1]. Populations containing relatively more unskilled workers (i.e. the young, the new recruits, the less educated, and certain minority groups) have higher levels of unemployment, and they are more exposed to aggregate labor market conditions. Even though there are numerous theoretical arguments in the economics literature for why unemployment rates differ by "skills", we know very little about the relative importance of these factors. I propose a novel method using occupation-specific hiring and laying off probabilities to explain the large cross sectional heterogeneity in unemployment rates across skill groups.

Understanding the mechanism that leads to joblessness among low skill workers is obviously important for designing appropriate, welfare maximizing policies. Should the government run large scale training programs to provide employable skills to the unemployed? Should policymakers make labor market institutions (minimum wages, UI benefits) skill-specific in order to better balance the costs and benefits of these policies? Or should the government increase employment protection in occupations where adjustment costs are otherwise "too low"? If we want to answer these questions, we need to understand first what causes the large cross-sectional differences in unemployment rates.

When one wants to understand why unskilled workers are more likely to be jobless, it is important to make a distinction between a *driving force* and an *economic mechanism*. *Driving forces* are factors that exogenously differ across skill groups and lead to different unemployment rates due to an *economic mechanism*. The various potential driving forces, identified and discussed in the literature, operate through one of four mechanisms: 1) Labor adjustment costs (e.g. training costs) reduce turnover; 2) Low skilled wages might be above market clearing levels (e.g. because of the minimum wage) that leads to an over-supply of unskilled workers; 3) The value of being unemployed is comparatively high for low skilled workers (e.g. because of the concave UI benefit formula or low productivity) reducing their job search efforts; 4) Some selection mechanisms might favor high skilled workers compared to low skilled ones (e.g. low skilled employees might work in industries with volatile revenues). These mechanisms have different predictions for skill-specific turnover. For example, theory predicts that higher adjustment costs simultaneously decrease job-creation and job-destruction. As long as these

[1] See, for example, Clark and Summers, 1981; Kydland, 1984; Keane and Prasad, 1993; Hoynes, 1999; Jaimovich and Siu, 2009 and Hoynes et al., 2012.

adjustment costs are responsible for skill-specific unemployment differences we would expect occupational hiring and laying off probabilities to correlate positively. In contrast, if low skill workers are more likely to be jobless because their productivity is too low (there is *skill mismatch* in the labor force) we would expect hiring rates to be lower and layoff rates to be higher among the unskilled. The idea in this paper is to use occupational turnover probabilities in combination with labor demand theory to learn about the economic mechanisms that lead to high unskilled unemployment.

Papers in the literature typically focus on a single driving force and use natural experiments to identify their employment effects. There is a large literature on the employment effects of the minimum wage,[2] the duration and level of UI benefits,[3] the mismatch between workers skills and firms' demands for these skills,[4] etc. I will review these literatures in detail in Section 2. These papers, however, rarely discuss the general implications of their results for skill-specific unemployment. For example, even though there is strong evidence that the generosity of the UI system crowds out paid work, we do not know whether the UI is responsible for the high unemployment rate among low skilled workers or not. Similarly, recent literature found evidence for a mismatch between firms' demand and workers' supply of skills, but we do not know how relevant this is for low skilled unemployment.

Another approach used in the literature is to use cross-country variation in labor market institutions to identify their employment effects on workers with difference skills. The results of this literature are controversial. Nickell (1997), Siebert (1997), Iversen and Wren (1998), Esping-Andersen (2000) and Saint-Paul (2004) argue that labor market rigidities in many European countries led to a dual labor market featuring inefficiently high unskilled unemployment. Card et al. (1996) and Oesch (2010), however, using more comprehensive analyses, found little evidence for this labor market rigidity hypothesis.

In this paper I propose an alternative method to learn why unemployment rates differ by skill. I compute monthly job loss and job finding probabilities in detailed occupations between 1978 and 2012 and I formally compute their contribution to the cross-sectional variation in occupational unemployment. Between 1978 and 2012 there have been four recessions enabling me to investigate occupational unemployment and turnover under very different labor market conditions. My approach is motivated by two points. First, a growing literature in labor economics has used occupations, or different occupational

[2]See Neumark and Wascher (2006) for a review.

[3]See, for example, Roed and Zhang (2003), Schmieder et al. (2010) and Hagedorn et al. (2013).

[4]Lazear and Spletzer (2012) and Sahin et al. (2012).

skill measures to proxy workers' skills[5,6]. To my knowledge, however, no one has used occupational turnover to investigate the important question of why low skilled unemployment is so high. Second, decomposing unemployment into job loss and job finding probabilities has been recently used to study fluctuations in the aggregate unemployment rate[7]. As Shimer (2012) argues, this is a useful exercise, as in search and matching models the job loss and the job finding probabilities only depend on exogenous factors. To my knowledge, however, no one has used this decomposition exercise to study the cross sectional variation in skill-specific unemployment rates. In this paper I use a similar decomposition method to Shimer (2012), but I apply it to the cross occupational unemployment differences rather than to the time series variation in the aggregate unemployment rate.

I establish three new empirical results. First, unemployment rate differences across occupations are very large. Second, workers in higher-skilled occupations face substantially lower chances of losing their jobs at all phases of the business cycle. Moreover, this differential is remarkably monotonic when occupational skills are measured as the average unemployment rate in the 2000 census in detailed (N=191) occupations. Third, unemployed workers whose last occupations was high skilled, face the same or slightly less chance of reemployment compared to workers whose last occupation was low skilled. The aggregate job finding probability varies strongly with the business cycle, but skill-specific hiring rates follow aggregate trends very closely. These qualitative results are robust to the use of alternative datasets (CPS vs. SIPP), to alternative methods to estimate transition rates (using observed transitions vs. spell duration data) and to the use of various control variables such as industries, education and demographics.

An important implication of my results is that understanding job separations is very important to understand the cross-sectional heterogeneity in unemployment rates. There is a recent trend in the macro labor literature to use a constant and exogenous job loss probability and to focus attention to the hiring decisions of firms in dynamic models of aggregate unemployment (Hall, 2005; Hagedorn and Manovskii, 2008; Pissarides, 2009; and Blanchard and Galí, 2010). This assumption is often justified by citing the influential paper of Shimer (2012)[8] who shows that fluctuations in the job loss

[5]The skill content of occupations has been used to explain recent trends in wage inequality and job polarization (Autor et al., 2003; Firpo et al., 2011; Acemoglu and Autor, 2011), job mobility and task specific human capital (Ingram and Neumann, 2006; Poletaev and Robinson, 2008; Abraham and Spletzer, 2009; Kambourov and Manovskii, 2009; Robinson, 2011) and learning and career decisions of workers (James, 2011; Yamaguchi, 2012).

[6]One caveat of this approach is that skill heterogeneity within occupations is ignored.

[7]Shimer (2012), Davis et al. (2006), Elsby et al. (2009), Fujita and Ramey (2009).

[8]Many papers cite the NBER working paper version of Shimer (2012), which came out in 2007.

probabilities over time are relatively small. Even though my results do not invalidate this assessment, I clearly show that in order to understand the cross-sectional heterogeneity in unemployment rates, assuming a constant job loss probability does not work and an endogenous job separation model is more appropriate.

The fact that workers in higher- and lower-skilled occupations face similar job finding probabilities at all phases of the business cycle might seem puzzling. I use a calibrated search and matching model to analyze how various parameters affect turnover by occupations. More precisely I try to single out parameters that 1) potentially differ across occupations; 2) predict that layoff and hiring rates move together; and 3) predict a much larger effect on layoff than on hiring rates. I think of this approach as an application of Ockham's razor. My methodology can identify parameters that can simultaneously predict the observed occupational differences in hiring and layoff rates. However, if more than two parameters are allowed to differ by occupations, then the empirically observed turnover rates do not identify them. Unfortunately, it seems highly likely that occupations differ in several dimensions, and thus, more data is needed to identify the relative importance of them.

In the calibration exercise I identify three parameters that can simultaneously explain the occupational differences in hiring and laying off rates. 1) The first parameter is a measure of firm specific skills, which is modeled as a type of hiring cost that is paid *after* the first wage negotiation. I show that adjustment costs in general decrease both job-creation and job-destruction. For reasonable parameter values the effect on hiring is small as long as these adjustment costs do not increase the outside option of workers. Search costs, for example, have large effect on hiring, because these costs increase the initial surplus of matches in equilibrium and workers will demand their share of this extra surplus. Hiring costs that are paid after the first wage negotiation, however, do not increase the initial surplus and consequently do not increase the outside option of workers. 2) Layoff costs of experienced workers. Similarly to firms specific skills, layoff costs have small effect on hiring as long as they do not increase the outside option of workers. I show that layoff costs of newly hired workers increase the outside option of workers, while layoff costs of experienced workers do not. 3) The variance of idiosyncratic productivity shocks. If low skilled occupations face larger productivity shocks, then, for reasonable parameter values, they will be more likely to be laid off, because large negative productivity shocks will be more common. Perhaps more surprisingly, larger productivity shocks increase the hiring rate as well, because of the option value of large positive productivity shocks in these occupations.

I argue that both firms specific skills and the variance of idiosyncratic productivity shocks play a role in occupational unemployment differences. In the literature recruitment costs have been shown to be substantial, equivalent to several months of the salary of an average worker (Oi, 1962, Manning, 2011 and Blatter et al., 2012). The largest component of total recruitment costs are *"adaptation costs"* due to the relatively low productivity of newly hired workers (Blatter et al., 2012) and their informal training by co-workers (Lerman et al., 2004; Leuven, 2005). Evidence suggests that these costs are larger for skilled workers (even proportional to their monthly wages). Adaptation costs are good candidates for explaining skill-specific unemployment differences because 1) the empirical estimates suggest large heterogeneity by skills; and 2) these costs are not paid instantaneously at hiring, and based on the arguments in the previous paragraph, they do not become a part of workers' outside option, limiting the negative effect on hiring rates. Using the Multi-City Study of Urban Inequality dataset I also show that the average adaptation period is significantly higher in skilled occupations that face lower layoff rates and lower unemployment.

The paper also addresses the role of potential confounding factors for identifying occupation-specific labor demand. For example, it is possible that the observed differences in layoff rates across occupations are due to industry specific shocks rather than occupational skills. However, in volatile industries, such as construction, manufacturing or extractive industries, the difference between the job loss probabilities of high and low skilled workers is even larger than in the aggregate. In general, the qualitative patterns in layoff and hiring across occupations remain the same even when industry, state and flexible demographic variables are controlled for.

The paper is organized as follows. Section 2 reviews the literature on low skilled unemployment. Section 3 discusses the data and the definitions of some key variables used in the paper. Section 4 provides a decomposition of occupational unemployment into occupational job loss and job finding probabilities. Section 5 discusses the implications of the empirical findings for labor demand models through calibrating a search and matching model with occupation-specific parameters. Section 6 carries out robustness checks of the empirical findings. Lastly, Section 7 capitulates the findings.

Table 1: Economic mechanisms and driving forces to explain low-skilled unemployment

Economic mechanism	**Driving force**	**Predicted high skilled - low skilled differences in**	
		Hiring rates	**Layoff rates**
Adjustment costs affect turnover	Search costs	-	-
	Training costs	-	-
	Layoff costs	-	-
Wage above market clearing level	Minimum wages	+	-
	Efficiency wages	-	+
	Collective wage bargaining	+	-
Workers outside option too large	Concave UI benefit formula	+	-
	Skill mismatch	+	-
Selection	Industry clustering	+	-
	Match specific shocks	?	?
	Crowding out	+	-

2 Economic mechanisms to explain low-skilled unemployment

This section reviews the most important ideas that came up in the literature to explain cross sectional unemployment differences across skill groups. Table 1 provides and overview, together with theoretical predictions on skill specific hiring and layoff rates.

The first mechanism to explain skill specific unemployment differences is that hiring and firing workers are not costless, and the costs of adjusting labor negatively affect turnover rates. This idea has been proposed by Oi (1962), who showed some evidence that adjustment costs are lower and labor turnover is higher among less skilled "Common laborers". Theory unambiguously predicts that adjustment costs negatively effect both job creation and job destruction[9]. The effect on equilibrium unemployment rates, however, is not straightforward and it will be analyzed later in Section 5. After the seminal work of Oi (1962), the concept of labor hoarding gained popularity in macroeconomics, because it could explain why labor productivity is procyclical[10]. However, we know very little about how labor hoarding differ by occupations.

The second candidate mechanism to explain skill differences in unemployment is that low skilled wages might be above market clearing levels that leads to an over-supply of unskilled workers. As opposed to adjustment costs, this mechanism predicts that skill specific hiring and layoff rates move in the

[9] There exists a few exceptions that will be discussed in Section 5.

[10] Fay and Medoff (1985), Fair (1985), Bernanke and Parkinson (1991), Aizcorbe (1992), Burnside et al. (1993), Burnside and Eichenbaum (1996), Basu (1996), Basu and Kimball (1997), Marchetti and Nucci (2001) and Liu and Spector (2005).

opposite direction. The driving force can be minimum wages; unions' bargaining practices, mandatory health insurance policies, or any other labor market institutions that compress wage dispersion in the workforce[11]. Minimum wages, at least in the US, are not indexed to occupational productivity, and thus, they are more likely to bind for low skilled workers. The minimum wage literature is rather inconclusive about whether the minimum wage affects employment, but most economists think the minimum wage does have a small negative effect on employment, particularly among the lowest skilled workers, such as teens (Neumark and Wascher, 2006). Collective bargaining might also lead to less dispersed wages[12], which might push low skilled wages above equilibrium levels.

The third candidate mechanism is that the value of being unemployed is relatively high for low skilled workers. The driving force can be specificities of the unemployment insurance (UI) system, the lack of adequate skills of some worker groups, or any other factors that influence the utility of working and the utility of not working. This mechanism also predicts that skill specific hiring and layoff rates move in the opposite direction. The value of unemployment is a primary factor determining the search effort of the unemployed. The generosity of the UI system, for example, has been found to be an important determinant of the unemployment rate (Roed and Zhang, 2003; Schmieder et al., 2010; Hagedorn et al., 2013). The strong concavity of the UI benefit formula might create a disincentive for low skilled workers to search for, and firms to create, low skilled jobs[13]. Skill shortage (or skill mismatch) is another factor that might influence the ratio of workers' productivity to the value of not working. Technological change in the last thirty years might have made the skill set of some workers obsolete (Autor et al., 2003; Acemoglu and Autor, 2011; Jaimovich and Siu, 2012; Lazear and Spletzer, 2012). If the productivity of these workers fell faster than their outside option, skill mismatch could have led to excess unemployment. It is also possible that there is a skill mismatch between employers' demand and workers' skills only in recessions leading to excess low skilled unemployment rates in recessions.

The last mechanism I consider involves some form of selection. Low skilled workers might work in industries with volatile demand shocks such as the construction sector or durable good manufacturing. It is also possible that the variance of match specific shocks is larger in low skilled jobs. This would be

[11] Occupations might also differ in the extent to which optimal efficiency wages are present. Efficiency wages, however, are more likely to be used in high skilled occupations, where workers carry out relatively complex tasks that are not easily observable for employers.

[12] See, for example, Freeman (1980), Card (2001), Card et al. (2004) and Frandsen (2012)

[13] Note, however, that the most credible evidence we have about the negative employment effects of the UI system is about the duration of the UI benefit as opposed to the replacement rate; and benefit duration does not vary across occupations.

the case if unskilled workers substitute and high skilled workers complement capital, which is fixed in the short run. (XXXadd citationXXX). Lastly, some researchers have argued that it is possible that skilled workers crowd out the unskilled from the labor market in recessions. This might happen if employers raise hiring standards in recessions[14], or skilled workers increase their search effort for low skilled jobs in a slack labor market[15]. Devereux (2004) has found some evidence for this mechanism in the PSID, although the magnitude of the effect was not found to be very large.

3 The monthly linked Current Population Survey

The primary dataset used in this paper is the 1978-2013 month-to-month linked waves of the Current Population Survey (CPS). The CPS uses a rotating panel survey design which enables researchers to link roughly 3/4 of the sample between consecutive months. These so-called semi-panels have been used by many researchers in the past to analyze patterns in worker turnover (See e.g. Blanchard and Diamond, 1990 and Shimer, 2012). The primary advantage of the CPS is its large size which enables me to estimate turnover rates in detailed occupations with reasonable precision.

The second advantage of the CPS is that it asks detailed questions about the last jobs of those unemployed who had a job in the last five years. Among others, we have information about the last occupations and last industries of the unemployed. This enables me to compute unemployment→employment transition probabilities by the last occupation of the unemployed. Unemployed persons who did not work in the past five years, including the new entrants, are excluded from the analysis.

In order to minimize the effect of transitions between employment, schooling and retirement, which might systematically differ by occupations, I restricted the sample to the prime age workforce, the 25 to 55 year old. I do not use any other sample restrictions, such as industries or gender.

The CPS uses the 3-digit census occupation classifications. In the most recent years it covered more than 500 different occupations. Unfortunately, there have been two major changes in the used classifications in 1983 and 2003 and two minor ones in 1991 and 2011. There are available occupational

[14] See Reder (1955); Teulings (1993); Solon et al. (1997); Evans (1999); Devereux (2004) or Büttner et al. (2010).

[15] See van Ours and Ridder (1995); Acemoglu (1999); Albrecht and Vroman (2002); Dolado et al. (2009); Khalifa (2009) or Chassamboulli (2011).

crosswalks, but they are not suitable for the purposes of this paper. The widely used crosswalks created by IPUMS[16], for example, is not entirely consistent over time as some occupations are only available in certain years. Moreover, some of the IPUMS occupations contain very few workers, and particularly few unemployed persons, which makes the occupation-specific unemployment rate and transition estimates noisy. To address these issues I created a slightly more aggregated, but consistent occupational crosswalk with 191 occupations[17]. The main purpose was to follow the IPUMS crosswalk as much as possible, but increase the number of workers in each occupation to at least roughly a hundred in every month by merging or redefining occupations. The secondary purpose was to have a good match between the the 1980 census definitions (used between 1983 and 2002) and the 2000 census definitions (used after 2002), as the pre-1982 definitions are significantly less detailed for skilled occupations. Consequently, the quality of the proposed crosswalk is slightly lower before 1982. None of the results of these papers are sensitive to the choice of occupational crosswalks.

4 Unemployment rates and transition probabilities by occupations

The first goal of this section is to estimate monthly job-loss and job-finding probabilities by detailed occupations. The second goal is to decompose the cross-occupational unemployment rate differences into contributions of the cross-occupational differences in job loss and job finding probabilities. My decomposition method is purely cross-sectional, and it can be used at any point in time, for example, in recessions and booms separately.

4.1 Definitions

1. Let E_{itx} denote whether individual i at month t is employed with a main job in occupation x. $E_{it\cdot}$ indicates whether he is employed in *any* occupation.

2. U_{itx} denotes whether individual i at month t is unemployed with a last job in occupation x. $U_{it\cdot}$ indicates whether he is unemployed independently of his last occupation.

[16] https://usa.ipums.org/usa/volii/occ_ind.shtml
[17] The crosswalk can be downloaded from https://sites.google.com/site/phudomiet/research.

3. I define unemployment rate in occupation x at month t as $u_{xt} = \frac{\sum U_{ixt}}{\sum U_{ixt} + \sum E_{ixt}}$.

4. Employment-unemployment transition probability in occupation x at month t is $p_{xt}^{EU} = \Pr\left(U_{i,t+1,\cdot} | E_{itx}\right)$. The occupational job loss probability, p_{xt}^{Loss} is defined as the probability of any job loss between t and $t+1$ which is larger than p_{xt}^{EU}, as some job-losers will find a new job by $t+1$.

5. Unemployment-employment transition probability in occupation x at month t is $p_{xt}^{UE} = \Pr\left(E_{i,t+1,\cdot} | U_{itx}\right)$. The occupational job finding probability, p_{xt}^{Find} is defined as the probability of any job finding between t and $t+1$ which is larger than p_{xt}^{UE}, as some job-finders lose their new job by $t+1$.

The linked CPS can be used to directly estimate the occupational unemployment rate and transition probabilities in all months between 1978 and 2012 in each of the 191 occupations. Then, using a procedure discussed in Section 4.2, one can estimate the occupational job loss and job finding probabilities.

The interpretation of the job loss probability is straightforward: It is the probability of job loss within one month among employed workers in occupation x. The interpretations of occupational unemployment rates and job finding probabilities are only trivial if workers do not change occupations. In the data, however, we see many workers finding jobs in occupations other than their last one. Ideally we would like to know not only where the unemployed workers are coming from, but also where they are searching for jobs. This latter object, however, cannot be identified without strong assumptions. Many papers (such as Lazear and Spletzer, 2012 and Sahin et al., 2012) use the same definition of occupational unemployment as I do. A particular concern is the crowding-out hypothesis: the possibility that high skilled workers flow into lower skilled jobs after job-loss with the intent of climbing up on the job-ladder on-the-job later on. Even in this case, however, the variables above are well defined objects: They show unemployment rates and transition probabilities among those whose most recent affiliation is with a given occupation. I think of the crowding-out hypothesis as a potential explanation for the patterns in the data as opposed to a bias. Thus, I will use the definitions above, and I will come back to the crowding-out hypothesis in Section 6. Overall, there seems to be some evidence for crowding-out, but its effect is limited, because occupation switchers tend to switch into similar occupations (see also Robinson, 2011).

4.2 Adjustments for time-aggregation and other measurement issues

The linked CPS has direct measures of the employment statuses of persons in consecutive months, but it is not observed what happens to the workers within the month. As some make more than one transitions between t and $t+1$, the observed transitions only take up a subset of all transitions in the given month. In the literature this is called the "time-aggregation bias" (see e.g. Shimer, 2012). Because tenure data is not available in the monthly CPS, one needs to use a statistical model to correct for the bias. The bias is expected to be larger for the job loss probability, because the average job finding probability is large and, thus, we expect quite a few job losers to find jobs within a month.

Shimer (2012) uses a statistical procedure to correct for time aggregation bias based on the following two assumptions:

1. There is no duration dependence in the job loss and job finding hazards.
2. The labor force participation rate is constant within each month.

Even though both of these assumptions are arguably strong, as Shimer (2012) shows, his simple and tractable methodology works quite well. In this paper I use the exact same methodology as Shimer for each occupations separately. Thus I need to make the following two assumptions:

1. There is no duration dependence in the job loss and job finding hazards in any occupations.
2. The size of the occupational labor force, $L_{xt} = \sum U_{ixt} + \sum E_{ixt}$ is constant within each month.

I also developed a procedure to handle cases where the occupational labor force has a constant trend within particular months and I will discuss the results in Section 6. Overall, my view is that the time aggregation bias is not a big problem for the analysis of cross-sectional differences in unemployment rates for the following reasons: The time aggregation bias in the job finding probability is small, because the job loss probabilities are small, too; The time aggregation bias in the job loss probabilities are larger, but they are quite similar across occupations, because, as I shall show, the job finding probabilities are very similar across occupations.

In most of this paper I focus only on the employment-unemployment and unemployment-employment transitions, and I ignore movements in and out of the labor force. The main reason is that the CPS does not ask about the last occupation of persons not in the labor force. [More on this]

[Discuss missings.]

[Discuss movers.]

4.3 Graphical analysis

Panel A and B of Figure 2 show the unemployment rates in different occupational groups in the last 35 years. Grey shaded areas are NBER recessions. Panel A shows the unemployment rates in three major occupational groups: 1. managers, professionals and technicians; 2. office, sales and administrative workers; 3. production workers, operators, laborers and service workers. Panel B shows the unemployment rates in three occupational tertiles, where occupations are ranked by their unemployment rates in the 2000 census. There are several interesting patterns in these graphs. First, even though the 2007 recession had the largest impact on the labor market, there was nothing unusual in terms of how different occupations were affected. Moreover, the last recession was also comparable in size to the aftermath of the double-dip recession of the 80s. Second, the unemployment rate varies a lot both across occupations and over time. While the unemployment rate among managers, professionals and technicians never exceeds five percent, it is rarely below ten percent among production and service workers. The third interesting finding is that unemployment tends to fluctuate more in occupations where there is already a high level of unemployment, but in a proportional sense the changes are similar. In the last recession, for example, all occupations experienced a doubling of the unemployment rates. In a level sense, however, the differences are enormous. It is important to note, that from a welfare point of view more concern should be given to level changes in employment probabilities. A Von Neumann-Morgenstern utility function is linear in probability and, thus, agents care about level, and not percent, changes in their unemployment probabilities.[18]

Panel C and D of Figure 2 show the occupational job loss and Panel E and F show the job finding probabilities. As is apparent, the job finding probabilities are more volatile over the business cycle than

[18] Ambiguity averse agents would disprefer employment probability fluctuations even more, because larger fluctuations would make it harder to predict these probabilities.

the job loss probabilities, which is in line with the macro labor literature (Shimer, 2012; Davis et al., 2006; Elsby et al., 2009; Fujita and Ramey, 2009). The average monthly job finding probability was roughly 40 percent in 1998, while it was below 20 percent in 2009. Even if the job finding probabilities are very volatile, little difference is seen between occupations. Finding a job is just as hard in skilled occupations as in unskilled ones both in recessions and in booms. In fact, the lowest skilled occupations, with the highest unemployment rate, seem to have higher rather than lower job finding probabilities, particularly in the last 15 years. The job loss probabilities, on the other hand, fluctuate less over time, but they show very large occupational differences in levels. The pattern in the occupational job loss probabilities basically track the patterns in occupational unemployment shown in Panel A and B.

4.4 Formal decomposition of occupational unemployment

The decomposition method used in this paper is the same as what Shimer (2012) used, apart from the fact that it is used for decomposing cross-sectional rather than time series variation in unemployment.

The goal is to decompose unemployment in a given time period t, where t can be a few months, years or the entire 1978-2013 period as well. First, I pool all the data at t in a pooled cross-sectional way. Second, I compute the average occupational unemployment rates, employment-unemployment and unemployment-employment transition probabilities, $u_{xt}, p_{xt}^{EU}, p_{xt}^{UE}$. Third, I adjust the transition probabilities for time-aggregation bias with the methodology described in the previous section to get the job loss and job finding probabilities $p_{xt}^{Loss}, p_{xt}^{Find}$. Third, I repeat the same exercise for the aggregate to get $u_t, p_t^{Loss}, p_t^{Find}$. These latter three variables are unemployment rates and transition probabilities averaged over occupations.

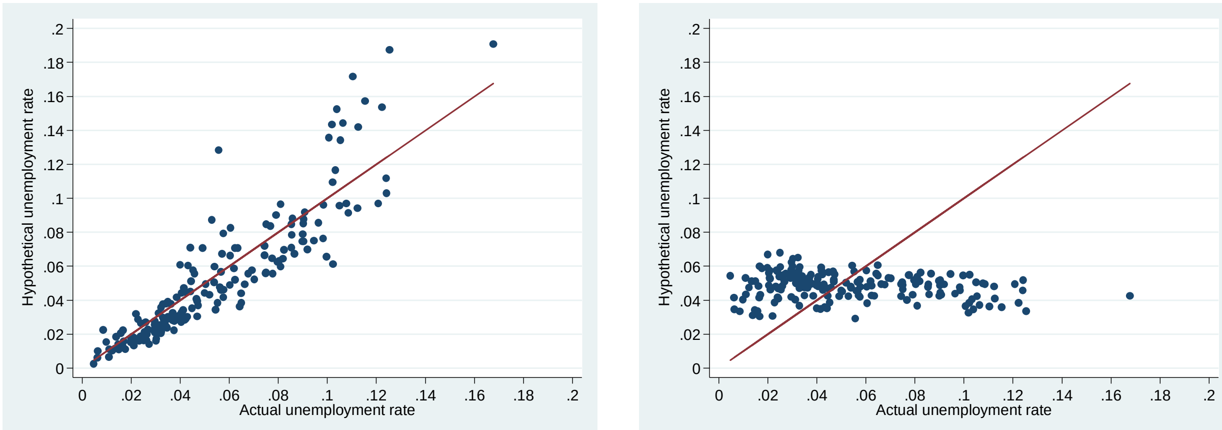
The next step is to define occupational unemployment rates "caused by" the occupational job loss and job finding probabilities. Based on Shimer (2012) I define the following hypothetical occupational unemployment rates:

$$u_{xt}^{Loss} = \frac{p_{xt}^{Loss}}{p_{xt}^{Loss} + p_t^{Find}} \quad (1)$$

$$u_{xt}^{Find} = \frac{p_t^{Loss}}{p_t^{Loss} + p_{xt}^{Find}} \quad (2)$$

Figure 1: Hypothetical occupational unemployment rates by actual occupational unemployment rates, Monthly CPS 1978-2013

Panel A: Fixed job finding probability, u_{xt}^{Loss} Panel B: Fixed job loss probability, u_{xt}^{Find}



*The hypothetical unemployment rates use the steady state approximation $u_{xt} \approx p_{xt}^{Loss}/(p_{xt}^{Loss} + p_{xt}^{Find})$, but the job finding (in Panel A) or the job loss (in Panel B) probabilities are replaced with the averages over occupations. The job loss and job finding probabilities are adjusted for time aggregation bias. Each dot represents one of the 191 occupations, and the line shows the 45 degree line.

These two hypothetical unemployment rates represent how much the occupational unemployment rate would be if the job finding or the job loss probabilities were the same as in the aggregate. The idea is based on the steady state approximation of the occupational unemployment rate $u_{xt} \approx p_{xt}^{Loss}/(p_{xt}^{Loss} + p_{xt}^{Find})$. (1) and (2) only differ from this approximation by fixing the job-loss or the job-finding probabilities to be the same across all occupations.

If differences in the job loss (job finding) probabilities across occupations are responsible for the cross-sectional variation in unemployment, u_{xt}^{Loss} (u_{xt}^{Find}) is expected to move closely with the actual unemployment rate u_{xt}. Figure 1 shows the scatter plots of u_{xt}^{Loss} and u_{xt}^{Find} by the actual unemployment rate u_{xt} when data from the entire 1978-2013 time period is pooled together. As we can see u_{xt}^{Loss} moves very closely with u_{xt} while the correlation between u_{xt}^{Find} and u_{xt} is a very small, negative number. It means that occupational differences in the job-finding rate has very little, and not systematic contribution to occupational unemployment; while differences in the job loss probabilities explain cross-occupational unemployment differences quite well.

Based on Shimer (2012) we can also compute the relative contributions of job loss and job finding probabilities from the following regressions:

$$u_{xt}^{Loss} = \alpha_{0t} + \alpha_{1t} u_{xt} + \varepsilon_{xt}^{Loss}$$
$$u_{xt}^{Find} = \beta_{0t} + \beta_{1t} u_{xt} + \varepsilon_{xt}^{Find}$$

Intuitively, coefficients α_{1t} and β_{1t} measure how closely the hypothetical unemployment rates move together with the actual unemployment rate at time t. There is no reason for the two coefficients to sum up to one, but in practice they are usually very close to that. Consequently, α_{1t} and β_{1t} can be thought of as the contributions of the job loss and job finding probabilities to unemployment differences across occupations.

Table 2: Relative contributions of job loss and job finding probabilities to the cross-sectional variation in unemployment

	Contribution of ...	
	job finding, β_{1t}	job loss, α_{1t}
All years	**-0.025**	**1.051**
1978-1981	0.001	1.020
1982-1983	0.015	0.937
1984-1987	0.041	0.959
1988-1990	-0.014	1.088
1991-1994	-0.022	1.074
1995-1997	-0.020	0.960
1998-2001	-0.015	0.978
2002-2004	-0.036	1.000
2005-2008	-0.047	1.046
2009-2013	-0.041	1.034

*The table shows coefficients from regressing hypothetical unemployment rates (u_{xt}^{Loss} and u_{xt}^{Find}) on actual unemployment rates in various time periods. The hypothetical unemployment rates use the steady state approximation $u_{xt} \approx p_{xt}^{Loss}/(p_{xt}^{Loss} + p_{xt}^{Find})$, but the job finding or the job loss probabilities are replaced with the averages over occupations. The job loss and job finding probabilities are adjusted for time aggregation bias. Each regression has 191 observations, the number of detailed occupations I use in the project. The regressions are weighted by the size of the occupational labor force, $l_{xt} = e_{xt} + u_{xt}$.

Table 2 shows the estimated values of α_{1t} and β_{1t} in different time periods. The first row shows results for averages in the entire 1978-2013 sample period, and the other rows show shorter sub-periods corresponding to times with similar aggregate unemployment rates. The hypothetical unemployment rate with fixed job finding probability moves in a one-to-one ratio with actual unemployment rate, while the hypothetical unemployment rate with fixed job loss probability varies very little with true rates of unemployment. In fact, the regressions show a slightly negative correlation between these two series. This means that, in general, occupations where the unemployment rate is high, the job finding probability also tends to be somewhat higher. Moreover, this result robustly holds throughout the business cycle as the estimated coefficients are very similar in all sub-periods. The only change over time is that the contribution of the job finding probability appears to become even more negative in the last 15 years.

This decomposition exercise confirms that the intuition drawn from the graphical analysis in the previous section holds even when detailed occupations, as opposed to major occupational groups are used. The robust conclusion is that even though the job finding probability varies greatly over the business cycle, it does not vary much across occupations neither in recessions, nor in booms. If anything, smaller job finding probabilities in occupations where the unemployment rate is smaller can be observed.

5 Calibration of an occupation-specific hiring and laying off model

In this section I try to identify mechanisms that can explain the observed patterns in occupational turnover. For this purpose I use a Mortensen and Pissarides (1994) type search and matching model with endogenous job creation and job destruction. The goal is to find parameters that, if made occupation-specific, can predict the observed occupational turnover probabilities and unemployment. More precisely, I am looking for parameters that predicts that hiring and layoff probabilities move in the same direction, but the effect on layoffs is large and the effect on hiring is small. The effect of the following parameters are analyzed:

1. *The flow value of unemployment* (its ratio to productivity): This parameter represents at least two distinct mechanisms:

    (a) *Skill mismatch*: Skill mismatch means that the demand for and the supply of some skills are not balanced. The search and matching models can pick this up in the following way: Occupations that are “over-demanded” are the ones where the value of unemployment compared to productivity is low and occupations that are “over-supplied” are the ones where the flow value of unemployment compared to productivity is high.

(b) The concavity of the UI benefit formula or any other institution that affect the flow value of unemployment.

2. *Various adjustment costs:* I will separately look at nine different cost terms. As I will show later, they can be grouped into two separate groups. Cost terms in one group have a large hiring elasticity (bullet (a) and (c) below) and cost terms in the other group have small hiring elasticity (bullet (b) and (d) below):

   (a) *"Sunk hiring costs"*: These costs are sunk at the first wage negotiation.

      i. *Search costs*: the cost of keeping a vacancy open, such as job advertisements or the cost of interviews. These costs are sunk, because they are paid before the worker and the firm forms the match.

      ii. *Sunk fixed hiring costs paid by firms*, such as adding a worker to the payroll, or paying a signing bonus, etc.

      iii. *Sunk fixed hiring costs paid by workers*, such as updating the CV, preparing for interviews, buying new clothes, etc.

   (b) *"Not sunk hiring costs"*: These costs are not sunk at the first wage negotiation, because, for example, they have not yet been paid:

      i. *Training costs paid by firms*: both formal and informal.

      ii. *Training costs paid by workers*, such as the hassle cost of learning new tasks, etc.

   (c) *The cost of laying off inexperienced, newly hired workers.*

      i. The cost that firms pay (such as severance payment, layoff taxes, etc.).

      ii. The cost that workers either pay (e.g. hassle cost) or receive (such as severance payment).

   (d) *The cost of laying off experienced workers.*

      i. The cost that firms have to pay (such as severance payment, layoff taxes, etc.)

      ii. The cost that workers either pay (e.g. hassle cost) or receive (such as severance payment)

3. *Matching efficiency,* which is a parameter of the matching function representing how easy it is to fill a vacancy.

4. *Bargaining power* of workers: Some might argue that managers and other "high-skilled" workers have more power than low skilled workers when they negotiate about their contracts. I call this a Marxist explanation of labor turnover.

5. *The variance of idiosyncratic productivity shocks.*

The section only considers steady state equilibrium outcomes. An important implicit assumption I employ is that occupations are perfectly segmented, people do not switch occupations.

5.1 The setup and solution of the model

The model uses the following assumptions:

1. It is a continuous time model.

2. There are $x \in \{1, ..., N_X\}$ occupations and workers are permanently assigned to one: no one can switch occupations.

3. The matching function in occupation x is a CRS, $m_{xt} = \eta_x v_{xt}^{\alpha} u_{xt}^{1-\alpha}$ where v_{xt} and u_{xt} refer to the number of vacancies and unemployed workers and η_x is the efficiency of the matching function. $\theta_{xt} = \frac{v_{xt}}{u_{xt}}$ denotes labor market tightness.

4. The vacancy filling rate is $q_{xt} = \frac{m_{xt}}{v_{xt}} = \eta_x \theta_{xt}^{\alpha-1}$ and the job finding rate is $f_{xt}^{F} = \frac{m_{xt}}{u_{xt}} = \eta_x \theta_{xt}^{\alpha} = \theta_{xt} q_{xt}$.

5. Wages are set by Nash bargaining, and workers' share is γ_x.

6. The production function of firm i is $\pi_{xit}(\varepsilon) = p_t s_x \varepsilon_{txi}$ where p_t is aggregate productivity, s_x is occupational productivity and ε_{txi} is a match specific shock component.

7. Adjustment cost terms:

   (a) The cost of keeping a vacancy is $s_x c_x^{SF}$. This cost is sunk at the first wage negotiation.

   (b) After matching a worker, firms have to pay a fix cost $s_x c_x^{FF}$.

   (c) Workers also have to pay a sunk fixed cost, $s_x c_x^{FW}$.

(d) Firms have to train the worker at a cost of $s_x c_x^{TF}$. This cost is not sunk at the first wage negotiation. In a more realistic model this cost term is not sunk, because it is not paid yet, it is only paid over time. In this simple model, the timing is kept simpler: The training cost is paid at the time of the first productivity shock (or analogously, firms pay training costs immediately, but firms and workers cannot renegotiate wages before the first shock.) The same simplifying assumption was used in Mortensen and Pissarides (1999), as well.

(e) Workers also have to pay a training cost $s_x c_x^{TW}$. This cost is not sunk either.

(f) Newly hired workers can be laid off with cost $s_x c_x^{LF0}$ and experienced workers can be laid off with cost $s_x c_x^{LF}$. Note: When a shock occurs, workers first become experienced, and then firms decide whether to retain them or not.[19]

(g) Newly hired workers incur a layoff cost of $s_x c_x^{LW0}$ and experienced ones $s_x c_x^{LW}$.

8. Match specific shocks follow a log-normal distribution, $\ln \varepsilon_{txi} \sim N\left(-\frac{\sigma_x^2}{2}, \sigma_x^2\right)$ and the arrival rate of shocks is λ. As we can see, the expected value of ε is normalized to $E\left(\varepsilon_{toi}\right) = 1$ independent of the variance of the shocks.

9. The flow value of unemployment is $s_x b_x$.

10. The interest rate is r_t.

11. New hires' idiosyncratic productivity is ε^0.

12. Free entry assures that the value of a vacancy is zero.

I only solve the model for steady state values, so from now on I neglect the time subscript, t. The values of open vacancies ($s_x V_x$), new ($s_x J_x^0$) and continuing jobs ($s_x J_x$) are

$$\begin{aligned}
r s_x V_x &= -s_x c_x^S + q_x s_x \left(J_x^0 - c_x^{FF} - c_x^T\right) = 0 \\
r s_x J_x^0 &= p s_x \varepsilon^0 - s_x w_x^0 + \lambda s_x \int_{R_x}^{\infty} J_x(\epsilon)\, dF_x(\epsilon) - \lambda s_x J_x^0 - \lambda F_x(R_x)\, s_x c_x^{LF} \\
r s_x J_x(\varepsilon) &= p s_x \varepsilon - s_x w_x(\varepsilon) + \lambda s_x \int_{R_x}^{\infty} J_x(\epsilon)\, dF_x(\epsilon) - \lambda s_x J_x(\varepsilon) - \lambda F_x(R_x)\, s_x c_x^{LF}
\end{aligned}$$

The reservation productivity (R_x) is the same for new and experienced workers, since all the continuation values are the same.

[19] This is a technical assumption that makes sure that the productivity threshold below which matches are destroyed is the same for experienced and inexperienced workers.

The workers' values of unemployment ($s_x U_x$) and being employed at a new or a continuing job are

$$\begin{aligned}
rs_xU_x &= s_xb_x + f_x^F s_x\left(W_x^0 - U_x - c_x^{FW} - c_x^{TW}\right)\\
rs_xW_x^0 &= s_xw_x^0 + \lambda s_x\int_{R_x}^{\infty} W_x(\epsilon)\,dF_x(\epsilon) + \lambda F_x(R_x)\,s_x\left(U_x - c_x^{LW}\right) - \lambda s_xW_x^0\\
rs_xW_x(\varepsilon) &= s_xw_x(\varepsilon) + \lambda s_x\int_{R_x}^{\infty} W_x(\epsilon)\,dF_x(\epsilon) + \lambda F_x(R_x)\,s_x\left(U_x - c_x^{LW}\right) - \lambda s_xW_x(\varepsilon)
\end{aligned}$$

s_x, the general skill level of occupations, enter all equations, and thus, all equations can be normalized by dividing through s_x. From now on, thus, all cost parameters as well as b_x, w_x and the value functions are normalized by the average occupational productivity.

Using standard arguments (see e.g. Mortensen and Pissarides, 1999) the equilibrium job destruction and job creation conditions are:

$$\begin{aligned}
\frac{c_x^S}{\eta_x}\theta_x{}^{1-\alpha} + c_x^{FF} &= (1-\gamma_x)\left[\frac{p\left(\varepsilon^0 - R_x\right)}{r+\lambda} - \left(c_x^{LW} + c_x^{LF} + c_x^{TF} + c_x^{TW}\right)\right]\\
&\quad - \left(\gamma_x c_x^{LF0} - (1-\gamma_x)\,c_x^{LW0}\right)\\
p\left[R_x + \frac{\lambda}{r+\lambda}\int_{R_x}^{\infty}(\epsilon - R_x)\,dF_x(\epsilon)\right] &= b_x + \frac{\gamma_x}{1-\gamma_x}\theta_x c_x^S + \eta_x\theta_{xt}^{\alpha}\left[\frac{\gamma_x}{1-\gamma_x}\left(c_x^{FF} + c_x^{LF0}\right) - \left(c_x^{FW} + c_x^{LW0}\right)\right]\\
&\quad - r\left(c_x^{LW} + c_x^{LF}\right)
\end{aligned}$$

Without loss of generality, the various cost terms can be grouped in the following way:

1. Let us define the expected sunk cost for the firm to fill a vacancy as

$$c_x^{SUNK,F} = \frac{c_x^S}{\eta_x}\theta_x^{1-\alpha} + c_x^{FF}$$

2. The total layoff cost of experienced workers is

$$c_x^L = c_x^{LF} + c_x^{LW}$$

3. The total training cost is

$$c_x^T = c_x^{TF} + c_x^{TW}$$

4. The bargaining weighted difference in the layoff costs of inexperienced workers is

$$c_x^{\Delta I} = \left(\gamma_x c_x^{LF0} - (1-\gamma_x)\, c_x^{LW0}\right)$$

This term is large if firms bear most of the costs of firing an inexperienced worker.

5. The normalized flow value of being unemployed is

$$b_x^n = b_x - f_x^F c_x^{FW}$$

The job-creation and job-destruction conditions become:

$$c_x^{SUNK,F} + c_x^{\Delta I} = (1-\gamma_x)\left[\frac{p\left(\varepsilon^0 - R_x\right)}{r+\lambda} - c_x^L - c_x^T\right] \tag{3}$$

$$p\left[R_x + \frac{\lambda}{r+\lambda}\int_{R_x}^{\infty}(\epsilon - R_x)\, dF_x(\epsilon)\right] = b_x^n + \frac{\eta_x \theta_x^{\alpha}}{1-\gamma_x}\left[\gamma_x c_x^{SUNK,F} + c_x^{\Delta I}\right] - r c_x^L \tag{4}$$

These equilibrium conditions are very similar to Mortensen and Pissarides (1999), but my model has more terms. The main lessons can be summarized as follows:

1. Training costs only appear in the job-creation condition. Interestingly, it does not matter who pays for training, the worker or the firm, the equilibrium is the same. The intuition is that training costs increase the initial surplus independently of who will pay for these costs in the future.

2. Search and sunk fixed costs of hiring that are paid by the firm are similar to each other, but they are different from training costs. They appear in both equations, because they increase the outside option of workers. [XXXMore on thisXXX]

3. The fix costs of employment that workers pay are similar to the flow value of unemployment. The intuition is that if the cost of search is high, workers dislike being unemployed more.

4. The cost of laying off experienced and inexperienced workers operate very differently in the model:

(a) Laying off experienced workers is similar to training costs, because the monthly interest rate, r, is small. Interestingly, it does not matter who pays for layoffs, the workers or the firms. The intuition is the same as for training costs. It also follows that severance payments, which are transfers from the firms to the workers at separations, have exactly zero effect on turnover, as long as these payments apply for experienced workers only.[20]

(b) Layoff costs of inexperienced workers are more similar to search and other sunk costs of hiring: They change the outside option of workers, and, as I shall show later, they have a large effect on job creation. Moreover, what matters in the model is the difference between the costs for firms and workers: the cost that firms pay decrease, and the costs that workers pay increase job creation.

5.2 Turnover elasticities in the model

The two equilibrium conditions in (3) and (4) exactly identify the two endogenous variables, R_x and θ_x as a function of all other parameters. Then the two endogenous parameters determine the equilibrium job loss and job finding rates. The goal in this section is to derive the elasticities of the job loss and job finding rates with respect to all parameters that are potentially occupation specific. The idea is to find parameters that can explain the empirically observed occupational turnover differences when all other parameters are fixed. Parameters that predicts that layoff and hiring probabilities move together but the effect on hiring is small are good candidates to explain the turnover patterns in the data.

I evaluate a slightly simpler version of the model, because, as I showed in the previous section, many parameters are expected to behave very similarly to each other. The job destruction and job creation conditions in the simplified model are

$$p\left[R+\frac{\lambda}{r+\lambda}\int_{R}^{\infty}(\epsilon-R)\,dF(\epsilon)\right] = b+\frac{\gamma}{1-\gamma}\theta c^{S}-rc^{L} \tag{5}$$

$$\frac{c^{S}}{\eta}\theta^{1-\alpha} = (1-\gamma)\left[\frac{p\left(\varepsilon^{0}-R\right)}{r+\lambda}-c^{L}-c^{T}\right] \tag{6}$$

[20]Some might find it unintuitive first, but on a second thought this has to be true in any reasonable model. A rational firm, that is expected to pay a layoff cost with probability 1 in the future, would build these costs in the wages early on. Anyone who wants to argue that severance payments for experienced workers affect turnover should assume that it somehow changes the bargaining power of workers.

Appendix 8.2 derives the elasticities of the job finding rate (e_X^F), the job loss rate (e_X^L) and their ratio $S_X^{F,L} = e_X^F / e_X^L$ for parameters $X \in \{b, \gamma, \eta, c^S, c^T, c^L, \sigma\}$. It turn out that the hiring elasticity e_X^F usually has a very simple form and its value can be calibrated using parameter estimates from the literature. The job destruction elasticity, however, cannot be calibrated from the literature, because, for example, it depends on the p.d.f. and the c.d.f. of the idiosyncratic shocks evaluated at the job-destruction threshold.

Therefore I do the following:

1. Even though I cannot directly compute the different elasticity ratios $S_X^{F,L}$-s I can compute their sign and their ratios to each other, and, thus, I can rank them.

2. I can calibrate the model to fit the aggregate turnover rates and then I can evaluate the elasticities around the aggregate equilibrium.

Table 3 summarizes what we can learn using the elasticity formulas and parameter estimates from the literature. Remember that our target for the elasticity ratio is $S_X^{F,L}$ is a small positive number. The last column substitutes values into the formulas in the second to last column. For details about the parameter choice see the discussion below. The main findings are:

1. The flow value of unemployment has the wrong, negative sign. It predicts that occupations with higher layoff rates should experience lower hiring rates (conditional on other differences).

2. The bargaining power of workers has zero effect on layoffs and, thus, $S_\gamma^{F,L} = \infty$. This result is driven by the assumption that $\alpha + \gamma = 1$, the Hosios condition.

3. Both search costs (or other sunk hiring costs) and matching efficiency has the right sign of $S_X^{F,L}$, but they appear to have even larger effects on hiring than the flow value of unemployment.

4. Both training costs (or other hiring costs that are not sunk at the first wage negotiation) and layoff costs of experienced worker are similar: They both predict a positive association between job loss and job finding rates, but, at least compared to b, they predict a much smaller effect on hiring rates, because $f^L \ll f^F$ (the monthly job-loss probability is much smaller than the job-finding probability). Further comments:

(a) One can show that training costs only have a mild effect on hiring rates in an endogenous job-destruction model. If job separations are exogenous, then training costs, similarly to search costs, have a large negative effect on hiring rates.

(b) Recall that only the layoff costs of experienced workers have a mild effect on hiring rates. Layoff costs of newly hired workers, similarly to search costs, are expected to crowd out hiring more strongly.

Now I solve the model for the aggregate and then I evaluate the turnover elasticities around the aggregate equilibrium. The steps of this procedure are the following way:

1. I pick some parameters from the literature.
2. I calibrate the model to fit the aggregate turnover probabilities.
3. I evaluate the elasticity formulas at these aggregate solutions.
4. I repeat this exercise for a large number of parameter value choices in (1) and I collect a reasonable range for the various elasticities.

In particular, I pick the following parameters from the literature:

1. Aggregate productivity is normalized to $p = 1$.
2. Monthly real interest rate is $r = 0.004$, which corresponds to a roughly 5 percent annual interest rate.
3. The Cobb-Douglas share of vacancies in the matching function is $\alpha = 0.4$, based on Pissarides and Petrongolo (2001) and many other papers.
4. The workers' share of the surplus is $\gamma = 0.6$, so that the Hosios condition is satisfied ($\alpha + \gamma = 1$) and the equilibrium is socially efficient.
5. Aggregate labor market tightness is $\theta_a = 0.72$, based on JOLTS data. See, for example, Pissarides (2009).

6. Aggregate job loss probability is $P_a^L \in \{0.01, 0.03\}$ and the job finding probability is $P_a^F \in \{0.3, 0.45\}$. The first numbers are based on my estimates from the CPS on the 25-55 year old sample, and the second numbers are Shimer's estimates based on 16-64 year old sample and a different methodology.

7. Aggregate search costs, c_a^S are somewhere between 0.2 and 0.3.

8. Aggregate training costs c_a^T are somewhere between 0.5 and 1.5. The value of 1 is a reasonable estimate. According to Blatter et al. (2012) newly hired workers are $\sim$ 30 percent less productive than experienced ones for roughly 3-4 months, which takes up the majority of recruitment costs. This comes down to a loss of $\sim$ 1 month of productivity altogether. Recall that theoretically c_a^T should represent the sum of the cost workers and firms pay, and thus, the productivity loss is a good approximation for c_a^T.

9. Aggregate layoff costs are $c_a^L = 0.1$. (XXXIt is not supposed to be large, but I need to get a better justification.XXX)

10. The flow value of unemployment b_a is somewhere between 0.7 and 0.9.

I use all possible combinations of 11 different, equally spaced values of parameters c_a^S, c_a^T and b_a and I use my turnover estimates and Shimer's separately. Altogether I consider $11 \times 11 \times 11 \times 2 = 2662$ cases.

Most numbers I use are based on the literature. My numbers for search costs (c_a^S) and the flow value of unemployment (b_a) are on the high side, because for lower values the model does not converge to a solution. When b and c^S are too small, the model predicts that laying off workers is never optimal, because the left hand side of (5) is always higher than the right hand side. Many papers in the literature use smaller values, but they use exogenous job destruction, so they do not face this problem. Note also that in my model the expected value of a productive match is larger than 1, because the lower productivity values are truncated due to endogenous separations.

The results are in Table 4 and 5. Table 4 uses my turnover estimates and Table 5 uses Shimer's numbers. In both tables, columns 2-4 show the elasticities for parameters $c_a^S = 0.25$, $c_a^T = 1$ and $b_a = 0.8$, which are the middle values in the considered range. The last columns show the range of possible values based on all the 2662 estimates. I discarded cases where the model did not converge (typically too low values of b_a and c_a^S). On top of that I also discarded a few cases where the model converged to extreme values of σ_ε or λ. These few cases also happened for too low values of b and c^S. Specifically I discarded cases where the standard deviation of idiosyncratic shocks were very large $\sigma_\varepsilon > 0.5$ or the monthly autocorrelation of idiosyncratic shocks were very small $\rho_\varepsilon = \exp(-\lambda) < 0.85$. From the 2662 cases the model did not converge in 432 cases and I further discarded 196 cases due to extreme values of σ_ε or ρ_ε.

The results of the calibration exercise are the following:

1. The flow value of unemployment predicts a negative relationship between layoff and hiring rates and it has a stronger effect on hiring rates than on layoff rates.
   (a) Main conclusion: Skill mismatch or the concavity of the UI formula is an unlikely candidate for explaining occupation specific turnover rates.
2. Worker's bargaining power only affects hiring rates.
   (a) Conclusion: A Marxist view of the labor market, in which some groups of workers have higher bargaining power than others, is an unlikely candidate for explaining occupation specific turnover rates.
3. Both search costs (and any other sunk hiring costs) and matching efficiency have larger effects on hiring rates than on layoff rates.
   (a) Conclusion: Search costs and matching efficiency are unlikely candidates for explaining occupation specific turnover rates.
4. Both training costs (and any other hiring costs that are not sunk) and layoff costs of experienced worker predict a smaller effect on hiring than on layoffs. My best estimates are still too large on hiring, but the empirical estimate is in the range of possible values:
   (a) Out of these two parameters training costs might be better candidates for explaining occupation specific turnover differences, because the hiring cost literature argues there is quite a bit of skill specific variation in them.

5. The standard deviation of idiosyncratic shocks, σ also predicts a positive association between layoff and hiring rates, and it appears to have a stronger effect on layoffs than on hiring.

    (a) Note: It is quite intuitive that in riskier "occupations", where σ is large, layoff rates are large. The reason that hiring rates are also larger is because there is an option value in high variance workers. In alternative specifications of the model this option value can be removed. For example, Mortensen and Pissarides (1994) assume that newly hired workers' productivity is the upper bound of a bounded distribution. In their specification there is no option value in high variance workers, and, consequently, σ lowers, rather than increases, job-creation.

    (b) Conclusion: This parameter can explain occupation specific turnover.

5.3 Conclusion and discussion

I identified three parameters predicting turnover differences across groups that are in line with my occupational turnover estimates. All the three parameters predict: 1. large group specific unemployment rate differences; 2. large differences in layoff rates; 3. small differences in hiring rates; and 4. a positive correlation between group specific job loss and job finding rates.

5.3.1 Skill biased adjustment costs and labor hoarding

Two parameters (training costs and layoff costs of experienced workers) are particular forms of adjustment costs. They predict that when firms face negative productivity shocks, they are more likely to hoard (a la Oi, 1962) their skilled workers, because the relatively large adjustment costs are more likely to exceed the expected loss of keeping the match alive. I showed that adjustment costs have relatively small effect on hiring rates, just like in the data, as long as the costs do not alter the outside option of workers. Firms specific skills are good examples for such adjustment costs. Because workers lose their firm specific skills after separations, their outside option is not affected by them. In the empirical literature of recruitment costs papers found that the largest component of total recruitment costs are so-called adaptation costs due to the relatively low productivity of newly hired workers (Blatter et al., 2012) and their informal training by co-workers (Lerman et al., 2004; Leuven, 2005). Evidence suggests that these costs are larger for skilled workers even proportional to their monthly wages, which is what matters in these models. Adaptation costs are good candidates for explaining skill-specific unemployment differences because 1) the empirical estimates suggest large heterogeneity by skills; and 2) these costs are not paid instantaneously at hiring, and based on the arguments above, they do not become a part of workers' outside option, limiting the negative effect on hiring.

Using the Multi-City Study of Urban Inequalities (MCSUI) dataset, I provide estimates of adaptation costs by occupations. This data was collected in 1992-1994, in order to understand why high rates of joblessness have persisted among minorities living in America's central cities. One important aspect of the study was the contacting of more than 3000 employers in four large US cities (Los Angeles, Boston, Detroit and Atlanta) to ask detailed questions about their hiring practices. Even though the intent of the study was to understand racial discrimination in hiring, the exhaustive information about the recruitment process makes this study valuable for broader purposes. The sampling procedure and the provided weights intend to represent employees who worked in Los Angeles, Boston, Detroit or Atlanta in 1992. They used the 3-digit 1980 SOC classification to code up the data. I created a cross-walk between this classification and the one used in the CPS. My measure of adaptation costs is based on the question "How many weeks or months does it take the typical employee in this position to become fully competent in it (assuming no previous experience)?"[21] Table 6 provides average values by ten occupation groups ranked by their unemployment rates in the 2000 census. As we can see occupational unemployment is very strongly and negatively related to the length of the adaptation period. The average length runs from ~3.5 months in the highest unemployment to ~13.5 months in the lowest unemployment occupations with an average of ~7 months. Blatter et al. (2012) estimated that during the adaptation period workers are roughly 30% less productive on average than an experienced worker. Using this approximation the adaptation cost estimates in the MCSUI run from roughly 1 month of wage in the highest unemployment occupations to 4 months of wage in the lowest unemployment ones, with an average of a little over 2 months of wage. Table 6 also shows that the adaptation costs are strongly skewed, as the median cost values are strictly smaller than the average.

[21]This measure is not perfect in the sense that it mixes up firm specific and general occupational specific adaptation costs. For the labor hoarding mechanism only the firm specific part matters. It is very hard, however, to ask about the two parts separately in surveys.

5.3.2 Skill biased productivity shocks

As I showed earlier in this section, the variance of idiosyncratic productivity shocks can also predict the occupational turnover patterns in the data. If low skilled occupations face larger productivity shocks, they are more likely to be laid off, but, based on my calibrations, the effect on hiring rates is not large.

It is possible that match specific productivity shocks are larger among unskilled workers because they work in industries with more volatile revenues. I call this the industry clustering hypothesis. Tables 7 and 8 show estimates of the employment-unemployment and unemployment-employment transition probabilities in four major industries: 1. construction, 2. manufacturing, 3. public administration, education and health, 4. all other industries. The industry clustering hypothesis predicts that the within industry variation in the job loss probabilities is small and the between industry variation is large. The tables show, however, that both the within and the between industry variations are quite large. In fact, the most volatile industries (such as construction) show a much larger cross-occupational variation in job loss than what we observed in the aggregate. Moreover, the occupational variation in job loss probabilities is even detectable in the most stable industries (such as public administration, health and education). I conclude that, even though the between industry variation in transition probabilities are large, they do not explain the cross occupational variation in turnover.

Capital-skill complementarity is another reason why match specific shocks might have larger variance in low skilled jobs. Capital is fixed in the short-run, and thus, production factors that complement(substitute) it have smaller(larger) fluctuations in productivity. It has been argued in the literature that skilled work and capital are complements [XXXcitationsXXX]. Occupation specific capital-complementarity data, however, is not available, so I cannot directly test this hypothesis.

Another reason why productivity shocks might be larger among unskilled workers is that it is more expensive to store their products compared to the products of the more skilled. One way firms can deal with temporary demand shocks is to increase inventories in bad times; and sell out these inventories in later periods when the demand conditions improve. This strategy is more profitable if storing the goods is relatively cheap. One can argue that high skilled work, such as idea generation, research, innovation, etc., is cheaper to store than low skilled work, which takes up physical space or is more linked to dealing with customers. Again, it is hard to find good data on the price of storing work by occupations.

5.3.3 Skill shortage, labor market institutions and structural unemployment

Many economic mechanism to explain skill specific unemployment differences predict a large variation in hiring rates. Perhaps the most interesting finding of this paper is the strong symmetry in job finding probabilities across occupations. Consequently, it seems unlikely that these mechanisms play an important role in unemployment rate differences by skills; unless, for some reason, many of these mechanisms operate at the same time, and they exactly cancel each other out.

As long as the minimum wage, or the concavity of the UI benefit formula are responsible for low skilled unemployment, we would expect to see smaller hiring rates in low skilled jobs. My results cast doubt on the importance of these factors to explain unemployment rate differences by skills, at least measured by occupations.

Many previous papers found evidence that some specificities of UI system increase the equilibrium unemployment rate. The most credible evidence, using regression discontinuity design, analyzed the effect of benefit duration and not the replacement rate. The duration of the benefits, however, is not occupation specific, at least in the US. The concavity of the UI formula, in principle, should make unemployment comparatively more valuable for low skilled workers. However, the unemployment benefits probably take up a relatively small fraction of the total value of being unemployed (Chodorow-Reich and Karabarbounis, 2013). It is also possible that higher paid skilled workers have more savings and they have better access to credit, muting the difference between the value of unemployment for high and low skilled workers.

My results also directly speak of a particular form of structural unemployment: a mismatch between firms' demand and workers' supply of skills. In recent papers, Lazear and Spletzer (2012) and Sahin et al. (2012) analyzed occupational skill mismatch using occupation-specific online job-vacancy data (The Help Wanted OnLine Index). They found that occupation-specific labor market tightness (the ratio of job vacancies and unemployment) shows large heterogeneity, but little cyclicality. As Lazear and Spletzer (2012) observes, this either indicates permanent skill mismatch (shortage of high skilled workers) or measurement error because high skilled jobs are more likely to be advertised online. The results of my paper supports the latter, measurement error argument, as high skilled workers do not seem to find jobs quicker than low skilled ones. [XXXAlso mention the Davis et al 2013 paper on vacancy yields, etc. Mention the Weaver-Osterman paper.XXX]

6 Robustness checks of the empirical findings

6.1 Alternative datasets and estimation methods

In Section 4 I used the linked monthly CPS to estimate turnover rates. This methodology has an important drawback: Due to non-random panel attrition, the linked CPS does not necessarily represent the US population. Movers, for example, are not followed in the CPS which might bias the turnover rates. I call this the "moving-bias".

To investigate moving bias, I reestimated occupation-specific turnover rates in the Survey of Income and Program Participation (SIPP), which follows movers, and represents the US population. I provide estimates in a boom period (2005-2006) with low aggregate unemployment rate and in a recession period (2009-2010) with high unemployment rate.

Before I present the results, it is worth noting a few data problems with the SIPP. SIPP enables the estimation of monthly (actually even weekly) transition rates using its detailed work history questions. The majority of the observations, however, are based on retrospective information, because SIPP only interviews persons once every four months. It turns out that transition rates that are computed from retrospective information are significantly and substantially lower than estimates computed from cross-wave information. Thus, I present results only based on cross-wave information.[22] Another problem is that SIPP does not ask the occupation of the unemployed at their last jobs, which is critical for computing occupation-specific job finding probabilities. The only way to handle this problem is to restrict the sample to persons who worked in the recent past, and use the previous waves to fill in the information about the last jobs. Thus, for estimating occupation specific job-finding probabilities, I

[22]Note, however, that in case retrospective information is suspect, the cross-wave information is still likely biased. As workers are more likely to be employed, and more likely to understate transitions in retrospective data, the cross-wave information likely understates job loss and over-states job finding.

restricted the samples to persons who worked in the last 12 months in all samples. Whether persons worked last year, however, is estimated differently in the SIPP and the CPS. In SIPP, it is based on observed work histories, while in the CPS, it is based on self reports of unemployment duration.

We can directly characterize the moving bias by comparing transition rates by moving status in the SIPP. Tables 9 and 10 show that, as expected, movers are more likely to be job-losers, particularly if they moved far away. At the same time, job finding is less obviously related to moving, but because the number of mover unemployed workers is not large in the sample, the estimates are not precise. More important, however, the moving bias seems to be very limited, because most persons in the 25-55 age range do not move between consecutive months. Transition probabilities computed for the total sample, and for the restricted non-moving samples are practically identical.

Tables 11 shows the month-to-month job loss probabilities, and Table 12 shows the aggregate job finding probabilities. In the SIPP sample, I actually carried out two estimates. In both cases the sample is those who were working at the last week at a given month. In "SIPP, all weeks", everyone who ever reported being unemployed throughout the next month is considered a job-loser. This specification deals with time-aggregation (that is with very fast reemployment). In "SIPP, month-month" everyone who is not working in the last week of the next month is considered a job loser. This specification does not deal with time aggregation. By comparing columns 1 and 2 we can see that a notable fraction of workers who lost their jobs, get a new job within a month. At the same time, time aggregation appears to matter less for job finding. Interestingly, employment-unemployment transition probabilities based on the linked CPS are similar to the SIPP month-month estimates, and the time aggregation adjusted job loss probabilities in the CPS gives similar results to the SIPP-all weeks estimates. This suggest that my method of time aggregation works well.

Table 13 shows job loss probabilities in three occupational groups ranked by their unemployment rates in the 2000 census. Table 14 shows the job finding probabilities. As we can see, there is large variation in job loss across occupations, and high occupational unemployment is associated with high occupational job loss probability using any of the methods. We can also see that even though there is large variation in job finding probabilities over time, but not across occupations. If something, we see a U-shaped relationship between occupational unemployment and occupational job finding probabilities. Typically the job finding probability is the largest in the occupations with the highest unemployment rate.

6.2 Control variables and selection

The main conclusion of the previous sections was that both the occupational job loss probabilities and the occupational job finding probabilities are larger in unskilled jobs with higher unemployment rates. We also saw that the job loss probabilities have a stronger and more systematic relationship with unemployment than the job finding probabilities. In this section I show that this results hold even when demographic variables and industries are controlled.

For the analysis I run linear probability models[23] of the following form:

$$y_{ixt} = \beta_0 + \beta_1 U_t + \beta_2 U_x + \beta_3 U_t \times U_x + \beta_4' X_{it} + \beta_5' U_t \times X_{it} + \varepsilon_{ixt}. \quad (7)$$

Subscript i, x and t refer to the person, the occupation and the month respectively. The left hand side variable, y_{ixt}, is a labor market transition dummy; U_t is the aggregate unemployment rate in a particular year; U_x is the occupational unemployment rate in the 2000 census in the detailed occupations; and X_{it} is a vector of control variables. Among the controls, I include various demographic variables (age, gender, race, education, marital status) and industry dummies. For easier interpretation of the interaction terms I demeaned both U_t and U_x. The control variables are all in dummy form, and the left out category is the 25-34 year old persons, who are married, have high school education or less, who are white and non-Hispanic, and who do not work in the construction, the manufacturing, the public administration, the health or the education sectors.

Coefficient β_1 measures the cyclicality of the transition probability in the average occupation. A positive β_1 means that the transition probability in question is countercyclical. Coefficient β_2 shows the level differences in the transition probabilities by occupations. A positive β_2 means that the transition is more likely in occupations with higher unemployment rates. Coefficient β_3 shows whether the cyclicality of the transition probability is higher or lower by occupations.

[23]Using non-linear probability models, such as probits or logits, give qualitatively very similar results, but those specifications are harder to read because of the many interaction terms.

Tables 15-18 show the results. I present three specifications in each table. Column 1 does not have any control variables; column 2 includes demographics and column 3 includes industry controls as well. Table 15 shows regressions with the job loss probability on the left hand side. As we can see, the job loss probability is countercyclical, as β_1 is positive. In the average occupation, a one percentage point increase in the aggregate unemployment rate is associated with a 0.13 percentage point increase in the job loss probabilities. We can also see that both the level and the cyclicality of the job loss probabilities are larger in occupations with higher unemployment rate. Controlling for demographics and industries modifies the coefficients slightly, but qualitatively the patterns are the same.

Tables 16 and 17 show the regressions with the job finding probabilities on the left hand side. In Table 16, any transitions between unemployment and non-employment are dropped, and in Table 17 unemployment-non-employment transitions are coded as zeros. The job finding probability is strongly pro-cyclical in both specifications. A one percentage point increase in the unemployment rate is associated with a 3-4 percentage point decrease in the job finding probability. We can also see that occupations with higher unemployment rates face larger chances of finding jobs and their job finding probability is also less cyclical. These results hold up in both specifications, but the the association is less strong when the unemployment-non employment transitions are coded as zeros. This indicates that leaving the labor force is somewhat more likely in low skilled, high unemployment occupations. This is verified in Table 18: Unemployment-non employment transitions are pro-cyclical, and they are larger and more cyclical in high unemployment occupations. Controlling for demographics and industries, again, affects the coefficients slightly, but qualitatively the patterns are the same.

Overall, the main qualitative results of the paper hold up even when demographics and industries are controlled.

6.3 The effect of occupation switches and crowding out

In the paper so far I ignored the problem of workers switching occupations. In the data there are many unemployed workers who find jobs in occupations that are different from their last one. One particular concern is crowding out: high skilled workers might take low skilled jobs and low skilled workers might be crowded out from the labor market. If this pattern is strong, then the job finding probability measured by the last occupations of workers might not be a good proxy of demand conditions in those occupations. For example, if workers are flowing out from a given occupation, then the job finding probabilities of these workers might overestimate the demand for these workers. Similarly, if many workers are flowing into an occupation, then the demand conditions might be higher than what the job finding probabilities show.

To test for crowding out, I created a crowding out index for each occupation. The index computes a normalized difference between the flows into and out of each occupation:

$$c_{xt} = \frac{\sum (U_{it\cdot} \rightarrow E_{i,t+1,x}) - \sum (U_{itx} \rightarrow E_{i,t+1,\cdot})}{\sum U_{it}}$$

The difference between the inflows and outflows is normalized by the number of unemployed workers at time t in occupation x. If $c_{xt} > 0$ then the occupation is crowded out by other occupations.

Table 19 shows the results. According to the crowding out hypothesis occupations with high unemployment rates should have positive c_{xt} values and occupations with low unemployment rates should have negative ones. We can see a little bit of evidence for that, but the effects are not large. It appears that most occupations have similar inflows and out outflows. This result is perhaps not surprising from the point of view of a Roy-model. Workers have expertise in diverse tasks, and "skilled" workers might not be as productive in "unskilled" jobs. Moreover, firms should also disprefer hiring skilled workers in unskilled jobs if these workers are expected to stay in these job only temporarily.

7 Conclusion

Using the linked monthly CPS, I computed job loss and job finding probabilities in detailed occupational groups between 1978 and 2012. Using a decomposition method I found that, in all phases of the business cycle, the variation in unemployment across occupations is driven entirely due to differences in the job loss rather than the job finding probabilities. Then, using a calibrated search and matching model I investigated what exogenous parameters can account for the observed occupational turnover differences. I found three parameters that, under provided conditions, predict occupational turnover probabilities that are roughly in line with those in the data. The first two parameters are types of adjustment costs that do not increase the outside option of workers: 1) firm specific skills that are acquired over time; and 2) layoff cost of experienced workers. The third parameter that can explain occupational turnover is the variance of idiosyncratic productivity shocks. I argue that both firm-specific skills and idiosyncratic productivity shocks are important contributors of low-skilled unemployment. However, the contribution of these parameters to cross occupational unemployment differences is not identified from the turnover data I used in this paper. Future data collection of these occupational parameters might help understanding their quantitative role in explaining cross-sectional differences in unemployment.

References

Abraham, K. G. and J. R. Spletzer (2009, May). New evidence on the returns to job skills. *American Economic Review 99*(2), 52–57.

Acemoglu, D. (1999, December). Changes in unemployment and wage inequality: An alternative theory and some evidence. *American Economic Review 89*(5), 1259–1278.

Acemoglu, D. and D. Autor (2011). *Skills, Tasks and Technologies: Implications for Employment and Earnings*, Volume 4 of *Handbook of Labor Economics*, Chapter 12, pp. 1043–1171. Elsevier.

Aizcorbe, A. M. (1992, July). Procyclical labour productivity, increasing returns to labour and labour hoarding in car assembly plant employment. *Economic Journal 102*(413), 860–73.

Albrecht, J. and S. Vroman (2002, February). A matching model with endogenous skill requirements. *International Economic Review 43*(1), 283–305.

Autor, D. H., F. Levy, and R. J. Murnane (2003, November). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics 118*(4), 1279–1333.

Basu, S. (1996, August). Procyclical productivity: Increasing returns or cyclical utilization? *The Quarterly Journal of Economics 111*(3), 719–51.

Basu, S. and M. S. Kimball (1997, February). Cyclical productivity with unobserved input variation. NBER Working Papers 5915, National Bureau of Economic Research, Inc.

Bernanke, B. S. and M. L. Parkinson (1991, June). Procyclical labor productivity and competing theories of the business cycle: Some evidence from interwar u.s. manufacturing industries. *Journal of Political Economy 99*(3), 439–59.

Blanchard, O. and J. Galí (2010, April). Labor markets and monetary policy: A new keynesian model with unemployment. *American Economic Journal: Macroeconomics 2*(2), 1–30.

Blanchard, O. J. and P. Diamond (1990). The Cyclical Behovior of the Gross Flows of U.S. Workers. *Brookings Papers on Economic Activity 21*(2), 85–156.

Blatter, M., S. Muehlemann, and S. Schenker (2012). The costs of hiring skilled workers. *European Economic Review 56*(1), 20 – 35.

Büttner, T., P. Jacobebbinghaus, and J. Ludsteck (2010). Occupational upgrading and the business cycle in west germany. *Economics - The Open-Access, Open-Assessment E-Journal 4*(10), 1–37.

Burnside, C. and M. Eichenbaum (1996, December). Factor-hoarding and the propagation of business-cycle shocks. *American Economic Review 86*(5), 1154–74.

Burnside, C., M. Eichenbaum, and S. Rebelo (1993, April). Labor hoarding and the business cycle. *Journal of Political Economy 101*(2), 245–73.

Card, D. (2001, January). The effect of unions on wage inequality in the u.s. labor market. *Industrial and Labor Relations Review 54*(2), 296–315.

Card, D., F. Kramarz, and T. Lemieux (1996, March). Changes in the relative structure of wages and employment: A comparison of the united states, canada, and france. Working Paper 5487, National Bureau of Economic Research.

Card, D., T. Lemieux, and W. Riddell (2004). Unions and wage inequality. *Journal of Labor Research 25*(4), 519–559.

Chassamboulli, A. (2011). Cyclical upgrading of labor and employment differences across skill groups. *The B.E. Journal of Macroeconomics 11*(1).

Chodorow-Reich, G. and L. Karabarbounis (2013, November). The cyclicality of the opportunity cost of employment. Working Paper 19678, National Bureau of Economic Research.

Clark, K. B. and L. H. Summers (1981). Demographic differences in cyclical employment variation. *Journal of Human Resources 16*(1), 61–79.

Davis, S. J., R. J. Faberman, and J. Haltiwanger (2006, Summer). The flow approach to labor markets: New data sources and micro-macro links. *Journal of Economic Perspectives 20*(3), 3–26.

Devereux, P. J. (2004, January). Cyclical quality adjustment in the labor market. *Southern Economic Journal 70*(3), 600–615.

Dolado, J., M. Jansen, and J. Jimeno (2009, 01). On-the-job search in a matching model with heterogeneous jobs and workers. *Economic Journal 119*(534), 200–228.

Elsby, M. W. L., R. Michaels, and G. Solon (2009, January). The ins and outs of cyclical unemployment. *American Economic Journal: Macroeconomics 1*(1), 84–110.

Esping-Andersen, G. (2000). *Why Deregulate Labour Markets?*, Chapter Who is Harmed by Labour Market Regulations? Quantitative Evidence, pp. 66–98. Oxford: Oxford University Press.

Evans, P. (1999). Occupational downgrading and upgrading in britain. *Economica 66*(261), pp. 79–96.

Fair, R. C. (1985, March). Excess labor and the business cycle. *American Economic Review 75*(1), 239–45.

Fay, J. A. and J. L. Medoff (1985, September). Labor and output over the business cycle: Some direct evidence. *American Economic Review 75*(4), 638–55.

Firpo, S., N. M. Fortin, and T. Lemieux (2011, February). Occupational tasks and changes in the wage structure. IZA Discussion Papers 5542, Institute for the Study of Labor (IZA).

Frandsen, B. R. (2012). Why unions still matter: The effects of unionization on the distribution of employee earnings. Working Paper.

Freeman, R. B. (1980, October). Unionism and the dispersion of wages. *Industrial and Labor Relations Review 34*(1), 3–23.

Fujita, S. and G. Ramey (2009, 05). The cyclicality of separation and job finding rates. *International Economic Review 50*(2), 415–430.

Hagedorn, M., F. Karahan, I. Manovskii, and K. Mitman (2013, October). Unemployment benefits and unemployment in the great recession: The role of macro effects. Working Paper 19499, National Bureau of Economic Research.

Hagedorn, M. and I. Manovskii (2008, September). The cyclical behavior of equilibrium unemployment and vacancies revisited. *American Economic Review 98*(4), 1692–1706.

Hall, R. E. (2005, March). Employment fluctuations with equilibrium wage stickiness. *American Economic Review 95*(1), 50–65.

Hoynes, H. (1999, June). The employment, earnings, and income of less skilled workers over the business cycle. NBER Working Papers 7188, National Bureau of Economic Research, Inc.

Hoynes, H., D. L. Miller, and J. Schaller (2012, Summer). Who suffers during recessions? *Journal of Economic Perspectives 26*(3), 27–48.

Ingram, B. F. and G. R. Neumann (2006, February). The returns to skill. *Labour Economics 13*(1), 35–59.

Iversen, T. and A. Wren (1998). Equality, employment, and budgetary restraint: The trilemma of the service economy. *World Politics 50*(4), pp. 507–546.

Jaimovich, N. and H. E. Siu (2009, June). The young, the old, and the restless: Demographics and business cycle volatility. *American Economic Review 99*(3), 804–26.

Jaimovich, N. and H. E. Siu (2012, August). The trend is the cycle: Job polarization and jobless recoveries. NBER Working Papers 18334, National Bureau of Economic Research, Inc.

James, J. (2011). Ability matching and occupational choice. Working Paper 1125, Federal Reserve Bank of Cleveland.

Kambourov, G. and I. Manovskii (2009, 02). Occupational specificity of human capital. *International Economic Review 50*(1), 63–115.

Keane, M. and E. Prasad (1993, December). Skill levels and the cyclical variability of employment, hours, and wages. *IMF Staff Papers 40*(4), 711–743.

Khalifa, S. (2009, April). Heterogeneous workers and occupations: Inequality, unemployment, and crowding out. *Southern Economic Journal 75*(4), 1141–1164.

Kydland, F. E. (1984, January). Labor-force heterogeneity and the business cycle. *Carnegie-Rochester Conference Series on Public Policy 21*(1), 173–208.

Lazear, E. P. and J. R. Spletzer (2012, September). The united states labor market: Status quo or a new normal? Working Paper 18386, National Bureau of Economic Research.

Lerman, R. I., S.-M. McKernan, and S. Riegg. (2004). The scope of employer-provided training in the united states: Who, what, where, and how much? In R. A. S. Christopher J. O'Leary and S. A. Wandner (Eds.), *Job Training Policy in the United States*. W.E. Upjohn Institute for Employment Research.

Leuven, E. (2005, 02). The economics of private sector training: A survey of the literature. *Journal of Economic Surveys 19*(1), 91–111.

Liu, T. and L. C. Spector (2005, January). Dynamic employment adjustments over business cycles. *Empirical Economics 30*(1), 151–169.

Manning, A. (2011). *Imperfect Competition in the Labor Market*, Volume 4 of *Handbook of Labor Economics*, Chapter 11, pp. 973–1041. Elsevier.

Marchetti, D. J. and F. Nucci (2001, November). Labor effort over the business cycle. Temi di discussione (Economic working papers) 424, Bank of Italy, Economic Research and International Relations Area.

Mortensen, D. T. and C. A. Pissarides (1994, July). Job creation and job destruction in the theory of unemployment. *Review of Economic Studies 61*(3), 397–415.

Mortensen, D. T. and C. A. Pissarides (1999). Job reallocation, employment fluctuations and unemployment. In J. B. Taylor and M. Woodford (Eds.), *Handbook of Macroeconomics*, Volume 1 of *Handbook of Macroeconomics*, Chapter 18, pp. 1171–1228. Elsevier.

Neumark, D. and W. Wascher (2006, November). Minimum wages and employment: A review of evidence from the new minimum wage research. NBER Working Papers 12663, National Bureau of Economic Research, Inc.

Nickell, S. (1997, Summer). Unemployment and labor market rigidities: Europe versus north america. *Journal of Economic Perspectives 11*(3), 55–74.

Oesch, D. (2010). What explains high unemployment among low-skilled workers? evidence from 21 oecd countries. *European Journal of Industrial Relations 16*(1), 39–55.

Oi, W. Y. (1962). Labor as a quasi-fixed factor. *Journal of Political Economy 70*(6), 538–555.

Pissarides, C. A. (2009, 09). The unemployment volatility puzzle: Is wage stickiness the answer? *Econometrica 77*(5), 1339–1369.

Pissarides, C. A. and B. Petrongolo (2001, June). Looking into the Black Box: A Survey of the Matching Function. *Journal of Economic Literature 39*(2), 390–431.

Poletaev, M. and C. Robinson (2008, 07). Human capital specificity: Evidence from the dictionary of occupational titles and displaced worker surveys, 1984-2000. *Journal of Labor Economics 26*(3), 387–420.

Reder, M. W. (1955). The theory of occupational wage differentials. *The American Economic Review 45*(5), pp. 833–852.

Robinson, C. (2011). Occupational mobility, occupation distance and specific human capital. University of Western Ontario, CIBC Centre for Human Capital and Productivity Working Papers 20115, University of Western Ontario, CIBC Centre for Human Capital and Productivity.

Roed, K. and T. Zhang (2003, January). Does unemployment compensation affect unemployment duration? *Economic Journal 113*(484), 190–206.

Sahin, A., J. Song, G. Topa, and G. L. Violante (2012, August). Mismatch unemployment. NBER Working Papers 18265, National Bureau of Economic Research, Inc.

Saint-Paul, G. (2004, Fall). Why are european countries diverging in their unemployment experience? *Journal of Economic Perspectives 18*(4), 49–68.

Schmieder, J. F., T. v. Wachter, and S. Bender (2010, February). The effects of unemployment insurance on labor supply and search outcomes : regression discontinuity estimates from germany. IAB Discussion Paper 201004, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg [Institute for Employment Research, Nuremberg, Germany].

Shimer, R. (2012, April). Reassessing the ins and outs of unemployment. *Review of Economic Dynamics 15*(2), 127–148.

Siebert, H. (1997, Summer). Labor market rigidities: At the root of unemployment in europe. *Journal of Economic Perspectives 11*(3), 37–54.

Solon, G., W. Whatley, and A. H. Stevens (1997, April). Wage changes and intrafirm job mobility over the business cycle: Two case studies. *Industrial and Labor Relations Review 50*(3), 402–415.

Teulings, C. N. (1993). The diverging effects of the business cycle on the expected duration of job-search. *Oxford Economic Papers 45*(3), pp. 482–500.

van Ours, J. C. and G. Ridder (1995). Job matching and job competition: Are lower educated workers at the back of the job queues? *European Economic Review 39*, 1717–1731.

Yamaguchi, S. (2012). Tasks and heterogeneous human capital. *Journal of Labor Economics 30*(1), pp. 1–53.

8 Appendix

8.1 Derivation of the equilibrium conditions

The value functions are:

$$
\begin{aligned}
0 &= -c_o^S + q_o\left(J_o^0 - c_o^{FF} - c_o^{TF}\right) \\
(r+\lambda)\, J_o^0 &= p\varepsilon^0 - w_o^0 + \lambda \int_{R_o}^{\infty} J_o(x)\, dF_o(x) - \lambda F_o(R_o)\, c_o^{LF} \\
(r+\lambda)\, J_o(\varepsilon) &= p\varepsilon - w_o(\varepsilon) + \lambda \int_{R_o}^{\infty} J_o(x)\, dF_o(x) - \lambda F_o(R_o)\, c_o^{LF}
\end{aligned}
$$

and

$$
\begin{aligned}
rU_o &= b_o + f_o^F\left(W_o^0 - U_o - c_o^{FW} - c_o^{TW}\right) \\
(r+\lambda)\, W_o^0 &= w_o^0 + \lambda \int_{R_o}^{\infty} W_o(x)\, dF_o(x) + \lambda F_o(R_o)\left(U_o - c_o^{LW}\right) \\
(r+\lambda)\, W_o(\varepsilon) &= w_o(\varepsilon) + \lambda \int_{R_o}^{\infty} W_o(x)\, dF_o(x) + \lambda F_o(R_o)\left(U_o - c_o^{LW}\right)
\end{aligned}
$$

The value functions can be rewritten as

$$
\begin{aligned}
(r+\lambda)\left[J_o(\varepsilon) + c_o^{LF}\right] &= p\varepsilon - w_o(\varepsilon) + rc_o^{LF} + \lambda \int_{R_o}^{\infty} \left[J_o(x) + c_o^{LF}\right] dF_o(x) \\
(r+\lambda)\left[W_o(\varepsilon) - U_o + c_o^{LW}\right] &= w_o(\varepsilon) + r\left(-U_o + c_o^{LW}\right) + \lambda \int_{R_o}^{\infty} \left[W_o(x) - U_o + c_o^{LW}\right] dF_o(x) \\
(r+\lambda)\left[J_o^0 + c_o^{LF0} - c_o^{TF}\right] &= p\varepsilon^0 - w_o^0 + (r+\lambda)\left(c_o^{LF0} - c_o^{TF}\right) - \lambda c_o^{LF} + \lambda \int_{R_o}^{\infty} \left[J_o(x) + c_o^{LF}\right] dF_o(x) \\
(r+\lambda)\left[W_o^0 - U_o + c_o^{LW0} - c_o^{TW}\right] &= w_o^0 - rU_o + (r+\lambda)\left(c_o^{LW0} - c_o^{TW}\right) - \lambda c_o^{LW} \\
&\quad + \lambda \int_{R_o}^{\infty} \left[W_o(x) - U_o + c_o^{LW}\right] dF_o(x)
\end{aligned}
$$

We can write the surpluses as

$$
(r+\lambda)\, S_o(\varepsilon) = (r+\lambda)\left[\left(J_o(\varepsilon) + c_o^{LF}\right) + \left(W_o(\varepsilon) - U_o(\varepsilon) + c_o^{LW}\right)\right]
$$

$$
\begin{aligned}
&= p\varepsilon + r\left(-U_o + c_o^{LW} + c_o^{LF}\right) + \lambda \int_{R_o}^{\infty} S_o(x)\, dF_o(x) && (8) \\
(r+\lambda) S_o^0 &= (r+\lambda)\left[\left(J_o(\varepsilon) + c_o^{LF0} - c_o^{TF}\right) + \left(W_o(\varepsilon) - U_o(\varepsilon) + c_o^{LW0} - c_o^{TW}\right)\right] \\
&= p\varepsilon^0 - rU_o + (r+\lambda)\left(c_o^{LF0} + c_o^{LW0} - c_o^{TF} - c_o^{TW}\right) - \lambda\left(c_o^{LF} + c_o^{LW}\right) && (9) \\
&\quad + \lambda \int_{R_o}^{\infty} S_o(x)\, dF_o(x) && (10)
\end{aligned}
$$

The derivative of the continuing surplus (8) with respect to the state variable is

$$
\frac{\partial S_o(\varepsilon)}{\partial \varepsilon} = \frac{p}{r+\lambda}
$$

Thus

$$
S_o(\varepsilon) = \frac{p(\varepsilon - R_o)}{r+\lambda}
$$

Subtracting (9) from (8) evaluated at the initial productivity level is

$$
\begin{aligned}
(r+\lambda)\left(S_o\left(\varepsilon^0\right) - S_o^0\right) &= (r+\lambda)\left(c_o^{LW} + c_o^{LF} - c_o^{LF0} - c_o^{LW0} + c_o^{TF} + c_o^{TW}\right) \\
S_o\left(\varepsilon^0\right) - S_o^0 &= c_o^{LW} + c_o^{LF} - c_o^{LF0} - c_o^{LW0} + c_o^{TF} + c_o^{TW}
\end{aligned}
$$

The initial surplus is

$$
S_o^0 = \frac{p\left(\varepsilon^0 - R_o\right)}{r+\lambda} - \left(c_o^{LW} + c_o^{LF} - c_o^{LF0} - c_o^{LW0} + c_o^{TF} + c_o^{TW}\right) \tag{11}
$$

(11) and the free entry condition implies the job creation condition:

$$
\begin{aligned}
\frac{c_o^S}{q_o} + c_o^{FF} &= J_o^0 - c_o^{TF} = \left(J_o^0 + c_o^{LF0} - c_o^{TF}\right) - c_o^{LF0} = (1-\gamma) S_o^0 - c_o^{LF0} \\
&= (1-\gamma)\left[\frac{p\left(\varepsilon^0 - R_o\right)}{r+\lambda} - \left(c_o^{LW} + c_o^{LF} - c_o^{LF0} - c_o^{LW0} + c_o^{TF} + c_o^{TW}\right)\right] - c_o^{LF0} \\
&= (1-\gamma)\left[\frac{p\left(\varepsilon^0 - R_o\right)}{r+\lambda} - \left(c_o^{LW} + c_o^{LF} + c_o^{TF} + c_o^{TW}\right)\right] - \left(\gamma c_o^{LF0} - (1-\gamma) c_o^{LW0}\right)
\end{aligned}
$$

In order to derive the job-destruction condition we need to write rU as a function of the surplus.

$$
\begin{aligned}
rU_o &= b_o + f_o^F\left(W_o^N\left(\varepsilon^0\right) - U_o - c_o^{FW} - c_o^{TW}\right) \\
&= b_o - f_o^F\left(c_o^{FW} + c_o^{LW0}\right) + f_o^F\left(W_o^0 - U_o + c_o^{LW0} - c_o^{TW}\right)
\end{aligned}
$$

$$
\begin{aligned}
&= b_o - f_o^F \left(c_o^{FW} + c_o^{LW0}\right) + f_o^F \gamma S_o^0 \\
&= b_o - f_o^F \left(c_o^{FW} + c_o^{LW0}\right) + f_o^F \frac{\gamma}{1-\gamma} \left(\frac{c_o^S}{q_o} + c_o^{FF} + c_o^{LF0}\right) \\
&= b_o + \frac{\gamma}{1-\gamma} \frac{f_o^F}{q_o} c_o^S + f_o^F \left[\frac{\gamma}{1-\gamma} \left(c_o^{FF} + c_o^{LF0}\right) - \left(c_o^{FW} + c_o^{LW0}\right)\right]
\end{aligned}
$$

Now we can substitute this expression into (8) to get the job destruction condition, where the surplus disappears:

$$
\begin{aligned}
p\left[R_o + \frac{\lambda}{r+\lambda} \int_{R_o}^{\infty} (\varepsilon - R_o)\, dF_o(x)\right] &= r\left(U_o - c_o^{LW} - c_o^{LF}\right) \\
&= b_o + \frac{\gamma}{1-\gamma} \frac{f_o^F}{q_o} c_o^S + f_o^F \left[\frac{\gamma}{1-\gamma} \left(c_o^{FF} + c_o^{LF0}\right) - \left(c_o^{FW} + c_o^{LW0}\right)\right] \\
&\quad - r\left(c_o^{LW} + c_o^{LF}\right) \\
&= b_o + \frac{\gamma}{1-\gamma} \theta_o c_o^S + \eta_o \theta_o^{\alpha} \left[\frac{\gamma}{1-\gamma} \left(c_o^{FF} + c_o^{LF0}\right) - \left(c_o^{FW} + c_o^{LW0}\right)\right] \\
&\quad - r\left(c_o^{LW} + c_o^{LF}\right)
\end{aligned}
$$

In the last line I uses the assumptions that $f_o^F = \eta_o \theta_o^{\alpha}$ and $q_o = \eta_o \theta_o^{\alpha - 1}$.

8.2 Derivation of the elasticities

The job creation and job destruction conditions can be written as:

$$
\begin{aligned}
0 &= p\left[R + \frac{\lambda}{r+\lambda} \int_{R}^{\infty} (x - R)\, dF(x)\right] - b - \frac{\gamma}{1-\gamma} \theta c^S + r c^L = D(R, \theta) \\
0 &= \frac{c^S}{\eta} \theta^{1-\alpha} - (1-\gamma) \left[\frac{p\left(\varepsilon^0 - R\right)}{r+\lambda} - c^L - c^T\right] = C(R, \theta)
\end{aligned}
$$

The idea behind deriving the elasticities will be the following.

1. First I derive the derivative of R and θ with respect to a particular parameter Y.
2. Using these results I derive the elasticity of the job loss and job finding probabilities with respect to Y.

For the first step is is useful to write the job loss and job finding conditions as

$$
\begin{aligned}
0 &= D\left(R\left(Y\right),\theta\left(Y\right),Y\right)\\
0 &= C\left(R\left(Y\right),\theta\left(Y\right),Y\right)
\end{aligned}
$$

Then I will take total derivatives:

$$
\begin{aligned}
0 &= \frac{\partial D}{\partial R}\frac{\partial R}{\partial Y}+\frac{\partial D}{\partial \theta}\frac{\partial \theta}{\partial Y}+\frac{\partial D}{\partial Y}\\
0 &= \frac{\partial C}{\partial R}\frac{\partial R}{\partial Y}+\frac{\partial C}{\partial \theta}\frac{\partial \theta}{\partial Y}+\frac{\partial C}{\partial Y}
\end{aligned}
$$

It is worth deriving the following derivatives:

$$
\begin{aligned}
\frac{\partial D}{\partial R} &= p\left(1-\frac{\lambda}{r+\lambda}\left(1-F\left(R\right)\right)\right)=p\left(\frac{r+\lambda F\left(R\right)}{r+\lambda}\right)=p\left(\frac{r+f^L}{r+\lambda}\right)\\
\frac{\partial D}{\partial \theta} &= -\frac{\gamma}{1-\gamma}c^S\\
\frac{\partial C}{\partial R} &= \frac{\left(1-\gamma\right)p}{r+\lambda}\\
\frac{\partial C}{\partial \theta} &= \left(1-\alpha\right)\frac{c^S}{\eta}\theta^{-\alpha}=\frac{\left(1-\alpha\right)c^S}{f^F}
\end{aligned}
$$

For the second step I use the definition of the job loss and job finding rates:

$$
\begin{aligned}
\frac{\partial f^F}{\partial Y} &= \frac{\partial \eta\theta^{\alpha}}{\partial Y}=\eta\alpha\theta^{\alpha-1}\frac{\partial \theta}{\partial Y}=\frac{\alpha f^F}{\theta}\frac{\partial \theta}{\partial Y}\\
\frac{\partial f^L}{\partial Y} &= \frac{\partial \lambda F\left(R\right)}{\partial Y}=\lambda f\left(R\right)\frac{\partial R}{\partial Y}
\end{aligned}
$$

Which lead to the following elasticities:

$$
\begin{aligned}
\varepsilon_Y^F &= \frac{\partial f^F}{\partial Y}\frac{Y}{f^F}=\frac{\alpha Y}{\theta}\frac{\partial \theta}{\partial Y}\\
\varepsilon_Y^L &= \frac{\partial f^L}{\partial Y}\frac{Y}{f^L}=\frac{f\left(R\right)Y}{F\left(R\right)}\frac{\partial R}{\partial Y}
\end{aligned}
$$

Note: If I assume log-normal distribution, then I could say something about the term $\frac{f(R)}{F(R)}$.

8.2.1 Elasticities with respect to b

Taking total derivatives

$$
\begin{aligned}
0 &= p\left(\frac{r+f^L}{r+\lambda}\right)\frac{\partial R}{\partial b} - \frac{\gamma}{1-\gamma}c^S\frac{\partial \theta}{\partial b} - 1 \\
0 &= \frac{(1-\gamma)\,p}{r+\lambda}\frac{\partial R}{\partial b} + \frac{(1-\alpha)\,c^S}{f^F}\frac{\partial \theta}{\partial b}
\end{aligned}
$$

Which implies:

$$
\begin{aligned}
\left(\frac{p}{r+\lambda}\right)\frac{\partial R}{\partial b} &= \frac{1}{r+f^L}\left(1+\frac{\gamma}{1-\gamma}c^S\frac{\partial \theta}{\partial b}\right) = -\frac{(1-\alpha)\,c^S}{(1-\gamma)\,f^F}\frac{\partial \theta}{\partial b} \\
\frac{\partial \theta}{\partial b} &= -\frac{1}{\frac{c^S}{(1-\gamma)}\left[\frac{(1-\alpha)(r+f^L)}{f^F}+\gamma\right]} \\
&= -\frac{(1-\gamma)\,f^F}{c^S\left((1-\alpha)\,(r+f^L)+\gamma f^F\right)} \\
\frac{\partial R}{\partial b} &= \frac{(1-\alpha)\,c^S}{(1-\gamma)\,f^F}\left(\frac{r+\lambda}{p}\right)\frac{(1-\gamma)\,f^F}{c^S\left((1-\alpha)\,(r+f^L)+\gamma f^F\right)} \\
&= \frac{(1-\alpha)\,(r+\lambda)}{p\left((1-\alpha)\,(r+f^L)+\gamma f^F\right)}
\end{aligned}
$$

The elasticities are

$$
\begin{aligned}
\varepsilon_b^F &= -\frac{\alpha b}{\theta}\frac{(1-\gamma)\,f^F}{c^S\left((1-\alpha)\,(r+f^L)+\gamma f^F\right)} \\
\varepsilon_b^L &= \frac{f\,(R)}{F\,(R)}\frac{b}{p}\frac{(1-\alpha)\,(r+\lambda)}{\left((1-\alpha)\,(r+f^L)+\gamma f^F\right)}
\end{aligned}
$$

The ratio:

$$
S_b^{F,L} = \frac{\varepsilon_b^F}{\varepsilon_b^L} = -\frac{(1-\gamma)\,f^F}{(1-\alpha)\,(r+\lambda)}\frac{p}{c^S}\frac{F\,(R)\,\alpha}{f\,(R)\,\theta}
$$

8.2.2 Elasticities with respect to γ

Taking total derivatives

$$
\begin{aligned}
0 &= p\left(\frac{r+f^L}{r+\lambda}\right)\frac{\partial R}{\partial \gamma} - \frac{\gamma}{1-\gamma}c^S\frac{\partial \theta}{\partial \gamma} - \frac{\theta c^S}{(1-\gamma)^2} \\
0 &= \frac{(1-\gamma)\,p}{r+\lambda}\frac{\partial R}{\partial \gamma} + \frac{(1-\alpha)\,c^S}{f^F}\frac{\partial \theta}{\partial \gamma} + \left[\frac{p\left(\varepsilon^0-R\right)}{r+\lambda} - c^L - c^T\right]
\end{aligned}
$$

$$= \frac{(1-\gamma)\,p}{r+\lambda}\frac{\partial R}{\partial \gamma} + \frac{(1-\alpha)\,c^S}{f^F}\frac{\partial \theta}{\partial \gamma} + \frac{c^S}{\eta}\frac{\theta^{1-\alpha}}{(1-\gamma)}$$

Which implies:

$$\begin{aligned}
\left(\frac{p\,(1-\gamma)}{r+\lambda}\right)\frac{\partial R}{\partial \gamma} &= \frac{1}{r+f^L}\left(\frac{\theta c^S}{1-\gamma} + \gamma c^S\frac{\partial \theta}{\partial \gamma}\right) = -\frac{(1-\alpha)\,c^S}{f^F}\frac{\partial \theta}{\partial \gamma} - \frac{c^S}{\eta}\frac{\theta^{1-\alpha}}{(1-\gamma)} \\
\frac{\partial \theta}{\partial \gamma} &= -\frac{\frac{\theta c^S}{1-\gamma} + \frac{c^S}{\eta}\frac{\theta^{1-\alpha}}{(1-\gamma)}\left(r+f^L\right)}{c^S\left[\frac{(1-\alpha)(r+f^L)}{f^F}+\gamma\right]} \\
&= -\frac{\theta}{1-\gamma}\frac{f^F+r+f^L}{((1-\alpha)\,(r+f^L)+\gamma f^F)} \\
\frac{\partial R}{\partial \gamma} &= \frac{r+\lambda}{(r+f^L)\,p\,(1-\gamma)}\left(\frac{\theta c^S}{1-\gamma} - \gamma c^S\frac{\theta}{1-\gamma}\frac{f^F+r+f^L}{((1-\alpha)\,(r+f^L)+\gamma f^F)}\right) \\
&= \frac{(r+\lambda)\,\theta c^S}{(r+f^L)\,p\,(1-\gamma)^2}\left(1 - \frac{\left(f^F+r+f^L\right)\gamma}{((1-\alpha)\,(r+f^L)+\gamma f^F)}\right) \\
&= \frac{(r+\lambda)\,\theta c^S}{p\,(1-\gamma)^2}\frac{1-\alpha-\gamma}{((1-\alpha)\,(r+f^L)+\gamma f^F)}
\end{aligned}$$

Interestingly this seems to be zero if the Hosios condition holds. Intuition? [I do not know. Let's come back to this]

The elasticities are

$$\begin{aligned}
\varepsilon_\gamma^F &= -\frac{\alpha\gamma}{1-\gamma}\frac{f^F+r+f^L}{((1-\alpha)\,(r+f^L)+\gamma f^F)} \\
\varepsilon_\gamma^L &= \frac{f\,(R)}{F\,(R)}\frac{(r+\lambda)\,\gamma\theta c^S}{p\,(1-\gamma)^2}\frac{1-\alpha-\gamma}{((1-\alpha)\,(r+f^L)+\gamma f^F)}
\end{aligned}$$

The ratio:

$$S_\gamma^{F,L} = \frac{\varepsilon_\gamma^F}{\varepsilon_\gamma^L} = -\frac{\left(f^F+r+f^L\right)(1-\gamma)}{(1-\alpha-\gamma)\,(r+\lambda)}\frac{p}{c^S}\frac{F\,(R)\,\alpha}{f\,(R)\,\theta} = S_b^{F,L}\left(\frac{f^F+r+f^L}{f^F}\right)\left(\frac{1-\alpha}{1-\alpha-\gamma}\right)$$

8.2.3 Elasticities with respect to c^T

Taking total derivatives

$$0 = p\left(\frac{r+f^L}{r+\lambda}\right)\frac{\partial R}{\partial c^T} - \frac{\gamma}{1-\gamma}c^S\frac{\partial \theta}{\partial c^T}$$

$$0 = \frac{(1-\gamma)\,p}{r+\lambda}\frac{\partial R}{\partial c^T} + \frac{(1-\alpha)\,c^S}{f^F}\frac{\partial \theta}{\partial c^T} + (1-\gamma)$$

Which implies:

$$\begin{aligned}
\left(\frac{p}{r+\lambda}\right)\frac{\partial R}{\partial c^T} &= \frac{1}{r+f^L}\left(\frac{\gamma}{1-\gamma}c^S\frac{\partial \theta}{\partial c^T}\right) = -\frac{(1-\alpha)\,c^S}{(1-\gamma)\,f^F}\frac{\partial \theta}{\partial c^T} - 1 \\
\frac{\partial \theta}{\partial c^T} &= -\frac{(1-\gamma)\left(r+f^L\right)}{c^S\left[\frac{(1-\alpha)(r+f^L)}{f^F}+\gamma\right]} \\
&= -\frac{(1-\gamma)\left(r+f^L\right)f^F}{c^S\left((1-\alpha)\left(r+f^L\right)+\gamma f^F\right)} \\
\frac{\partial R}{\partial c^T} &= -\frac{1}{r+f^L}\frac{r+\lambda}{p}\left(\frac{\gamma}{1-\gamma}c^S\frac{(1-\gamma)\left(r+f^L\right)f^F}{c^S\left((1-\alpha)\left(r+f^L\right)+\gamma f^F\right)}\right) \\
&= -\left(\frac{\gamma\,(r+\lambda)\,f^F}{p\left((1-\alpha)\left(r+f^L\right)+\gamma f^F\right)}\right)
\end{aligned}$$

The elasticities are

$$\begin{aligned}
\varepsilon^F_{c^T} &= -\frac{\alpha}{\theta}\frac{c^T}{c^S}\frac{(1-\gamma)\left(r+f^L\right)f^F}{\left((1-\alpha)\left(r+f^L\right)+\gamma f^F\right)} \\
\varepsilon^L_{c^T} &= -\frac{f(R)}{F(R)}\frac{c^T}{p}\frac{\gamma\,(r+\lambda)\,f^F}{\left((1-\alpha)\left(r+f^L\right)+\gamma f^F\right)}
\end{aligned}$$

The ratios:

$$S^{F,L}_{c^T} = \frac{\varepsilon^F_{c^T}}{\varepsilon^L_{c^T}} = \frac{(1-\gamma)\left(r+f^L\right)}{\gamma\,(r+\lambda)}\frac{p}{c^S}\frac{F(R)\,\alpha}{f(R)\,\theta} = -S^{F,L}_b\frac{(1-\alpha)}{\gamma}\frac{\left(r+f^L\right)}{f^F}$$

8.2.4 Elasticities with respect to c^S

Taking total derivatives

$$\begin{aligned}
0 &= p\left(\frac{r+f^L}{r+\lambda}\right)\frac{\partial R}{\partial c^S} - \frac{\gamma}{1-\gamma}c^S\frac{\partial \theta}{\partial c^S} - \frac{\gamma}{1-\gamma}\theta \\
0 &= \frac{(1-\gamma)\,p}{r+\lambda}\frac{\partial R}{\partial c^S} + \frac{(1-\alpha)\,c^S}{f^F}\frac{\partial \theta}{\partial c^S} + \frac{\theta^{1-\alpha}}{\eta} \\
&= \frac{(1-\gamma)\,p}{r+\lambda}\frac{\partial R}{\partial c^S} + \frac{(1-\alpha)\,c^S}{f^F}\frac{\partial \theta}{\partial c^S} + \frac{\theta}{f^F}
\end{aligned}$$

Which implies:

$$\begin{aligned}
\left(\frac{p}{r+\lambda}\right)\frac{\partial R}{\partial c^S} &= \frac{1}{r+f^L}\left(\frac{\gamma}{1-\gamma}\left(c^S\frac{\partial\theta}{\partial c^S}+\theta\right)\right) = -\frac{(1-\alpha)\,c^S}{(1-\gamma)\,f^F}\frac{\partial\theta}{\partial c^S} - \frac{\theta}{(1-\gamma)\,f^F} \\
\gamma f^F\left(c^S\frac{\partial\theta}{\partial c^S}+\theta\right) &= -\left(r+f^L\right)(1-\alpha)\,c^S\frac{\partial\theta}{\partial c^S} - \left(r+f^L\right)\theta \\
\frac{\partial\theta}{\partial c^S} &= -\frac{\left(r+f^L+\gamma f^F\right)\theta}{c^S\left[\left(r+f^L\right)(1-\alpha)+\gamma f^F\right]} \\
\frac{\partial R}{\partial c^S} &= -\frac{r+\lambda}{p}\frac{1}{r+f^L}\left(\frac{\gamma}{1-\gamma}\left(c^S\frac{\left(r+f^L+\gamma f^F\right)\theta}{c^S\left[\left(r+f^L\right)(1-\alpha)+\gamma f^F\right]}-\theta\right)\right) \\
&= -\frac{r+\lambda}{p}\frac{1}{r+f^L}\left(\frac{\gamma\theta}{1-\gamma}\left(\frac{\left(r+f^L+\gamma f^F\right)-\left(r+f^L\right)(1-\alpha)-\gamma f^F}{\left[\left(r+f^L\right)(1-\alpha)+\gamma f^F\right]}\right)\right) \\
&= -\left(\frac{\gamma}{1-\gamma}\frac{\theta}{p}\left(\frac{(r+\lambda)\,\alpha}{\left(r+f^L\right)(1-\alpha)+\gamma f^F}\right)\right)
\end{aligned}$$

The elasticities are

$$\begin{aligned}
\varepsilon^F_{c^S} &= -\frac{\alpha\left(r+f^L+\gamma f^F\right)}{\left[\left(r+f^L\right)(1-\alpha)+\gamma f^F\right]} \\
\varepsilon^L_{c^S} &= -\frac{f(R)}{F(R)}\frac{c^S}{p}\frac{\gamma}{1-\gamma}\frac{(r+\lambda)\,\alpha\theta}{\left(r+f^L\right)(1-\alpha)+\gamma f^F}
\end{aligned}$$

The ratios:

$$S^{F,L}_{c^S} = \frac{\varepsilon^F_{c^S}}{\varepsilon^L_{c^S}} = \frac{\left(r+f^L+\gamma f^F\right)}{(r+\lambda)\,\theta}\frac{1-\gamma}{\gamma}\frac{p}{c^S}\frac{F(R)}{f(R)} = -S^{F,L}_b\frac{(1-\alpha)\left(r+f^L+\gamma f^F\right)}{\alpha\gamma f^F}$$

8.2.5 Elasticities with respect to c^L

Taking total derivatives

$$\begin{aligned}
0 &= p\left(\frac{r+f^L}{r+\lambda}\right)\frac{\partial R}{\partial c^L} - \frac{\gamma}{1-\gamma}c^S\frac{\partial\theta}{\partial c^L} + r \\
0 &= \frac{(1-\gamma)\,p}{r+\lambda}\frac{\partial R}{\partial c^L} + \frac{(1-\alpha)\,c^S}{f^F}\frac{\partial\theta}{\partial c^L} + (1-\gamma)
\end{aligned}$$

Which implies:

$$\left(\frac{p}{r+\lambda}\right)\frac{\partial R}{\partial c^L} = \frac{1}{r+f^L}\left(\frac{\gamma}{1-\gamma}c^S\frac{\partial\theta}{\partial c^L} - r\right) = -\frac{(1-\alpha)\,c^S}{(1-\gamma)\,f^F}\frac{\partial\theta}{\partial c^L} - 1$$

$$
\begin{aligned}
\frac{\partial\theta}{\partial c^L} &= -\frac{(1-\gamma) f^L}{c^S\left[\frac{(1-\alpha)(r+f^L)}{f^F}+\gamma\right]} \\
&= -\frac{(1-\gamma) f^L f^F}{c^S\left((1-\alpha)(r+f^L)+\gamma f^F\right)} \\
\frac{\partial R}{\partial c^L} &= -\frac{1}{r+f^L}\frac{r+\lambda}{p}\left(\frac{\gamma}{1-\gamma}c^S\frac{(1-\gamma) f^L f^F}{c^S\left((1-\alpha)(r+f^L)+\gamma f^F\right)}+r\right) \\
&= -\frac{1}{r+f^L}\frac{r+\lambda}{p}\left(\frac{\gamma f^L f^F + r\left((1-\alpha)\left(r+f^L\right)+\gamma f^F\right)}{\left((1-\alpha)(r+f^L)+\gamma f^F\right)}\right) \\
&= -\frac{(r+\lambda)\left(r(1-\alpha)+\gamma f^F\right)}{p\left((1-\alpha)(r+f^L)+\gamma f^F\right)}
\end{aligned}
$$

The elasticities are

$$
\begin{aligned}
\varepsilon^F_{c^L} &= -\frac{\alpha}{\theta}\frac{c^L}{c^S}\frac{(1-\gamma) f^L f^F}{\left((1-\alpha)(r+f^L)+\gamma f^F\right)} \\
\varepsilon^L_{c^L} &= -\frac{f(R)}{F(R)}\frac{c^L}{p}\frac{(r+\lambda)\left(r(1-\alpha)+\gamma f^F\right)}{\left((1-\alpha)(r+f^L)+\gamma f^F\right)}
\end{aligned}
$$

The ratios:

$$
\begin{aligned}
S^{F,L}_{c^L} &= \frac{\varepsilon^F_{c^L}}{\varepsilon^L_{c^L}} = \frac{(1-\gamma) f^L f^F}{(r+\lambda)\left(r(1-\alpha)+\gamma f^F\right)}\frac{p}{c^S}\frac{F(R)\,\alpha}{f(R)\,\theta} = -S^{F,L}_b\frac{(1-\alpha) f^L}{r(1-\alpha)+\gamma f^F} \\
&= S^{F,L}_{c^T}\frac{\gamma f^F}{\left(r(1-\alpha)+\gamma f^F\right)}\frac{f^L}{r+f^L}
\end{aligned}
$$

Which is slightly smaller than the elasticity ratio with respect to training costs.

8.2.6 Elasticities with respect to η

Taking total derivatives

$$
\begin{aligned}
0 &= p\left(\frac{r+f^L}{r+\lambda}\right)\frac{\partial R}{\partial\eta} - \frac{\gamma}{1-\gamma}c^S\frac{\partial\theta}{\partial\eta} \\
0 &= \frac{(1-\gamma)\,p}{r+\lambda}\frac{\partial R}{\partial\eta} + \frac{(1-\alpha)\,c^S}{f^F}\frac{\partial\theta}{\partial\eta} - \frac{c^S}{\eta^2}\theta^{1-\alpha}
\end{aligned}
$$

Which implies:

$$
\left(\frac{p}{r+\lambda}\right)\frac{\partial R}{\partial\eta} = \frac{1}{r+f^L}\left(\frac{\gamma}{1-\gamma}c^S\frac{\partial\theta}{\partial\eta}\right) = \frac{c^S\theta^{1-\alpha}}{(1-\gamma)\,\eta^2} - \frac{(1-\alpha)\,c^S}{(1-\gamma)\,f^F}\frac{\partial\theta}{\partial\eta}
$$

$$
\begin{aligned}
\frac{\partial\theta}{\partial\eta} &= \frac{\left(r+f^L\right)\theta^{1-\alpha}}{\eta^2\left[\frac{(1-\alpha)(r+f^L)}{f^F}+\gamma\right]} \\
&= \frac{\left(r+f^L\right)\theta^{1-\alpha}\eta\theta^{\alpha}}{\eta^2\left[(1-\alpha)\left(r+f^L\right)+\gamma f^F\right]} \\
&= \frac{\left(r+f^L\right)\theta}{\eta\left[(1-\alpha)\left(r+f^L\right)+\gamma f^F\right]} \\
\frac{\partial R}{\partial\eta} &= \frac{1}{r+f^L}\frac{r+\lambda}{p}\left(\frac{\gamma}{1-\gamma}c^S\frac{\left(r+f^L\right)\theta}{\eta\left[(1-\alpha)\left(r+f^L\right)+\gamma f^F\right]}\right) \\
&= \frac{\gamma}{1-\gamma}\frac{c^S}{p}\frac{\theta\left(r+\lambda\right)}{\eta\left[(1-\alpha)\left(r+f^L\right)+\gamma f^F\right]}
\end{aligned}
$$

The layoff elasticity is

$$
\varepsilon_\eta^L = \frac{f\left(R\right)}{F\left(R\right)}\frac{c^S}{p}\frac{\gamma}{1-\gamma}\frac{\theta\left(r+\lambda\right)}{\left((1-\alpha)\left(r+f^L\right)+\gamma f^F\right)}
$$

The hiring elasticity is slightly more complicated than before:

$$
\begin{aligned}
\varepsilon_\eta^F &= 1+\frac{\left(r+f^L\right)\alpha}{(1-\alpha)\left(r+f^L\right)+\gamma f^F} \\
&= \frac{r+f^L+\gamma f^F}{(1-\alpha)\left(r+f^L\right)+\gamma f^F}
\end{aligned}
$$

The ratios:

$$
\begin{aligned}
S_\eta^{F,L} &= \frac{\varepsilon_\eta^F}{\varepsilon_\eta^L} = \frac{(1-\gamma)\left(r+f^L+\gamma f^F\right)}{\gamma\left(r+\lambda\right)}\frac{p}{c^S}\frac{F\left(R\right)}{f\left(R\right)\theta} = -S_b^{F,L}\frac{1-\alpha}{\alpha}\frac{1}{\gamma}\frac{\left(r+f^L+\gamma f^F\right)}{f^F} \\
&= S_{c^S}^{F,L}
\end{aligned}
$$

8.2.7 Elasticity with respect to σ_ε

Let's assume that the idiosyncratic shocks follow a log-normal distribution, $\ln\varepsilon \sim N\left(-\frac{\sigma_\varepsilon^2}{2},\sigma_\varepsilon^2\right)$, and I will compute the elasticities with respect to σ_ε, the dispersion of idiosyncratic shocks. In this case the partial integral in the job destruction condition takes the form:

$$
\begin{aligned}
\int_R^\infty x dF\left(x\right) &= \Phi\left(\frac{\sigma_\varepsilon}{2}-\frac{\ln R}{\sigma_\varepsilon}\right) \\
\int_R^\infty \left(x-R\right)dF\left(x\right) &= \Phi\left(\frac{\sigma_\varepsilon}{2}-\frac{\ln R}{\sigma_\varepsilon}\right)-R\Phi\left(-\frac{\sigma_\varepsilon}{2}-\frac{\ln R}{\sigma_\varepsilon}\right)
\end{aligned}
$$

The job destruction condition becomes:

$$0 = p\left[R + \frac{\lambda}{r+\lambda}\left(\Phi\left(\frac{\sigma_\varepsilon}{2} - \frac{\ln R}{\sigma_\varepsilon}\right) - R\Phi\left(-\frac{\sigma_\varepsilon}{2} - \frac{\ln R}{\sigma_\varepsilon}\right)\right)\right] - b - \frac{\gamma}{1-\gamma}\theta c^S + rc^L$$

The total derivatives

$$\begin{aligned}
0 &= p\left(\frac{r+f^L}{r+\lambda}\right)\frac{\partial R}{\partial \sigma_\varepsilon} - \frac{\gamma}{1-\gamma}c^S\frac{\partial \theta}{\partial \sigma_\varepsilon} \\
&\quad + \frac{\lambda}{r+\lambda}p\left(\phi\left(\frac{\sigma_\varepsilon}{2} - \frac{\ln R}{\sigma_\varepsilon}\right)\left(\frac{1}{2}(R,\theta) + \frac{\ln R}{\sigma_\varepsilon^2}\right) - R\phi\left(-\frac{\sigma_\varepsilon}{2} - \frac{\ln R}{\sigma_\varepsilon}\right)\left(-\frac{1}{2} + \frac{\ln R}{\sigma_\varepsilon^2}\right)\right) \\
&= p\left(\frac{r+f^L}{r+\lambda}\right)\frac{\partial R}{\partial \sigma_\varepsilon} - \frac{\gamma}{1-\gamma}c^S\frac{\partial \theta}{\partial \sigma_\varepsilon} + A(\sigma_\varepsilon) \\
0 &= \frac{(1-\gamma)p}{r+\lambda}\frac{\partial R}{\partial \sigma_\varepsilon} + \frac{(1-\alpha)c^S}{f^F}\frac{\partial \theta}{\partial \sigma_\varepsilon}
\end{aligned}$$

where

$$A(\sigma_\varepsilon) = \frac{\lambda}{r+\lambda}p\left(\phi\left(\frac{\sigma_\varepsilon}{2} - \frac{\ln R}{\sigma_\varepsilon}\right)\left(\frac{1}{2} + \frac{\ln R}{\sigma_\varepsilon^2}\right) - R\phi\left(-\frac{\sigma_\varepsilon}{2} - \frac{\ln R}{\sigma_\varepsilon}\right)\left(-\frac{1}{2} + \frac{\ln R}{\sigma_\varepsilon^2}\right)\right)$$

Which implies:

$$\begin{aligned}
\left(\frac{p}{r+\lambda}\right)\frac{\partial R}{\partial \sigma_\varepsilon} &= \frac{1}{r+f^L}\left(\frac{\gamma}{1-\gamma}c^S\frac{\partial \theta}{\partial \sigma_\varepsilon} - A(\sigma_\varepsilon)\right) = -\frac{(1-\alpha)c^S}{(1-\gamma)f^F}\frac{\partial \theta}{\partial \sigma_\varepsilon} \\
\frac{\partial \theta}{\partial \sigma_\varepsilon} &= \frac{(1-\gamma)A(\sigma_\varepsilon)f^F}{c^S[(1-\alpha)(r+f^L)+\gamma f^F]} \\
\frac{\partial R}{\partial \sigma_\varepsilon} &= -\frac{(1-\alpha)c^S}{(1-\gamma)f^F}\left(\frac{r+\lambda}{p}\right)\frac{(1-\gamma)A(\sigma_\varepsilon)f^F}{c^S[(1-\alpha)(r+f^L)+\gamma f^F]} \\
&= -\left(\frac{r+\lambda}{p}\right)\frac{A(\sigma_\varepsilon)(1-\alpha)}{[(1-\alpha)(r+f^L)+\gamma f^F]}
\end{aligned}$$

The hiring elasticity can still be computed similarly to previous parameters:

$$\varepsilon^F_{\sigma_\varepsilon} = \frac{\alpha\sigma_\varepsilon}{\theta}\frac{(1-\gamma)A(\sigma_\varepsilon)f^F}{c^S[(1-\alpha)(r+f^L)+\gamma f^F]}$$

The layoff elasticity, however, is more complicated:

$$\begin{aligned}
\varepsilon^L_{\sigma_\varepsilon} &= \frac{\sigma_\varepsilon}{F(R)}\left(f(R)\frac{\partial R}{\partial \sigma_\varepsilon} + \frac{\partial F(R)}{\partial \sigma_\varepsilon}\right) \\
\varepsilon^L_{\sigma_\varepsilon} &= \frac{\sigma_\varepsilon}{F(R)}\left(-f(R)\left(\frac{r+\lambda}{p}\right)\frac{A(\sigma_\varepsilon)(1-\alpha)}{[(1-\alpha)(r+f^L)+\gamma f^F]} + \frac{\partial F(R)}{\partial \sigma_\varepsilon}\right)
\end{aligned}$$

$$= \quad f(R)\,\frac{\sigma_\varepsilon}{F(R)}\left(R\left(\frac{1}{2}-\frac{\ln R}{\sigma_\varepsilon}\right)-\left(\frac{r+\lambda}{p}\right)\frac{A(\sigma_\varepsilon)(1-\alpha)}{[(1-\alpha)(r+f^L)+\gamma f^F]}\right)$$

This is a non-trivial expression so I do not even try to relate it to other elasticities.

Table 3: Formulas for the ratios of the hiring and laying off elasticities with respect to different parameters

Parameters (X)	$S_X^{F,L} = e_X^F / e_X^L$		Ratio of $S_X^{F,L}$ to $S_b^{F,L}$	
	Formula	Sign	Formula	Estimate
Flow value of unemployment, b	$-\frac{(1-\gamma)f^F}{(1-\alpha)(r+\lambda)}\frac{p}{c^S}\frac{F(R)\alpha}{f(R)\theta}$	$-$	1	1
Worker's bargaining power, γ	$-\frac{\left(f^F+r+f^L\right)(1-\gamma)}{(1-\alpha-\gamma)(r+\lambda)}\frac{p}{c^S}\frac{F(R)\alpha}{f(R)\theta}$	?	$\left(\frac{f^F+r+f^L}{f^F}\right)\left(\frac{1-\alpha}{1-\alpha-\gamma}\right)$	infinity
Matching efficiency, η	$\frac{\left(r+f^L+\gamma f^F\right)}{r+\lambda}\frac{1-\gamma}{\gamma}\frac{p}{c^S}\frac{F(R)}{f(R)\theta}$	$+$	$-\left(\frac{r+f^L+\gamma f^F}{f^F}\right)\left(\frac{1-\alpha}{\alpha\gamma}\right)$	-1.5
Search costs, c^S	$\frac{\left(r+f^L+\gamma f^F\right)}{r+\lambda}\frac{1-\gamma}{\gamma}\frac{p}{c^S}\frac{F(R)}{f(R)\theta}$	$+$	$-\left(\frac{r+f^L+\gamma f^F}{f^F}\right)\left(\frac{1-\alpha}{\alpha\gamma}\right)$	-1.5
Training costs, c^T	$\frac{(1-\gamma)\left(r+f^L\right)}{\gamma(r+\lambda)}\frac{p}{c^S}\frac{F(R)\alpha}{f(R)\theta}$	$+$	$-\left(\frac{r+f^L}{f^F}\right)\left(\frac{1-\alpha}{\gamma}\right)$	-0.04
Layoff costs of experienced workers, c^L	$\frac{(1-\gamma)f^L f^F}{(r+\lambda)(r(1-\alpha)+\gamma f^F)}\frac{p}{c^S}\frac{F(R)\alpha}{f(R)\theta}$	$+$	$-\frac{(1-\alpha)f^L}{r(1-\alpha)+\gamma f^F}$	-0.03
Sd of idiosyncratic shocks, σ_ε	Too complex. See Appendix.			

Table 4: Best estimates and ranges of reasonable values for the turnover elasticities in the SM model. Using my turnover estimates.

	e_X^F	e_X^L	$S_X^{F,L}$	Range of $S_X^{F,L}$
Empirical estimate			0.05	
Flow value of unemployment, b	-1.14	0.147	-7.746	(-25.832)-(-0.306)
Worker's bargaining power, γ	-1	0	inf	(inf)-(inf)
Matching efficiency, η	1.025	0.083	12.381	(0.488)-(41.292)
Search costs, c^S	-0.41	-0.033	12.381	(0.488)-(41.292)
Training costs, c^T	-0.02	-0.066	0.305	(0.012)-(1.018)
Layoff costs of experienced workers, c^L	-0.001	-0.007	0.216	(0.009)-(0.72)
Sd of idiosyncratic shocks, σ	0.141	0.548	0.257	(0.008)-(0.805)

8.3 Tables and figures

Table 5: Best estimates and ranges of reasonable values for the turnover elasticities in the SM model. Using Shimer's turnover estimates.

	e_X^F	e_X^L	$S_X^{F,L}$	Range of $S_X^{F,L}$
Empirical estimate			0.05	
Flow value of unemployment, b	-1.121	0.101	-11.119	(-36.774)-(-0.592)
Worker's bargaining power, γ	-1	0	inf	(inf)-(inf)
Matching efficiency, η	1.036	0.057	18.28	(0.973)-(60.461)
Search costs, c^S	-0.415	-0.023	18.28	(0.973)-(60.461)
Training costs, c^T	-0.048	-0.075	0.641	(0.034)-(2.12)
Layoff costs of experienced workers, c^L	-0.004	-0.008	0.563	(0.03)-(1.861)
Sd of idiosyncratic shocks, σ	0.154	0.828	0.187	(0.008)-(0.631)

Table 6: Estimates of average adaptation period in weeks by occupational unemployment, Multi-City Study of Urban Inequality dataset

Occupational unemployment	$Avg(t)$	$Avg(\ln t)$	$exp\,[Avg(\ln t)]$	$median\,(t)$	N
lowest decile	57.47	3.34	28.08	24	142
2nd	48.39	3.18	24.16	24	218
3rd	38.96	2.59	13.31	12	104
4th	31.48	2.86	17.39	24	258
5th	25.87	2.69	14.80	14	515
6th	26.88	2.38	10.77	12	559
7th	22.02	2.28	9.80	8	334
8th	21.01	2.31	10.03	12	513
9th	16.57	2.03	7.62	8	337
highest decile	14.26	1.76	5.79	4	263
Total sample	29.32	2.55	12.80	12	3243

*Adaptation period measures the time it takes for an average worker in the position to become fully competent. Occupational unemployment is defined as the average unemployment rate in the 2000 census in each of my 191 occupations. Deciles are taken in the 2000 census by dividing the population into 10 roughly equal groups based on their occupations. Higher number means higher unemployment rate in the occupation.

Table 7: Job loss and job finding probabilities by occupational unemployment deciles and major industries, linked monthly CPS, 1987-2013, Age 25-55

	Construction				Manufacturing			
	p^{EU}		p^{UE}		p^{EU}		p^{UE}	
	boom	recession	boom	recession	boom	recession	boom	recession
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
lowest decile	0.006	0.006	0.265	0.211	0.003	0.005	0.279	0.189
2nd	0.007	0.011	0.375	0.270	0.004	0.005	0.266	0.198
3rd	0.005	0.014	0.307	0.240	0.005	0.007	0.294	0.175
4th	0.012	0.013	0.344	0.198	0.006	0.007	0.281	0.199
5th	0.011	0.012	0.323	0.233	0.006	0.008	0.307	0.201
6th	0.018	0.026	0.417	0.289	0.009	0.011	0.325	0.215
7th	0.033	0.038	0.353	0.317	0.014	0.015	0.308	0.225
8th	0.030	0.037	0.391	0.269	0.018	0.020	0.306	0.227
9th	0.039	0.051	0.442	0.331	0.021	0.023	0.305	0.250
highest decile	0.048	0.058	0.385	0.313	0.027	0.028	0.342	0.276
Total	0.030	0.037	0.399	0.305	0.012	0.014	0.308	0.227

*The tables shows employment unemployment and unemployment-employment transition probabilities. The 10 occupational groups are deciles, based on the unemployment rates in the occupations in the 2000 census. Lowest decile means occupations with the lowest unemployment rates in 2000. Recession refers to time periods with high aggregate unemployment rates: 1982-1983; 1991-1994; 2002-2004; 2009-2013. Booms cover the rest of the years between 1978 and 2013.

Table 8: Job loss and job finding probabilities by occupational unemployment deciles and major industries, linked monthly CPS, 1987-2013, Age 25-55

	Public sector, Health, Education				Other industries			
	p^{EU}		p^{UE}		p^{EU}		p^{UE}	
	boom	recession	boom	recession	boom	recession	boom	recession
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
lowest decile	0.004	0.005	0.468	0.365	0.004	0.005	0.323	0.240
2nd	0.004	0.004	0.323	0.245	0.006	0.007	0.335	0.230
3rd	0.004	0.006	0.308	0.233	0.006	0.008	0.311	0.215
4th	0.007	0.008	0.403	0.286	0.006	0.007	0.309	0.223
5th	0.006	0.007	0.345	0.269	0.008	0.010	0.343	0.240
6th	0.006	0.008	0.324	0.223	0.011	0.013	0.349	0.238
7th	0.011	0.014	0.372	0.261	0.016	0.017	0.360	0.256
8th	0.009	0.011	0.315	0.212	0.017	0.020	0.332	0.244
9th	0.011	0.013	0.303	0.245	0.023	0.025	0.332	0.250
highest decile	0.012	0.012	0.283	0.238	0.028	0.032	0.346	0.271
Total	0.006	0.007	0.354	0.269	0.012	0.014	0.339	0.245

*The tables shows employment unemployment and unemployment-employment transition probabilities. The "other industries" category covers the following sectors: Extractive; Transportation and utilities; Wholesale and retail trade; Finance; Professional and business services; personal services; and agriculture. The 10 occupational groups are deciles, based on the unemployment rates in the occupations in the 2000 census. Lowest decile means occupations with the lowest unemployment rates in 2000. Recession refers to time periods with high aggregate unemployment rates: 1982-1983; 1991-1994; 2002-2004; 2009-2013. Booms cover the rest of the years between 1978 and 2013.

Table 9: job loss probabilities by moving status, SIPP sample

	Total	Nonmover	Moved, same county	Moved, same state	Moved, different state	Other
2005	0.013	0.012	0.036	0.034	0.073	0.027
	[0.000]**	[0.000]**	[0.010]**	[0.014]*	[0.024]**	[0.011]*
2006	0.011	0.011	0.006	0.039	0.033	0.022
	[0.001]**	[0.001]**	[0.005]	[0.020]	[0.025]	[0.010]*
2009	0.021	0.021	0.026	0.045	0.091	0.029
	[0.001]**	[0.001]**	[0.008]**	[0.020]*	[0.032]**	[0.012]*
2010	0.016	0.016	0.024	0.027	0.077	0.036
	[0.001]**	[0.001]**	[0.008]**	[0.019]	[0.028]**	[0.014]**
N	279376	275654	1753	591	360	1018

*Robust and clustered standard errors on the individual level. * and ** denote significance at 5 and 1 percent.

Table 10: job finding probabilities by moving status, SIPP sample

	Total	Nonmover	Moved, same county	Moved, same state	Moved, different state	Other
2005	0.317	0.317	0.378	0.320	0.150	0.279
	[0.009]**	[0.009]**	[0.080]**	[0.153]*	[0.092]	[0.088]**
2006	0.320	0.320	0.392	0.295	0.431	0.174
	[0.013]**	[0.013]**	[0.105]**	[0.195]	[0.302]	[0.153]
2009	0.214	0.215	0.228	0.162	0.100	0.101
	[0.006]**	[0.006]**	[0.054]**	[0.093]	[0.069]	[0.046]*
2010	0.207	0.206	0.268	0.239	0.252	0.212
	[0.006]**	[0.006]**	[0.067]**	[0.102]*	[0.109]*	[0.073]**
N	18936	18522	194	49	55	112

*Robust and clustered standard errors on the individual level. * and ** denote significance at 5 and 1 percent.

Table 11: Aggregate job loss probabilities in different samples using different estimation methods, Age 25-55

	SIPP		Linked monthly CPS	
	Any transition	Month-month	Adjusted for time aggregation	Transition probability
2005	0.013	0.010	0.012	0.010
2006	0.011	0.009	0.013	0.010
2009	0.021	0.017	0.019	0.017
2010	0.016	0.014	0.017	0.015

*The table shows monthly job loss probabilities in the SIPP and CPS. The data is in long, person-month, format. Column "Any transition" shows the probability of reporting job loss in any weeks of the given month. Column "Month-month" shows job loss probabilities between the 4th weeks of the consecutive months. Column "Transition probability" shows job loss probabilities between consecutive months in the CPS. Column "Adjusted for time aggregation" adjusts the job loss probabilities with the procedure described in Section 4.2 in order to approximate any job loss in the given month.

Table 12: Aggregate job finding probabilities in different samples using different estimation methods, Age 25-55

	SIPP		Linked monthly CPS	
	Any transition	Month-month	Adjusted for time aggregation	Transition probability
2005	0.317	0.306	0.341	0.339
2006	0.32	0.307	0.370	0.368
2009	0.214	0.203	0.211	0.209
2010	0.207	0.199	0.209	0.207

*The table shows monthly job finding probabilities in the SIPP and CPS. The data is in long, person-month, format. Column "Any transition" shows the probability of reporting job finding in any weeks of the given month. Column "Month-month" shows job finding probabilities between the 4th weeks of the consecutive months. Column "Transition probability" shows job finding probabilities between consecutive months in the CPS. Column "Adjusted for time aggregation" adjusts the job finding probabilities with the procedure described in Section 4.2 in order to approximate any transitions in the given month.

Table 13: Job loss probabilities in different samples using different estimation methods, by occupational unemployment tertiles, Age 25-55

		SIPP		Linked monthly CPS	
		Any transition	Month-month	Adjusted for time aggregation	Transition probability
2005	Lowest	0.007	0.006	0.006	0.005
	Medium	0.012	0.010	0.010	0.009
	Highest	0.020	0.016	0.023	0.019
2006	Lowest	0.006	0.005	0.006	0.005
	Medium	0.009	0.007	0.011	0.009
	Highest	0.020	0.016	0.025	0.020
2009	Lowest	0.011	0.009	0.009	0.008
	Medium	0.019	0.016	0.016	0.014
	Highest	0.036	0.029	0.036	0.032
2010	Lowest	0.009	0.008	0.007	0.007
	Medium	0.015	0.012	0.014	0.013
	Highest	0.028	0.022	0.032	0.029

*The table shows monthly job loss probabilities in the SIPP and CPS. The data is in long, person-month, format. Column "Any transition" shows the probability of reporting job loss in any weeks of the given month. Column "Month-month" shows job loss probabilities between the 4th weeks of the consecutive months. Column "Transition probability" shows job loss probabilities between consecutive months in the CPS. Column "Adjusted for time aggregation" adjusts the job loss probabilities with the procedure described in Section 4.2 in order to approximate any job loss in the given month. Lowest, medium and highest tertiles are defined based on the unemployment rates in the occupations in the 2000 census.

Table 14: Job finding probabilities in different samples using different estimation methods, by occupational unemployment tertiles, Age 25-55, Worked last year

		SIPP		Linked monthly CPS
		Any transition	Month-month	Transition probability
2005	Lowest	0.389	0.380	0.357
	Medium	0.342	0.336	0.348
	Highest	0.380	0.361	0.358
2006	Lowest	0.404	0.401	0.369
	Medium	0.304	0.290	0.360
	Highest	0.362	0.344	0.395
2009	Lowest	0.230	0.227	0.217
	Medium	0.237	0.222	0.197
	Highest	0.238	0.219	0.236
2010	Lowest	0.246	0.244	0.234
	Medium	0.274	0.260	0.205
	Highest	0.287	0.273	0.256

*The table shows monthly job finding probabilities in the SIPP and CPS. The data is in long, person-month, format. Column "Any transition" shows the probability of reporting job finding in any weeks of the given month. Column "Month-month" shows job finding probabilities between the 4th weeks of the consecutive months. Column "Transition probability" shows job finding probabilities between consecutive months in the CPS. Column "Adjusted for time aggregation" adjusts the job finding probabilities with the procedure described in Section 4.2 in order to approximate any transitions in the given month. Lowest, medium and highest tertiles are defined based on the unemployment rates in the occupations in the 2000 census.

Table 15: OLS regressions of job loss, linked monthly CPS, 1987-2013, Age 25-55

	[1]	[2]	[3]
Demeaned aggregate unemployment rate ($U_t^{aggregate}$)	0.131	0.195	0.143
	[0.003]**	[0.009]**	[0.010]**
Demeaned occupational unemployment rate ($U_{2000}^{occupation}$)	0.359	0.318	0.279
	[0.002]**	[0.002]**	[0.002]**
$U_t^{aggregate} \times U_{2000}^{occupation}$ interaction	3.585	2.93	2.172
	[0.169]**	[0.185]**	[0.185]**
Constant	0.013	0.014	0.013
	[0.000]**	[0.000]**	[0.000]**
Demographic controls		Y	Y
Demographic$\times U_t^{aggregate}$ interactions		Y	Y
Industry controls			Y
Industry$\times U_t^{aggregate}$ interactions			Y
N	13,337,680	13,337,680	13,337,680

*The aggregate unemployment rate is the average unemployment rate in the given year. Occupational unemployment is the average unemployment rate in detailed occupations in the 2000 census. Demographic controls include education (some college; at least BA vs. high school or less), age (35-44; 45-55 vs. 25-34), gender, African American, Hispanic, single statuses. Industry controls include: construction, manufacturing, public/health/education vs. all other industries. Robust standard errors clusterd on the individual level. * and ** indicate statistical significance at 5 and 1 percent respectively.

Table 16: OLS regressions of job finding, linked monthly CPS, 1987-2013, Age 25-55, unemployment-non participation transitions dropped

	[1]	[2]	[3]
Demeaned aggregate unemployment rate ($U_t^{aggregate}$)	-3.838	-4.359	-4.23
	[0.057]**	[0.156]**	[0.165]**
Demeaned occupational unemployment rate ($U_{2000}^{occupation}$)	0.325	0.504	0.373
	[0.030]**	[0.033]**	[0.034]**
$U_t^{aggregate} \times U_{2000}^{occupation}$ interaction	5.582	5.438	6.385
	[1.896]**	[2.068]**	[2.157]**
Constant	0.308	0.337	0.329
	[0.001]**	[0.003]**	[0.003]**
Demographic controls		Y	Y
Demographic$\times U_t^{aggregate}$ interactions		Y	Y
Industry controls			Y
Industry$\times U_t^{aggregate}$ interactions			Y
N	565125	565125	565125

*The aggregate unemployment rate is the average unemployment rate in the given year. Occupational unemployment is the average unemployment rate in detailed occupations in the 2000 census. Demographic controls include education (some college; at least BA vs. high school or less), age (35-44; 45-55 vs. 25-34), gender, African American, Hispanic, single statuses. Industry controls include: construction, manufacturing, public/health/education vs. all other industries. * and ** indicate statistical significance at 5 and 1 percent respectively.

Table 17: OLS regressions of job finding, linked monthly CPS, 1987-2013, Age 25-55, unemployment-non participation transitions coded as zero

	[1]	[2]	[3]
Demeaned aggregate unemployment rate ($U_t^{aggregate}$)	-2.913	-3.632	-3.489
	[0.049]**	[0.133]**	[0.141]**
Demeaned occupational unemployment rate ($U_{2000}^{occupation}$)	0.151	0.294	0.139
	[0.025]**	[0.027]**	[0.028]**
$U_t^{aggregate} \times U_{2000}^{occupation}$ interaction	7.17	6.325	8.063
	[1.608]**	[1.747]**	[1.816]**
Constant	0.254	0.294	0.282
	[0.001]**	[0.002]**	[0.002]**
Demographic controls		Y	Y
Demographic$\times U_t^{aggregate}$ interactions		Y	Y
Industry controls			Y
Industry$\times U_t^{aggregate}$ interactions			Y
N	681538	681538	681538

*The aggregate unemployment rate is the average unemployment rate in the given year. Occupational unemployment is the average unemployment rate in detailed occupations in the 2000 census. Demographic controls include education (some college; at least BA vs. high school or less), age (35-44; 45-55 vs. 25-34), gender, African American, Hispanic, single statuses. Industry controls include: construction, manufacturing, public/health/education vs. all other industries. * and ** indicate statistical significance at 5 and 1 percent respectively.

Table 18: OLS regressions of unemployment-non participation transitions, linked monthly CPS, 1987-2013, Age 25-55

	[1]	[2]	[3]
Demeaned aggregate unemployment rate ($U_t^{aggregate}$)	-0.975	-0.454	-0.399
	[0.043]**	[0.116]**	[0.124]**
Demeaned occupational unemployment rate ($U_{2000}^{occupation}$)	0.375	0.393	0.54
	[0.021]**	[0.023]**	[0.024]**
$U_t^{aggregate} \times U_{2000}^{occupation}$ interaction	-3.11	0.317	-1.804
	[1.388]*	[1.539]	[1.611]
Constant	0.171	0.126	0.139
	[0.001]**	[0.002]**	[0.002]**
Demographic controls		Y	Y
Demographic$\times U_t^{aggregate}$ interactions		Y	Y
Industry controls			Y
Industry$\times U_t^{aggregate}$ interactions			Y
N	681538	681538	681538

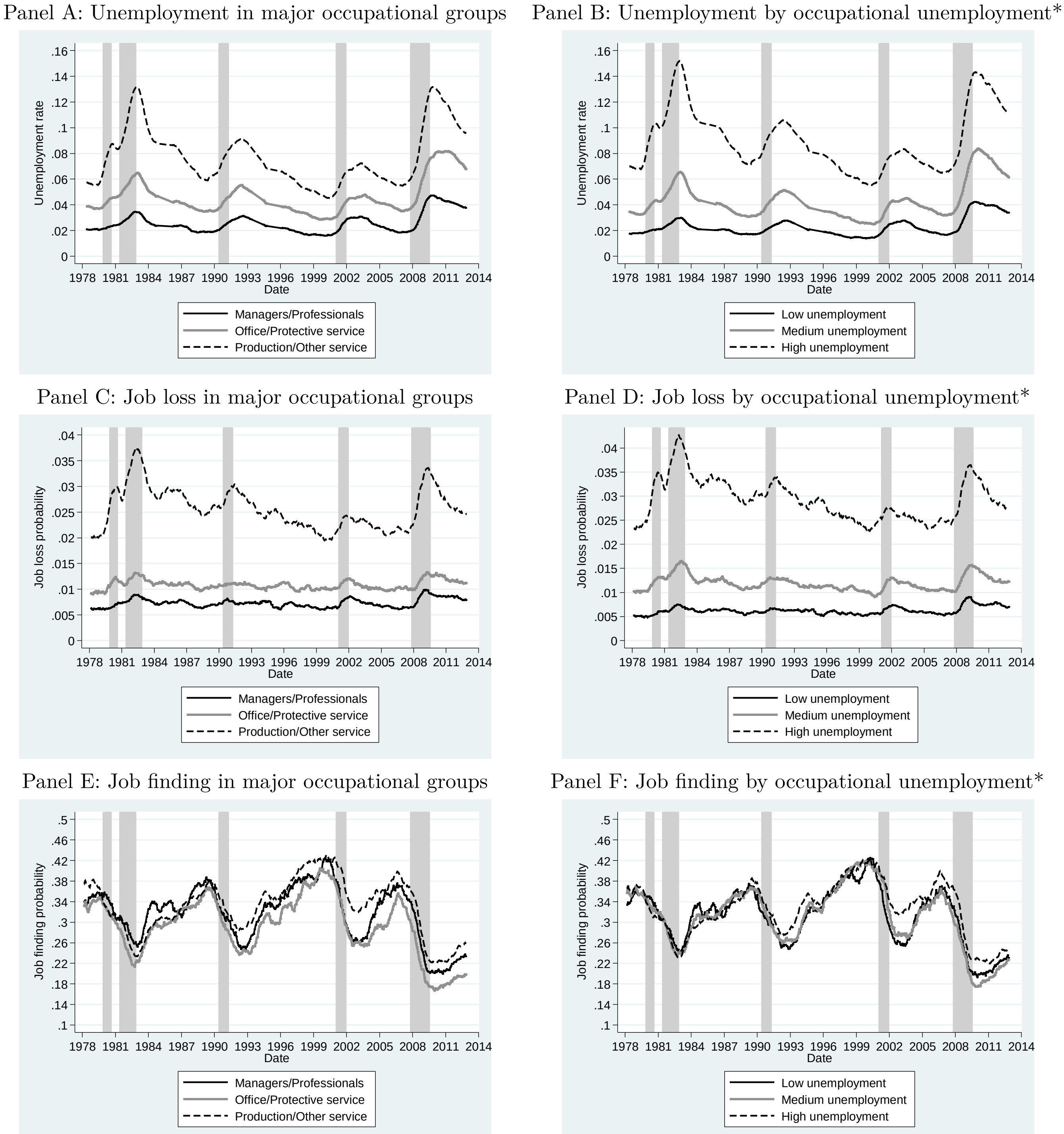
*The aggregate unemployment rate is the average unemployment rate in the given year. Occupational unemployment is the average unemployment rate in detailed occupations in the 2000 census. Demographic controls include education (some college; at least BA vs. high school or less), age (35-44; 45-55 vs. 25-34), gender, African American, Hispanic, single statuses. Industry controls include: construction, manufacturing, public/health/education vs. all other industries. * and ** indicate statistical significance at 5 and 1 percent respectively.

Table 19: Crowding out index by occupational unemployment deciles and labor market conditions, linked monthly CPS, 1987-2013, Age 25-55

	boom	recession
lowest decile	-0.002	0.003
2nd	-0.044	-0.026
3rd	-0.021	-0.014
4th	-0.043	-0.041
5th	-0.004	-0.009
6th	0.003	-0.005
7th	0.013	0.009
8th	-0.006	-0.005
9th	0.009	0.014
highest decile	0.023	0.020

*The table shows the crowding out index in 10 occupational groups defined by their unemployment rates in the 2000 census. The index is ratio: The numerator is the difference between unemployment-employment transitions into and out of the occupational group; and the denominator is the number of unemployed persons in the given occupation. Positive values indicate crowding out by other occupations as the inflows exceeds the outflows. Recession refers to time periods with high aggregate unemployment rates: 1982-1983; 1991-1994; 2002-2004; 2009-2013. Boom refers to all other years.

Figure 2: Unemployment rates, monthly job-loss and job-finding probabilities by occupational groups, March CPS 1978-2013



*Occupational unemployment is defined as the unemployment rate in the 2000 census in detailed occupations, and tertiles are taken in the 2000 census. All series are yearly moving averages of the monthly values. The job loss and job finding probabilities are adjusted for time-aggregation bias.