

**Essays in Macro and Labor Economics**

**A DISSERTATION  
SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL  
OF THE UNIVERSITY OF MINNESOTA  
BY**

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**IN PARTIAL FULFILLMENT OF THE REQUIREMENTS  
FOR THE DEGREE OF  
Doctor of Philosophy**

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**June, 2013**

# Acknowledgements

I would like to thank my adviser, Victor Rios-Rull, whose encouragement and help throughout my PhD was invaluable. I could not have been at Minnesota without him. To my face, his door was always open and behind my back he was always paving my roads in unseen but important ways. I cannot thank Fatih Guvenen enough for trying to impart the technique, demeanour and philosophy of a top-notch economist. As his RA, I should have been paying him as a private tutor instead and I could not thank him enough for all that he taught me throughout my graduate career. Jonathan Heatcote, Aaron Sojourner and Elena Pastorino also were wonderful for my final defense.

In my chapter on long-term unemployment I benefited from conversations with Alex Bick, Dirk Kreuger, Iourri Manovski, Ellen McGrattan, Amanda Michaud, Josep Pijoan-Mas, Kjetil Storesletten, Laura Sunder-Plassmann, Ludo Visschers, the participants of The Chicago Fed Search and Matching Workshop, The Penn Macro Club, The University of Illinois Summer Workshop, and Minnesota Macro-Labor Workshop. My chapter on occupational match quality benefited from collaboration with Fatih Guvenen, Burhan Kuruscu and Satoshi Tanaka. I would also like to thank Andy Glover, Elena Pastorino, and Michelle Rendall for useful discussions and the Defense Manpower Data Center for help with understanding the Armed Services Vocational Aptitude Battery.

Finally and most importantly, I need to thank and acknowledge my parents, Jamie and Ellen Wiczer, my brother Michael Wiczer and my partner, Christine O'Connell. All of whom supported me throughout.

# Dedication

To my grandparents. All of whom taught me much more significant lessons than anything in my PhD, but also who always encouraged me to value education and who always showed they were proud.

## Abstract

The first chapter studies the rate of long-term unemployment, which spiked during the Great Recession. To help explain this, I exploit the systematic and counter-cyclical differences in unemployment duration across occupations. This heterogeneity extends the tail of the unemployment duration distribution, which is necessary to account for the observed level of long-term unemployment and its increase since 2007. This chapter introduces a model in which unemployment duration and occupation are linked; it measures the effects of occupation-specific shocks and skills on unemployment duration. Here, a worker will be paid more for human capital in his old occupation but a bad shock may make those jobs scarce. Still, their human capital partly “attaches” them to their prior occupation, even when searching there implies a longer expected duration. Hence, unemployment duration rises and becomes more dispersed across occupations. Redistributive shocks and business cycles, as in the Great Recession, exacerbate this effect.

For quantitative discipline, the model matches data on the wage premium to occupational experience and the co-movement of occupations’ productivity. The distribution of duration is then endogenous. For comparison’s sake, if a standard model with homogeneous job seekers matches the job finding rate, then it also determines expected duration and understates it. That standard model implies just over half of the long-term unemployment in 1976-2007 and almost no rise in the recent recession. But, with heterogeneity by occupation, this chapter nearly matches long-term unemployment in the period 1976-2007 and 70% of its rise during the Great Recession.

The second chapter studies the link between wage growth and the match of a worker’s occupation and skills. The notion here is that if human capital accumulation depends on match quality, poor matches can have long-lasting effects on lifetime earnings. I build a model that incorporates such a mechanism, in which human capital accumulation is affected by imperfect information about one’s self. This informational friction leads to matches in which a worker accumulates human capital more slowly and has weaker earnings growth.

To get direct evidence, the chapter pieces together two sets of data on the skills used by an occupation and the skills a worker is particularly good at. Data on occupations describes occupations by the intensity with which they use many dimensions of workers' knowledge, skills and abilities. To pair, we have data on tests taken by respondents in a panel that tracks occupations and earnings. The test designers created a mapping between their tests and the occupational descriptors, which allows us to create two measures. The first measure of match quality is just the dot product between the dimensions of workers' skills and utilization rate of these skills by occupations. The second measure mismatch relative to an optimal matching computed using the Gale-Shapley algorithm for stable pairs. In both, worse matches have significantly slower returns to occupational tenure. With the most conservative estimate, plus or minus one standard deviation of mismatch affects the return to occupational tenure by 1% per year.

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# Chapter 1

## Introduction

This dissertation consists of two chapters.

- Chapter 1, “Long-term Unemployment,” quantifies how workers’ occupations contribute to their unemployment duration and its cyclical variation. It first introduces data on unemployment duration and how well one’s prior occupation forecasts expected duration. It then presents a model in which occupational skills attach a worker to jobs related to these skills while business-cycle frequency shocks affect the types of jobs that are available.
- Chapter 2, “Occupational Skills and Lifetime Earnings,” explores the link between lifetime earnings and the quality of match between a worker’s skills and his occupation’s skill requirements. It creates two measures of match quality using data on workers’ skills and the intensity with which an occupation uses them. It shows that these have significant effects on the return to occupational tenure and presents a model in which this might be the case.

## Chapter 2

# Long-term Unemployment: Attached and Mismatched?

### 2.1 Introduction

During recessions, there is a fall in the average rate at which unemployed workers find jobs and this implies an increase in unemployment duration and the share of long-term unemployed. However, the observed rise in unemployment duration during recessions outpaces that predicted by the fall in the average finding rate. In general, if all unemployed workers find jobs at the same rate, then duration is exponentially distributed, but this understates the tail of the observed distribution, which is quite fat. If this single finding rate matches the average finding rate, it understates the share of long-term unemployed by almost a half. Cyclically, the average finding rate implies only  $\frac{3}{4}$  of the standard deviation of the mean unemployment duration time-series. Even more, since 2007 the fall in the average finding rate captures less than  $\frac{2}{3}$  of the rise in long-term unemployment, which more than doubled. Instead, one must allow for heterogeneity—some workers will take much longer to find a job than others.

In this paper, I incorporate heterogeneity by introducing occupations into an otherwise standard search and matching model, à la Pissarides (2000). In it, jobs require occupation-specific skills and their productivity is affected by occupation-specific shocks. Workers who become unemployed are still “attached” to their prior occupation: their skills are still suited for this occupation and so they are relatively unproductive in other

jobs who are, in turn, reluctant to hire them. At the same time, their prior occupation will reward their skills, and so they skew their search towards jobs with this higher wage. The result is the workers from an occupation with a cyclically low finding rate suffer longer unemployment duration than workers from other occupations.

I show that the data is consistent with this mechanism; there are sizable differences in the job finding rate conditional on one's prior occupation and this dispersion is counter-cyclical. I incorporate the mechanism into a model with occupations and search and study the properties of unemployment duration. Finally, I set the model's state to match counter-parts in the Great Recession and then test whether it can replicate the distribution of unemployment duration in this period.

To generate cyclical fluctuations in long-term unemployment, the model generates counter-cyclical dispersion in finding rate and duration between occupations. For this equilibrium result, I assume that occupations differ in their cyclical sensitivity. Hence, some occupations fare better than others in a recession. Those attached to the wrong occupation will suffer longer unemployment spells than searchers skilled in other occupations. This makes the tail of the distribution of unemployment duration extend by even more than would be implied by the fall in the average finding rate. We see this same feature in the data: counter-cyclical dispersion that contributes to the elongation of the tail of duration.

As I have begun to emphasize, this chapter is important because standard search theory misses in its predictions for long-term unemployment, but understanding cyclical fluctuations in long-term unemployment is also important because they play a large part in fluctuations in the average unemployment rate. As pointed out by Hornstein (2012), much of the fluctuation in unemployment is due to the variation in the finding rate and much of the variation in the finding rate comes from the finding rate associated with longer durations. The same counter-cyclical dispersion in the finding rate that makes long-term unemployment rise during recession also contributes to fluctuations in the unemployment rate.

Quantitatively, can my mechanism generate the rise in long-term unemployment observed during the Great Recession and recessions generally? To put this differently, if recessions affect searchers differently depending upon their prior occupation, how much of the rise of long-term unemployment can be accounted for by searchers whose

occupations suffer greatly during a recession?

To associate quantities with the effects of my mechanism I map my model to data. I estimate the wage loss associated with switching occupations after a separation. This quantifies the motive for workers to search within their own occupation. On the other side, I measure the occupational productivity that drives fluctuations in the hiring demand in each occupation. The model then predicts how much searchers will favor their old occupation and how much this will prolong their unemployment.

I use data on workers employment, occupation and wage histories in the Survey of Income and Program Participation (SIPP) from 1996-2007 to estimate the fall in wages workers will face if they begin a job in a new occupation. Because the wages are only observable from occupations optimally chosen by searchers, I take a structural approach to this estimation. The same endogenous selection biases exist in model-generated data, so I use indirect inference to estimate the structural parameters governing wage loss.

To estimate the process of occupation-specific shocks, I again employ a structural approach. Because workers who change occupations lose human capital and are less productive, observed output per capita is endogenous. I use indirect inference with data on observed output per capita to estimate the joint process for exogenous shocks to occupational productivity. The specification of these shocks prescribes that “mismatch” is a *cyclical* phenomenon: shocks are mean-reverting and the increase in dispersion comes largely from heterogeneity in their cyclical sensitivity.

This basic mechanism—some unemployed searchers are “mismatched” because their skills do not resemble those used in the more highly productive occupations—helps explain why unemployment duration rises more in recession. This effect increases unemployment duration beyond that which can be explained by a single matching rate. Since 1976, standard deviation of the log of average unemployment duration was 0.24. A standard search and matching model, as presented in Pissarides (2000), predicts only 5% of this volatility. In contrast, my model predicts two-thirds.

Important for realistic long-term unemployment, the cross-sectional standard deviation of duration is counter-cyclical. In the data its correlation with average unemployment is 0.37. In the model, the correlation is 0.6, while any model with a single rate generates no dispersion. Dispersion is counter-cyclical because occupations’ productivity differs in cyclically sensitivity and adjustments costs are asymmetric. In other



words, the dispersion in productivity increases symmetrically in high and low ebbs of the cycle but adding labor is slower than shedding it.

This cyclical asymmetry also relates to a very important intuition about the cyclicity of the value of skills. In recessions the value of skills rises, and this makes it harder to switch occupations. The reasoning is two-fold: non-linearity in the returns—induced by the less-volatile outside options—and endogenous separation rates that are higher for unskilled workers. When an aggregate productivity shock hits, both experienced and inexperienced lose productivity symmetrically, but the total size of the match surplus was always smaller for the inexperienced workers; hence, their probability of separation rises by more and proportionately because their outside option in unemployment is still high.

As a side benefit, the model delivers a “hook” in the Beveridge curve. The efficiency of matching is endogenous and pro-cyclical, a correlation of 0.44 with average productivity. So the probability an average job applicant finds a match is lower in recession than would be predicted by the average number of vacancy postings. When the matching efficiency falls in recession, that shifts out the Beveridge curve, which also appears as an upward hook. All of this occurs because workers can choose where to search, and by searching more where there are relatively few vacancies, as in their own occupation, they lower the average matching efficiency.

Finally, I use this model to measure how much of the drastic increase in duration during the Great Recession can be attributed to the mismatch between unemployed workers’ occupation-specific skills and the set of occupation-specific productivity shocks. To begin this exercise, I take as given the state of the economy: (i) the distribution of unemployed workers split by prior occupation in 2007 and (ii) the history of aggregate and occupation-specific labor productivity shocks from 2008-2010. The model then determines the unemployment dynamics. In this period, the rise in long-term unemployment duration was particularly striking, an 88% increase. The model generates a 70% rise, whereas the average finding rate from the data implies only half of the increase and a simple Mortensen-Pissarides model implies almost no rise.

The experiment in the model also includes unemployment insurance extensions, which grew to 24 months. To measure their impact, I compare the baseline, including the extensions, to an identical world in which the extensions do not occur. I find

that without the unemployment benefit extensions, the rise of long-term unemployment would have been 30% lower. This result is consistent with a body of work that finds unemployment benefits played a role in the increase in unemployment in the period. However, unemployment benefit extensions are certainly not the only factor in the increase in unemployment duration.

The rest of the paper proceeds as follows: in Section 2.2 I review related literature and then discuss some motivating data on unemployment duration in Section 2.3. In Sections 2.4 and 2.5 I describe the model and my quantitative strategy, respectively. A discussion of its business cycle properties follows in Section 2.6. I test it with data from the Great Recession in Section 2.7 and then conclude in Section 2.8.

## 2.2 Related Literature

To understand the nature of a recession, I borrow from a long literature on counter-cyclical risk. Lilien (1982) and Abraham and Katz (1986) present competing views for why the dispersion of employment growth across sectors should widen in a recession. Whereas Lilien (1982) and many others since have speculated that the variance of idiosyncratic shocks is itself stochastic and counter-cyclical, the other side attributes counter-cyclical dispersion to differences in the cyclical sensitivity. In some contexts, endogenous variables such as unemployment and vacancies could be used to discriminate the two specifications, but Hosios (1994) casts doubt, showing that dispersion shocks may entail vacancy and unemployment co-movements very much like aggregate shocks. His results shows why a asymmetric shocks may bring very large changes in unemployment, as we have observed. This paper takes a specification that most closely follows Abraham and Katz (1986), but also incorporates some stochastic dispersion components via a process of unobservable factors. My heterogeneity in cyclical sensitivity means that productivity dispersion responds symmetrically to expansion and recessions. However, the dispersion across occupations in labor variables—employment growth, unemployment rate, and unemployment duration—is counter cyclical due to asymmetries in the structure of the model.

In the Great Recession, several studies have approached to what extent it was asymmetric and what are the ramifications of this asymmetry. On the one hand, Lazear and

Spletzer (2012) are skeptical that unemployment is “structural,” but acknowledges that there is industrial asymmetry in the effect of the recession and that “mismatch” rose during the recession. Hobijn (2012), on the other hand, posits that the peculiar composition of new job postings across occupation and industry has significantly slowed the number of successful new matches in the recession and recovery. In this camp, Mehrotra and Sergeyev (2012) use factor analysis to isolate shocks that affect only certain sectors, a technique used in this paper as well. They find strong evidence that the recession affected different sectors differently. Finally, Sahin et al. (2012) try to connect the unemployment rate to the asymmetry of vacancy postings and unemployed workers across occupations. They find the effect of “mismatch” is at most  $\frac{1}{3}$  of the increase in unemployment in the Great Recession.

My model builds on the “islands” structure of Lucas and Prescott (1974), who introduce this basic trade-off faced by agents in my model: an unemployed worker must choose whether to stay or go. I have some common ancestry with Alvarez and Shimer (2011) and Carrillo-Tudela and Visschers (2013) in that all extend Lucas and Prescott (1974) to include within-islands unemployment. In Carrillo-Tudela and Visschers (2013) as here, unemployment occurs because of search and matching frictions as in Pissarides (2000) as well as between island unemployment. Workers may be unemployed because they are misallocated across islands or because of search frictions that exist on all islands. In both papers, workers develop specific human capital that affects their probability to search elsewhere and both have non-trivial distributions of finding rates that are lower among longer unemployed workers. Compared to Carrillo-Tudela and Visschers (2013), the nature of shocks and market structure is quite different. I include occupation-specific shocks and search islands are segmented by occupation and prior occupation, whereas their islands are more diverse, labelled by human-capital and match quality, and non-aggregate shocks are to match quality. I also model endogenous separations differently from them, as I follow den Haan et al. (2000). And whereas unemployed workers search directionally in my model, theirs may stay or sample the distribution. Finally, the dynamics of the islands in my model is quite different from theirs. Their islands can shut down leading to “rest unemployment,” in which workers wait for an island to reappear, and contributes significantly to unemployment in their model but not in mine. Given these differences in the theoretical structure, our mappings to data

are also quite different, e.g., the reallocative force in my model, occupational shocks, come from productivity, whereas they use workers' flows and the distribution of finding rates.

Occupation-specific human capital plays a crucial role in my model, as it is the source of heterogeneity amongst the unemployed. Ljungqvist and Sargent (1998) also study how searchers may be unemployed for longer because of their human capital from their prior job. They focus on how the secular increase in "turbulence," which they map to transitory income shocks, implies a long-term increase in unemployment duration in Europe. In their mechanism, the long-term unemployed are separated workers whose skills are lost (antiquated) and chose to enjoy their relatively high unemployment benefit. Their job-finding rate is low because their unemployment benefits increase their outside option. On the other hand, skilled unemployed in my model are still suitable employees in their own occupation. They have relatively low job-finding rate outside their own occupation because they have a high outside option in another sector and because they rarely search in these other labor markets. However, workers in my model are still quite employable in their own occupations. These two models will deliver starkly different policy implications regarding targeted spending and changes to unemployment benefits, both of which will be explored in greater detail. Furthermore, my model derives wage and finding rates by equilibrium, whereas theirs does not.

In my framework, as in Ljungqvist and Sargent (1998), unemployment duration and finding rate are negatively-correlated because of composition effects. For both, workers enter unemployment with characteristics that lower their matching probability and, definitionally, are a larger fraction of the long-term unemployed than the rest of the unemployed workers. There is a long tradition of papers analyzing the negative correlation between unemployment duration and job finding rate. Clark and Summers (1979), Machin and Manning (1999) and Elsby et al. (2008) all chronicle this feature in the US and Europe in both expansions and recessions. According to this literature, the correlation is remarkably robust, but its cause is more difficult to discern. Heckman (1991) describe the econometric task of identifying "true" duration dependence, when an individual's finding rate falls because of the duration of his unemployment spell, or composition. Heckman and Singer (1984) establishes some separability conditions under which identification can be unravelled, and Heckman (1991) expands on this further.

Starkly, my model is going to abstract from duration dependence and will study only the composition effect generated by the mechanism.

The empirical side of this study borrows from a literature on earnings dynamics and occupational choice. The focus on occupation-specific human capital is, in large part, justified by work such as Kambourov and Manovskii (2009b), which emphasizes its importance in wage determination. The occupation choice process built into my equilibrium model will bear strong resemblance to the conditional logit model estimated by Boskin (1974). Finally, Altonji et al. (2009) also use indirect inference to estimate earnings in a richer environment but with some of the same complications. They consider a model of wage determination with the discrete choice to switch jobs. To smooth over this discrete choice, they use a logit-like model first proposed in Smith and Keane (2004), a feature already present in the structure of my model.

### 2.3 Descriptive Data on Unemployment Duration

In the Great Recession, unemployment duration<sup>1</sup> rose unprecedentedly, as shown in Figures 2.1 through 2.3. Notably, this rise went beyond that expected by a uniform fall in the job finding rate. In Figure 2.2, I plot the fraction of long-term unemployed. Complementary, Figure 2.3 plots the true unemployment duration and that which is implied by single finding rate that matches outflows from unemployment. The single finding rate's duration is always lower than the true duration, because some workers have exceptionally long durations, which pulls up the average.

Essentially, all this discussion boils down to Jensen's inequality. To illustrate, suppose individuals have finding rate rate  $f_t^i$  and  $f_t^*$  is the finding rate that matches the aggregate monthly flow from unemployment to employment. This is to say  $f_t^* = 1 - \frac{u_{t+1} - u_{t+1}^{<1}}{u_t}$ , where  $u_{t+1}^{<1}$  are the unemployed for less than one period, i.e. the newly

---

<sup>1</sup>Everywhere in this paper unless otherwise noted, unemployment duration refers to the expected time before a match into employment. The BLS defines unemployment duration as the average time unemployed of the current pool of unemployed people. This however, conflates slow finding rate with the inflow rate of unemployed. If there are many newly unemployed people, this will tend to *reduce* duration by their measure.

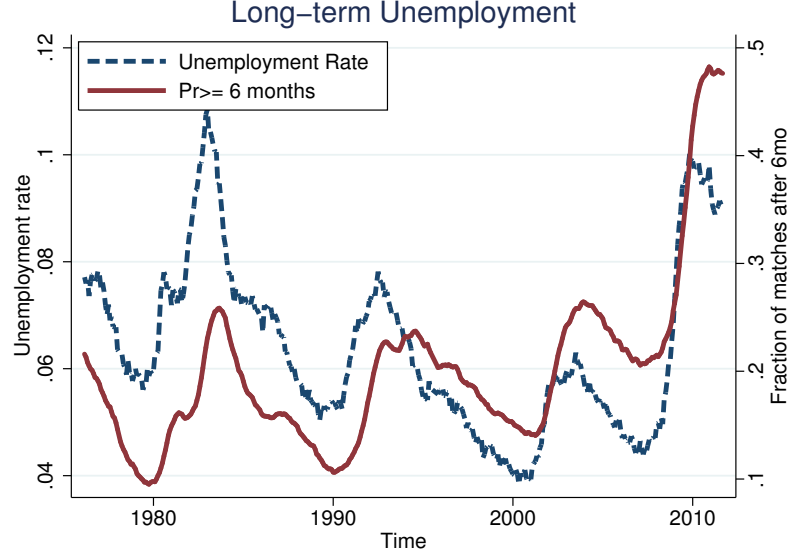


Figure 2.1: The unemployment rate (dashed, left axis) and fraction of unemployed whose expected duration is  $\geq 6$  mo.

separated workers. As pointed out by Shimer (2012), whether  $f_t^i = f_t^* \forall i$  or not

$$\int_i f_t^i di = f_t^* = 1 - \frac{u_{t+1} - u_{t+1}^{<1}}{u_t}$$

However, the expected duration with heterogeneous finding rate will be quite different:

$$\int_i \frac{1}{f_t^i} di \geq \frac{1}{f_t^*}$$

Many others have rejected that  $f_t^i = f_t^* \forall i$  in the US and elsewhere, see e.g. Machin and Manning (1999) or Elsby et al. (2008)<sup>2</sup>. I use the unemployment duration question in the CPS to construct a non-parametric Kaplan-Meier estimator for the hazard rate from unemployment to employment. For individuals of duration  $d$ , the estimator  $f_t^d$ , is the cumulative hazard over a month for finding employment. As in Clark and Summers (1979), I count those who leave the labor force as if they were not in the at-risk

<sup>2</sup>It is often the practice to convert monthly rates into continuous time rates. I leave all finding rates at a monthly interval for consistency with this paper's model, which will be discrete time with month-long periods.

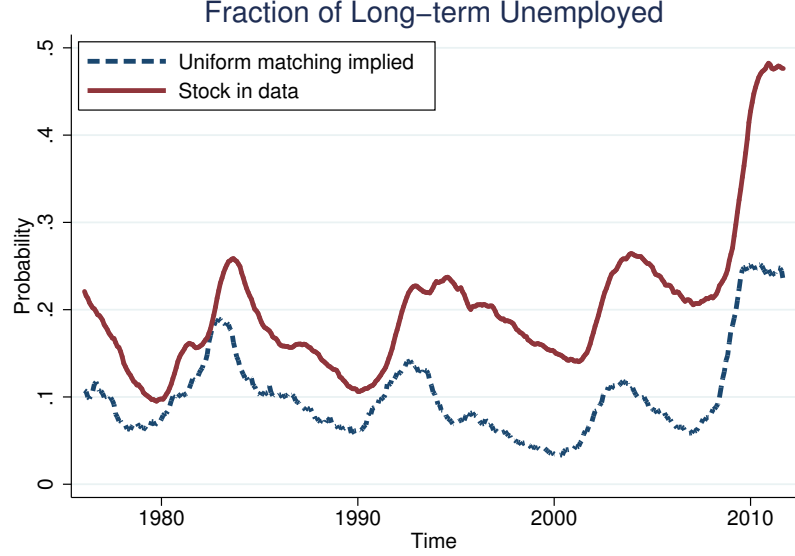


Figure 2.2: The probability of at least 6 months unemployment before finding a job

population

$$f_t^d = \frac{F_{t+1}^d}{u_t^d - I_{t+1}^d} \quad (2.1)$$

Where  $u_t^d$  are the unemployed in duration bin  $d$ ,  $F_{t+1}^d$  are the subset who find employment in the next period and  $I_{t+1}^d$  are those who leave the labor force in period  $t + 1$ . As can be seen in Figure 2.4, there is considerable heterogeneity in finding rate. Moreover, in the Great Recession there was a large fall in the finding rate and especially for longer-durations.

These fluctuations at long durations are borne out in Figures 2.2 and 2.3, which were constructed using the durations implied by the estimator in Equation 2.1. These show that the finding rate at long durations can greatly affect unemployment duration over the cycle.

### 2.3.1 Unemployment duration and occupation

This paper will link the apparent heterogeneity in finding rates to differences by prior occupation. Further, I will show that this heterogeneity is affected by business cycles.

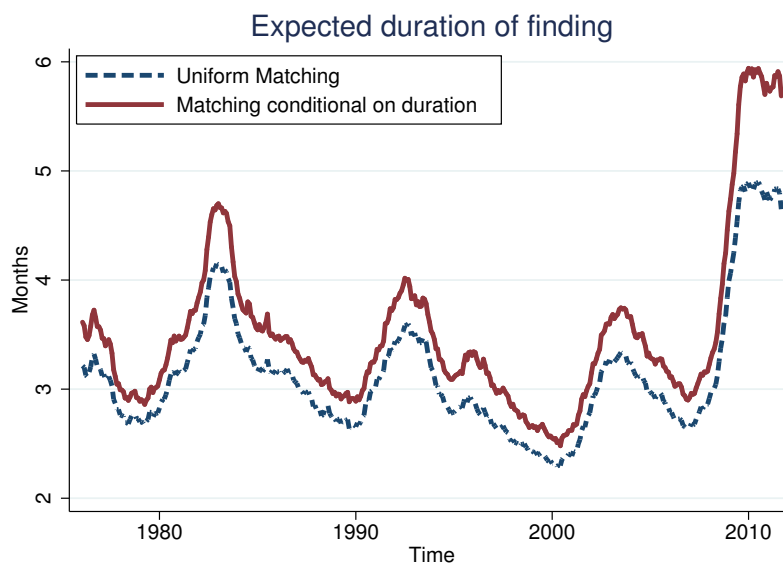


Figure 2.3: The mean duration before finding a job

While other studies, e.g. Hornstein (2012), attribute differences in finding rate to inherent and unobservable heterogeneity, the connection to prior occupation has several advantages. Most importantly, my take is more “structural” in attributing causality to agents’ primitive choices in which the incentives are observable. If observed dispersion in finding rate is due to attachment to one’s prior occupation, then this heterogeneity is not policy neutral, as implied by giving individuals’ unobservable fixed-effects. Moreover, unemployment duration fluctuates greatly and differently in different cycles. With a more structural interpretation, we can predict what conditions affect this. In particular, duration will increase if occupation-specific skills become more important or there is more mismatch between highly productive occupations and the skills of the unemployed.

Why is prior occupation a good dimension on which to separate people? A good deal of scholarship has been devoted to the importance of occupation-specific experience and skills. Kambourov and Manovskii (2009b) were very influential in highlighting the returns to occupational tenure as being larger than other forms of tenure, such as employer or industry tenure. In their baseline, they attribute to occupational tenure a 5-year return between 12-20%. Sullivan (2010) adds some nuance to this result, pointing



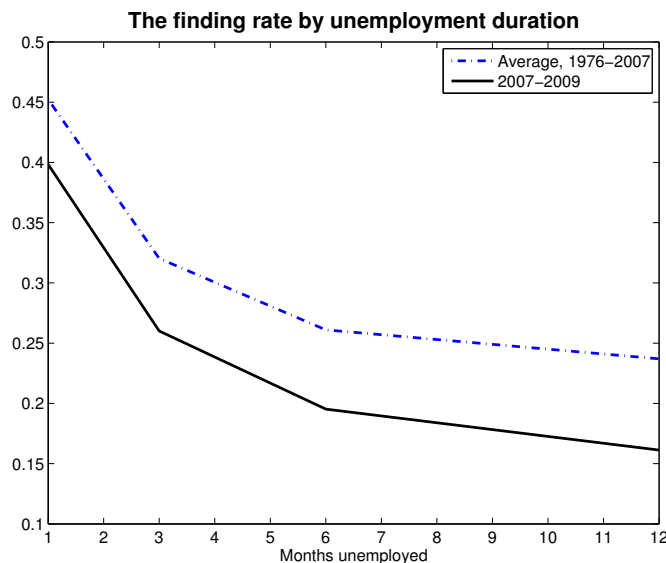


Figure 2.4: The job finding rate falls as the duration increases

out that, on average, occupational tenure has higher returns than industry tenure though there are some jobs in which industry matters more, e.g. management. He uses NSLY data, rather than PSID as in Kambourov and Manovskii (2009b), but still finds average 5-year returns between 15-25%. Occupational returns are between twice and eight times as high as industry returns when both are included in the regression. All of these studies have to deal with two significant problems that make estimates of the return less certain. First, adding experience in occupation, industry and employer to a simple wage regression is fraught with problems of endogeneity because if the unobservable quality of the match is better it will tend to last longer. Altonji and Shakotko (1987) present one instrumental strategy but this is not without its problems, discussed later in the quantitative section. The weight of the evidence, however, points to occupation-specific skills being especially important.

Unemployment is observably different depending on one's prior occupation. As can be seen in Figures 2.5(a) and 2.5(b), unemployment differs across occupations both in its length and breadth. The left are the differences in unemployment rate across occupations<sup>3</sup>. Note that this dispersion is generally counter-cyclical. The correlation between

<sup>3</sup>For occupation  $j$ , this is the number of unemployed whose prior occupation was  $j$  divided by those working and unemployed that last worked in  $j$ .

the aggregate unemployment rate and the log of unemployment across occupations is 0.3.

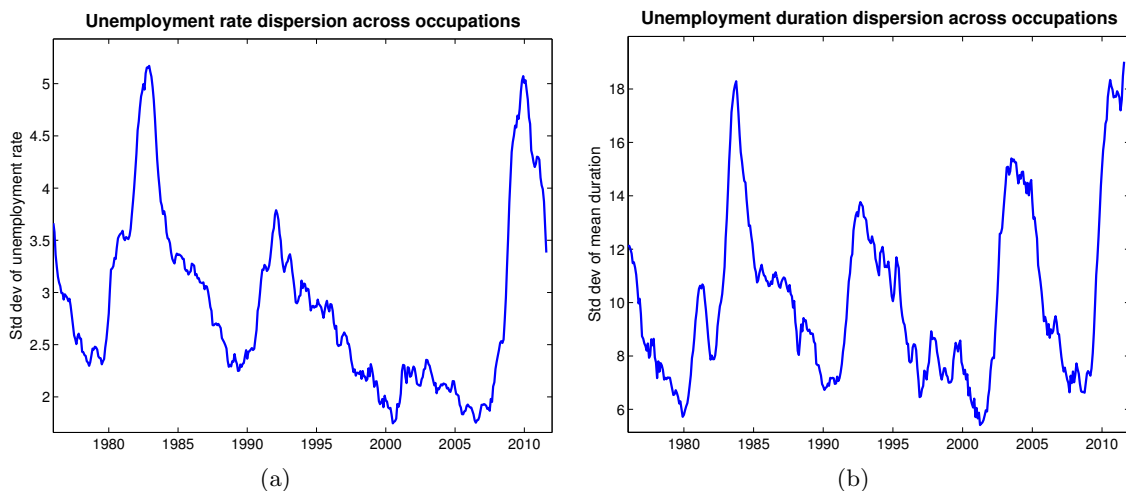


Figure 2.5: Dispersion across occupations is counter-cyclical

Even more important for this study, Figure 2.5(b) shows that the expected duration of unemployment varies across occupations. This dispersion is consistent with unemployed workers who are attached to their prior occupation. Otherwise, if all workers abandoned their old skills and minimized their duration, every unemployed worker would have the same finding rate. Just like unemployment dispersion, the dispersion in duration is counter-cyclical: if attachment differentiates searchers, recessions exacerbate these effects. It is slightly less cyclical than unemployment dispersion; the correlation between the unemployment rate and log-duration is 0.37.

Looking more closely at the micro-level data behind counter-cyclical dispersion, unemployment duration is longer for those that switch occupations and that this effect increased markedly in the Great Recession. In Table 2.1, I present the results of a simple regression of unemployment duration on occupation and industry switching dummies. Its form is  $\text{weeks unemployed} = D_{occ_t \neq occ_{t-1}} + D_{ind_t \neq ind_{t-1}} + \text{demographics} + t$ . We care about the crucial coefficients on the dummy for switching occupation,  $D_{occ_t \neq occ_{t-1}}$ , and for comparison's sake, also industry  $D_{ind_t \neq ind_{t-1}}$ . Here, a linear trend controls for the secular trend in unemployment duration, but a more flexible specification does not affect the results on the key coefficients.

	1978-2007		2008-2010	
	Coef	Std Err	Coef	Std Err
Occupation Switch	8.68	(0.294)	18.98	(0.844)
Industry Switch	4.53	(0.293)	4.44	(0.839)

Table 2.1: Coefficients on occupational switching from a regression of unemployment duration

So, how much of the downward-sloping employment finding rate can be explained purely by occupation-level heterogeneity? Figure 2.6 takes the mean finding rate within a given occupation since 1976 and then constructs the hazard rate at durations 1, 3, 6 and 12 months by taking the population weighted average<sup>4</sup> finding rate over occupations. It is important to emphasize that this is not a complete answer to the central question of this paper. Figure 2.6 takes the finding rate for individuals within occupations without considering the endogenous choice they are making of whether or not to switch occupations and, thus, change their finding rate. Rather, it takes as given what they choose to do. If some workers from an occupation are less likely than others to abandon their occupation than merely justified by their desire to preserve their skills, e.g. one's occupation has utility value, then the data will have even more heterogeneity. Conversely, if workers are more willing to switch for whatever reason, then occupation-level hazard rates will understate the heterogeneity in finding rates due to occupation-specific human capital.

Looking at Figure 2.6, the mean finding rate within an occupation misses much of the heterogeneity, especially of the very fast job finders. Still, the hazard has a downward slope because some occupations have, on average slower finding rates. Hence, this level of heterogeneity introduces more long-term unemployment than with a constant hazard. The Great Recession seemed to cause a near parallel shift down for the hazard function, rather than rotating it as we see with full heterogeneity. This shows that pure occupation-level heterogeneity cannot explain all of the rise in long-term unemployment, though it picks up some.

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<sup>4</sup>Weights here are by the fraction of the unemployed population at that duration. Hence, if  $x_\ell$  is the fraction of workers initially from a given occupation finding at rate  $f_\ell$ , those in the at-risk population by duration  $d$  are  $x_\ell e^{-f_\ell d}$ .

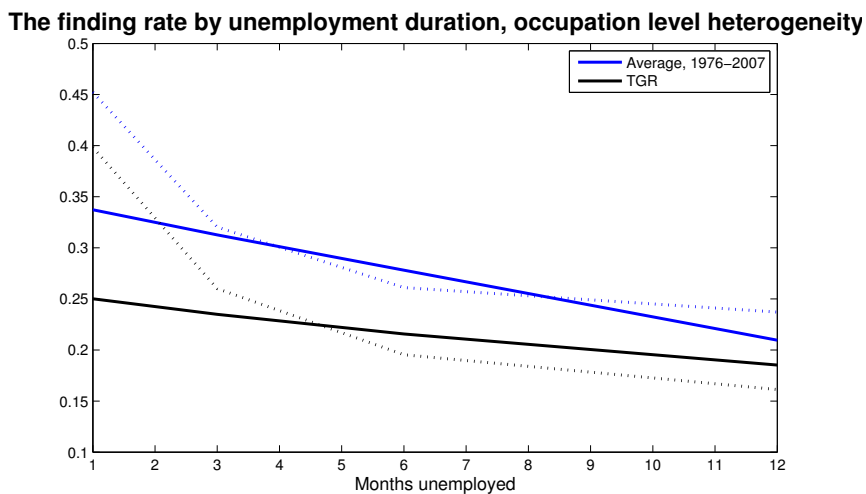


Figure 2.6: Finding rate using only occupation-level heterogeneity. Dotted lines are the actual finding rates

While Figures 2.5 and 2.6 are illustrative that unemployment is different across occupations, they are merely illustrative. As already alluded, the finding rate by occupation includes multiple confounding phenomena aside from the mechanism in question, the effect of human capital. In reality, search behavior systematically differs across occupations for reasons other than only those implied by human capital. Also, occupations may experience unemployment differently because of unobservable characteristics associated with occupation choice. For example, some occupations may attract older or younger workers who generally have different finding rates. These other factors will affect the occupation-level heterogeneity we observe but are not really attributable to the occupation-specific skills.

To isolate and quantify the effect on duration of one's attachment over the business cycle, I will estimate the skill loss associated with moving between occupations and how productivity evolves jointly across occupations. I now present my model, which joins these two forces, one pulling workers away from their occupation and the other keeping them in place.

## 2.4 The Model

I will present a model of directed search where the search markets are occupations. Occupations experience productivity shocks and moving across occupations incurs a cost. The model is designed to be mapped to data, so that parameters can be calibrated and so that the costs of moving across occupations and the process for occupation-specific shocks can both be structurally estimated. Then, the model will address:

1. Are business cycle fluctuations in unemployment and duration due to mismatch?
2. Can the productivity changes and skill distribution in the Great Recession explain long-term unemployment?

To address the first question, I analyze simulated histories from the model feeding in the productivity process and occupation switching costs that match the data. For the second, I begin with a pool of unemployed whose prior occupation matches that seen at the beginning of the Great Recession. I feed in shocks that match those observed in this recession and use the model to generate fluctuations in finding rates.

The model highlights the basic trade-off faced by agents: whether to stay and search narrowly within their own occupation or to leave and search more broadly. In the former, there will generally be a lower finding rate, but their return is higher. By switching they get a lower wage upon matching but it may increase their chance of getting a job. This is described graphically in Figure 2.7.

When the economy is hit by shocks, this behavior affects unemployment duration through two channels. First, because occupations differ in their cyclical sensitivity, during a downturn workers from harder hit occupations have particularly low finding rates. Second, because separations are endogenous and occupation-specific, the workers from low-ebb occupations are both disproportionately represented in the unemployment pool and also have a low finding rate. Again, this effect is worse during recessions.

### 2.4.1 Technology and preferences

Time is discrete. Production is split into  $J$  “occupations,” and workers have skills suited for an occupation. New workers coming from occupation  $\ell$  provide  $\omega_{\ell d}$  when they arrive in destination occupation  $d$ . The premium to experience is that  $\omega_{\ell\ell} = 1$  and  $\omega_{\ell d} < 1$ .

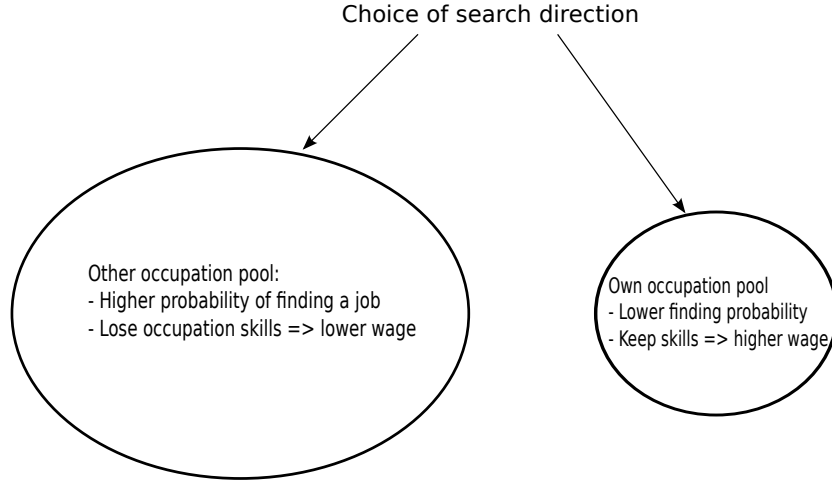


Figure 2.7: A searcher decides whether to look narrowly or outside of his field

Labor in an occupation is aggregated linearly in each type. So, if  $x_{\ell d}$  is the measure of workers working in  $d$  who last worked in  $\ell$  then the productive labor force of  $d$  is  $L'_d = \sum_{\ell=0}^J \omega_{\ell d} x'_{\ell d}$ . Note that production is done by the labor force at the end of the period after all transitions have completed, hence it uses  $L'_d$  rather than  $L_d$  that came into the period.

Buffeting these occupations are idiosyncratic shocks  $z_d$ , which are affected by the average level of productivity,  $Z$  and a set of factors  $\mathbf{f}_t$  that are unobservable but help determine co-movements. Aggregate productivity follows a simple AR(1) process and the vector of factors follows a VAR. Hence, productivity shocks are described the by system

$$Z_t = \rho_Z Z_{t-1} + \epsilon_t \quad (2.2)$$

$$z_{d,t} = \lambda_{f,d} \mathbf{f}_t + \lambda_{Z,d} Z_t + \rho_z z_{d,t-1} + (1 - \rho_z) \zeta_{d,t} \quad (2.3)$$

$$\mathbf{f}_t = \Gamma \mathbf{f}_{t-1} + \eta_t \quad (2.4)$$

For future notation, it will be helpful to define  $\mathcal{Z}$  as the state of the joint  $Z, \mathbf{f}, \{z_d\}$  process. The dispersion in coefficients  $\lambda_{Z,d}$  model differences in cyclical sensitivity while the factors  $\mathbf{f}_t$  and loadings  $\lambda_{f,d}$  allow for co-movements amongst some occupations in addition to the aggregate cycle. The form is meant to be a parsimonious model for

covariance because there are 22 occupations and so a dense estimate for  $E[\zeta\zeta']$  is infeasible.

Several additional shocks govern worker transitions. They become experienced at rate  $\tau$  meaning they provide productivity  $\omega_{dd} = 1$ . If an experienced worker is separated, he can keep that experience if he matches with the same occupation. Those who are separated while inexperienced become unattached to any occupation, and upon matching with an occupation  $d$  will provide  $\omega_{0d}$ .

To model endogenous separations, workers who enter the period with a job draw disutility from work,  $\xi_i \sim H$ . If large enough, it will provoke a separation. The separation policy will have a cutoff property, so for each type there will exist a  $\bar{\xi}$  such that for  $\xi < \bar{\xi}$  the match is no longer profitable the separation probability is  $s = H(\bar{\xi})$ . These shocks are i.i.d., following den Haan et al. (2000) who show that persistence of these shocks is not necessary to match dynamics of separations. By modelling separation-inducing shocks as preferences rather than productivity shocks, I deviate from den Haan et al. (2000) and most of the earlier literature. The problem is that productivity shocks complicate the task of matching observed productivity fluctuations. With productivity shocks, the bottom of the productivity distribution is laid off first in a recession, shifting up the mean of the distribution. This “cleansing” over the cycles means that the primitive shocks are more volatile than those observed.<sup>5</sup>

When they are searching for a job, there is also another shock  $\psi \sim F$  that captures their love of the new job. At the beginning of a period of searching, the agent  $i$  sees shocks from each occupation he may choose,  $\{\psi_{i,j}\}_{j=1}^J$ , but only experiences  $\psi_{i,d}$  in his destination occupation if he successfully finds a job.

Agents utility is linear and they enjoy consumption on top of the shocks. To summarize, worker  $i$  who stays matched the entire period will experience flow utility  $c_i + \xi_i$ . If that worker was newly matched in occupation  $d$  in that period he experiences  $c_i + \psi_{i,d}$ .

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<sup>5</sup>den Haan et al. (2000) elide this nuance.

### 2.4.2 Unemployment benefits

Workers who are unemployed receive a flow utility  $b_i$ . If they are still eligible for benefits,  $e = 1$ , this is a 50% replacement of their former salary.<sup>6</sup> With probability  $\delta$  benefits expire,  $e = 0$ , and then they receive food stamp support, as in Nakajima (2012), at 17% of average earnings. This random expiration modelling technique dates to Fredriksson and Holmlund (2001) and significantly reduces computational load and when I discuss the quantitative results, I will delve further into the implications of this simplification.

Note that unemployed workers do not enjoy leisure utility, which Hagedorn and Manovskii (2008) and others have shown plays an important role in matching the volatility of vacancy postings. This is because those working experience disutility from work and that plays a similar role in reducing the expected surplus from a match. In the baseline version of the model, I will set  $\delta = 0$  but discuss as an extension when it takes more realistic values.

### 2.4.3 Search and market structure

Each type of applicant  $(\ell, d, e)$  has its own labor search market  $m \in M$ , where  $M = \{(\ell, d, e) : \ell \in \{0, \dots, J\}, d \in \{1, \dots, J\}, e \in \{0, 1\}\}$ . The indices stand for the prior occupation,  $\ell$ , destination to which the worker is applying,  $d$ , and unemployment benefit status,  $e$ . The segmented search markets imply that there is a tightness  $\theta$  for workers with productivity level  $\omega_{\ell, d}$  and with benefits  $e$ , i.e. anything that could determine the value of the surplus other than aggregate variables. The matching function has constant returns to scale and the standard conditions on derivatives. The finding rate for workers is  $p(\theta^m)$  and for firms is  $q(\theta^m) = p(\theta^m)/\theta^m$ , where  $q' < 0 < p' < \infty$ .  $\kappa$  is the posting cost.

An individual unemployed worker with prior experience  $\ell^*$  and eligibility  $e^*$  chooses a vector  $\{g^m\}_{m \in M_{\ell^*, e^*}}$  as the probability of applying to destination markets  $m$ .  $M_{\ell^*, e^*}$  is the set of markets for which this worker can apply,  $M_{\ell^*, e^*} = \{(\ell, d, e) | \ell = \ell^*, d \in \{1, \dots, J\}, e = e^*\}$ . Given the state of the worker, denote the tightness he faces in market  $m$  as  $\theta^m$ . Hence, his realized match probability is going to be  $\sum_{m \in M_{\ell^*, e^*}} g^m p(\theta^m)$ .

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<sup>6</sup>I give 50% replacement of the average earnings of experienced or inexperienced workers. This is only a tiny difference in benefit but saves me from adding an entire state.



Wages are renegotiated each period by generalized Nash bargaining. Hence, they depend upon the output of the match,  $z_d \omega_{\ell d}$  and the preference shocks  $(\xi, \psi)$ . The firm's bargaining weight is  $\mu$ . This renegotiation ensures that separations are mutual and that no Pareto-improving transfer could occur.

## Timing

The timing is such that first all uncertainty is revealed, then matches are made and finally they produce. This means that there may be unemployment stints lasting less than a single period which helps match flows in the data to the discrete time model.

The period is divided into stages as follows:

1. Shocks to productivity
2. Employed workers become experienced
3. Random utilities are realized
4. Separations occur
5. Workers choose their search direction and matches happen
6. Production and consumption occurs
7. Benefits expire

### 2.4.4 Households

I now describe the recursive problem of workers in this economy. For all households, the state is  $x, \mathcal{Z}$  and their type. The individual's type is defined by  $\ell, d, e$ , the experience, current occupation and benefit eligibility. The value for unemployed workers enjoying benefits is  $U(\ell, 0, 1, x, \mathcal{Z})$ , those with expired benefits is  $U(\ell, 0, 0, x, \mathcal{Z})$  and  $U(\ell, d, 1, x, \mathcal{Z})$  for employed workers. For expositional clarity, I will subdivide the problem into two component value functions  $U_w, U_b$  for working and unemployed workers, respectively.

The value function, written from the perspective of stage 1, is then

$$U(\ell, d, e, x, \mathcal{Z}) = \mathbb{I}_{d>0} U_w(\ell, d, 1, x, \mathcal{Z}) + \mathbb{I}_{d=0} U_b(\ell, 0, e, x, \mathcal{Z}) \quad (2.5)$$

Note that,  $w^m, s^m, \bar{\xi}^m, g^m, \theta^m$  are all functions of the aggregate state  $(x, \mathcal{Z})$ , but notational convenience I suppress this dependence. The component value-functions are:

$$U_w(\ell, d, 1, x, \mathcal{Z}) = \max_{\bar{\xi}^{\ell d 1}} (1 - \tau \mathbb{I}_{\ell \neq d}) \left[ \left( 1 - s^{\ell d 1} \right) \left( \int_{\bar{\xi}^{\ell d 1}}^0 w^{\ell d 1}(\xi, 0) + \xi dh(\xi) + \beta EU(\ell, d, 1, x', \mathcal{Z}') \right) + s^{\ell d 1} U_b(0, 0, 1, x, \mathcal{Z}) \right] + \tau \mathbb{I}_{\ell \neq d} U_w(d, d, e, x, \mathcal{Z}) \quad (2.6)$$

$$U_b(\ell, 0, e, x, \mathcal{Z}) = \int_{\psi} \max_{\{g^m\}_{m \in M_{\ell, e}}} \sum_{m \in M_{\ell, e}}^J p(\theta^m) g^m (w(0, \psi_m) + \psi_m + \beta E[U(\ell, d \in m, 1, x', \mathcal{Z}')]) + \left( 1 - \sum_m p(\theta^m) g^m \right) (b(\ell, 0, e) + \beta E[U_b(\ell, 0, e', x', \mathcal{Z}')]) df(\{\psi_m\}) \quad (2.7)$$

Note that if  $\ell = d$ , then  $\tau \mathbb{I}_{\ell \neq d} = 0$  and

$$U_w(d, d, 1, x, \mathcal{Z}) = \max_{\bar{\xi}^{dd1}} \left( 1 - s^{dd1} \right) \left( \int_{\bar{\xi}^{dd1}}^0 w^{dd1}(\xi, 0) + \xi dh(\xi) + \beta EU(d, d, 1, x', \mathcal{Z}') \right) + s^{dd1} U(d, 0, 1, x, \mathcal{Z}) \quad (2.8)$$

All workers take as given equilibrium conditions on  $\theta^m, w^m$ , which are described below. Expectations for the law of motion of  $\mathcal{X}(x) = x'$  is consistent with the actual law of motion. Note that  $s^m$  already includes the integration over  $\xi$ , i.e.  $s^m = H(\bar{\xi}^m)$

## Firms

The representative multi-worker firm produces using many occupations and posts vacancies in any labor market,  $\{v^m\}_{m \in M}$ . With aggregation, these vacancies will determine tightness in each market, but the individual firm takes tightness,  $\{\theta^m\}$ , and wages,  $\{w^m\}$  as given. In addition, the firm takes as given the distribution of  $\psi$  that will arrive, induced by the household's maximizing direction choice. Call  $\tilde{F}$  this extreme value distribution. Because production is linear in workers there is no externality problem à la Stole and Zwiebel (1996). However, using a single firm employing multiple types of

workers simplifies the problem of what happens when a worker becomes experienced.

$$\begin{aligned} \Pi(\mathbf{L}, x, \mathcal{Z}) = \max_{\{v^m\}_{m \in M}} \sum_{\ell=0, d=1}^J \left[ \omega_{\ell d} z_d L'_{\ell d} - \left( L'_{\ell d} - \sum_{e \in \{0,1\}} v^{\ell d e} q(\theta^{\ell d e}) \right) \int_{\bar{\xi}^{\ell d}}^0 w^{\ell d 1}(\xi, 0) dh(\xi) \right] \\ - \sum_m \int_{\psi} v^m q(\theta^m) w^m(0, \psi) d\tilde{f}(\psi) + \kappa v^m + \beta E[\Pi(\mathbf{L}', x', \mathcal{Z}')] \end{aligned} \quad (2.9)$$

Where the law of motion for the labor force  $\mathbf{L}'$  is given by:

$$L'_{\ell d} = (1 - \tau)(1 - \hat{s}^{\ell d 1})L_{\ell d} + q(\theta^{\ell d 0})v^{\ell d 0} + q(\theta^{\ell d 1})v^{\ell d 1} \quad (2.10)$$

$$L'_{dd} = (1 - \hat{s}^{dd 1})L_{dd} + q(\theta^{dd 1})v^{dd 1} + q(\theta^{dd 0})v^{dd 0} \quad (2.11)$$

Here, the  $\hat{s}$  denotes the firms' expectations the aggregate separation policies. Of course, in equilibrium all these expectations will be consistent with aggregate behavior.

The wage bill depends on cut-offs,  $\{\bar{\xi}^m\}$  and the distributions of  $\{\psi_m\}$  induced by the searchers' problems. However, because these shocks are not persistent it is enough for the firm to know the aggregate state when for their forecast value in the next period.

### 2.4.5 Equilibrium

To define equilibrium, I give conditions for tightness and wages, which play the role of prices, and the laws of motion for workers of various types. A recursive competitive equilibrium is

- A set of functionals

$$\begin{aligned} - U : \{0, J\}^2 \times \{0, 1\} \times [0, 1]^{2(J+1)^2} \times \mathbb{R}^4 \rightarrow \mathbb{R}_+ \\ - \Pi : [0, 1]^{J(J+1)} \times [0, 1]^{2(J+1)^2} \times \mathbb{R}^4 \rightarrow \mathbb{R}_+, \end{aligned}$$

- Policy functions:

$$\begin{aligned} - \{g^m\}_{m=0}^{2J(J+2)} \text{ where } g^m : \mathbb{R}_+^J \times \{0, J\}^2 \times \{0, 1\} \times [0, 1]^{2(J+1)^2} \times \mathbb{R}^4 \rightarrow [0, 1] \\ - \{\bar{\xi}^m\}_{m=0}^{J(J+2)} \text{ where } \bar{\xi}^m : \{0, J\}^2 \times \{0, 1\} \times [0, 1]^{2(J+1)^2} \times \mathbb{R}^4 \rightarrow \mathbb{R}_- \\ - \{v^m\}_{m=0}^{2J(J+2)} \text{ where } v^m : [0, 1]^{J(J+1)} \times [0, 1]^{2(J+1)^2} \times \mathbb{R}^4 \rightarrow \mathbb{R}_+ \end{aligned}$$

- Wages,  $\{w^m\}_{m=0}^{2J(J+2)}$ , where  $w^m : \mathbb{R}_- \times \mathbb{R}_+ \times [0, 1]^{2(J+1)^2} \times \mathbb{R}^4 \rightarrow [0, 1]$

- Market tightness,  $\{\theta^m\}_{m=0}^{2J(J+2)}$ , where  $\theta^m : [0, 1]^{2(J+1)^2} \times \mathbb{R}^4 \rightarrow [0, 1]$

Though not primary equilibrium objects, it will ease notation to first define the aggregate number of applicants,  $a^m$ , in each market  $m = \ell, d, e$

$$a^m = \begin{cases} \bar{g}^m \left( x_{\ell 01} + \bar{s}^{\ell \ell 1} (x_{\ell \ell 1} + \tau \sum_{j \neq \ell} x_{j \ell 1}) \right) & \ell > 0, e = 1 \\ \bar{g}^m \left( x_{001} + (1 - \tau) \sum_{j=0}^J \sum_{k \neq j} \bar{s}^{jk1} x_{jk1} \right) & \ell = 0, e = 1 \\ \bar{g}^m (x_{\ell d 0}) & e = 0 \end{cases}$$

Here  $\bar{g}^m$ , and  $\bar{s}^m$  are both evaluated at the average (defined below). Distinguishing these from the agent-level counterparts matters a great deal for  $\bar{g}^m$  because while the linearity implies that in equilibrium  $g^m \in \{0, 1\}$  but averaging over,  $\bar{g}^m \in [0, 1]$

- Tightness in market  $m = (\ell, d, e)$  satisfies  $\theta^m = \frac{v^m}{a^m}$
- Expectations  $\mathcal{X}(x)$  are consistent with aggregate laws of motion, where policies  $\bar{g}^{\ell d}$  are evaluated at the aggregate,  $\bar{g}^m(\cdot) = \int_{\psi_i} g^m(\psi_i; x, \mathcal{Z}) dF(\psi)$

$$x'_{dd1} = (1 - \bar{s}^{dd1}) \left( x_{dd1} + \tau \sum_{\ell=0, \ell \neq d}^J x_{\ell d1} \right) + p(\theta^{dd1}) a^{add1} + p(\theta^{dd0}) a^{add0} \quad (2.12)$$

$$x'_{\ell d1} = (1 - \bar{s}^{dd1}) (1 - \tau) x_{\ell d1} + p(\theta^{\ell d1}) a^{\ell d1} + p(\theta^{\ell d0}) a^{\ell d0} \quad (2.13)$$

$$x'_{\ell 01} = \left( 1 - \sum_d \bar{g}^{\ell d1} p(\theta^{\ell d1}) \right) \left( (1 - \delta) x_{\ell 01} + \bar{s}^{\ell \ell 1} \left( x_{\ell \ell 1} + \tau \sum_{j \neq \ell} x_{j \ell 1} \right) \right) \quad (2.14)$$

$$x'_{001} = \left( 1 - \sum_d \bar{g}^{0d1} p(\theta^{0d1}) \right) \left( (1 - \delta) x_{001} + (1 - \tau) \sum_{d=1}^J \sum_{l=0, l \neq d}^J \bar{s}^{\ell d1} x_{\ell d1} \right) \quad (2.15)$$

$$x'_{\ell 00} = \left( 1 - \sum_d \bar{g}^{\ell d0} p(\theta^{\ell d0}) \right) x_{\ell 00} + \delta \left( 1 - \sum_d \bar{g}^{\ell d1} p(\theta^{\ell d1}) \right) x_{\ell 01} \quad (2.16)$$

- The firm is representative, so  $L_{\ell d} = x_{\ell d1}$

A few endogenous variables are pinned down in equilibrium:

- There is free entry, so tightness satisfies:

$$\kappa = q(\theta^{\ell d e}) \left( \omega_{\ell d} z_d - \int_{\psi} w^{\ell d e}(0, \psi) d\tilde{f}(\psi) + \beta E \Pi_{\ell d}(\{x'_{kj1}\}_{k,j}, x', \mathcal{Z}') \right) \quad (2.17)$$

Where  $\Pi_{\ell d}$  is the derivative with respect to  $L_{\ell d}$

- Separations are mutual and the cutoff satisfies

$$\omega_{\ell d} z_d + \bar{\xi}^{\ell d 1} + \beta E[U_w(\ell, d, 1, x', \mathcal{Z}') + \Pi_{\ell d}(\{x'_{kj1}\}_{k,j}, x', \mathcal{Z}')] = \begin{cases} U_w(\ell, 0, 1, x, \mathcal{Z}) & \ell = d \\ U_b(0, 0, 1, x, \mathcal{Z}) & \ell \neq d \end{cases} \quad (2.18)$$

- Wages  $w^{\ell de}(\xi, \psi)$  are set by bargaining, where with firms' weight is  $\mu$ .

$$w^{\ell de}(\xi, \psi) = (1 - \mu) (\omega_{\ell d} z_d + \beta E \Pi_{\ell d}(\{x'_{kj1}\}_{k,j}, x', \mathcal{Z}')) - \mu (\xi + \psi - b + \beta E U_w(\ell, d, 1, x', \mathcal{Z}') - \beta E U_b(\ell, 0, e, x', \mathcal{Z}')) \quad (2.19)$$

Note that wages depend on the entire distribution of shocks, because the workers' outside option allows him to move around. This has the effect of compressing wages across occupation types for inexperienced workers who will readily switch and also raising them compared to their more experienced counterparts except in the most productive occupation in the economy.

## 2.4.6 Discussion of the model assumptions and equilibrium

### Work history truncation

I truncate the work history after two periods, so that those who lose a job when inexperienced become “unattached” rather than storing two periods of their work history. This assumption imbues the model with several, mostly innocuous, peculiarities especially with regard to wage dynamics. Wages in this model fluctuate non-monotonically over one's tenure. They are higher in the first period of employment than the second, and then rise again upon gaining tenure. This is because the outside option in the worker's first period is to stay unemployed but with skills from to his own occupation, i.e.  $b(\ell, 0, 1, \cdot) + \beta E[U_b(\ell, 0, 1, x', \mathcal{Z}')]$ . In subsequent periods if he matched in a new occupation, then the outside option becomes  $b(\ell, d, 1, \cdot) + \beta E[U(0, 0, 1, x', \mathcal{Z}')]$ . He is penalized both by a lower unemployment benefit and a lower continuation value that reflects lost human capital. To avert this problem, I would have define the problem of workers who are displaced after having labor history  $\ell, d$ , and extend the state space

an additional element. Instead, I assume that human capital from occupation  $\ell$  is lost upon taking a job type  $d$ . This lumps together work histories  $(\ell, d, e) \forall \ell, d : \ell \neq d$  into a category  $(0, 0, e)$ .

Clearly, histories need to be truncated somewhere to keep the problem tractable. I choose this setup because it gets the problem of unemployed workers correct even if it misses the problem of currently employed workers. It simplifies the process by which old, unused skills depreciate by just assuming that it is immediate.

#### 2.4.7 Cyclical dynamics of finding rate heterogeneity

A crucial result of the model is that the dispersion of unemployment duration is counter-cyclical. To deliver this, there must be a mechanism such that occupation switching takes longer in recession. Remember Table 2.1, which shows that switchers are unemployed for longer and the effect is larger in the Great Recession. Achieving this effect in the model is part of how it delivers counter-cyclical dispersion in unemployment duration across occupations. In a recession, the occupations that are most cyclically sensitive have the worst productivity and the workers attached to this occupation are unemployed for a very long time whether they find a job in their own or other occupations.

There are two channels that slow the finding rate for recession-affected occupations and slow reallocation away from them. The first is the same as a standard search and matching model, the surplus size falls and vacancy postings decline. The second, is that occupation switching becomes more difficult. The reasoning for this is subtle: the total size of the surplus for experienced workers is larger and hence less elastic with respect to a productivity shock. This logic is the same as that of Hagedorn and Manovskii (2008), which shows that vacancies are much more volatile in a market in which the total match surplus is small. The same size shock to the flow value of a match has a large effect on the relative size of the surplus and hence a large effect on vacancy posting.

In the context of my model, this effect means a higher volatility of vacancies in markets for switchers in which the value of the match  $\omega_{\ell d} z_d - \xi + \beta(E[U_w(\cdot) + \Pi_{dd}(\cdot)])$  is smaller and hence closer to the flow value of unemployment  $b + \beta E[U_b(\cdot)]$ . In recessions, few postings imply that it is more difficult to switch, burnishing the unemployment rate of occupations that are hit hardest by the recession. Figure 2.8 graphically depicts this intuition for the greater cyclical volatility of “switcher” markets.

Related, the experience premium within an occupation is pro-cyclical. This means inexperienced workers are relatively expensive during recessions. To put this differently,  $\frac{\omega_{dd}}{\omega_{ld}} > \frac{w_{dd}^g}{w_{ld}^g} > \frac{w_{dd}^b}{w_{ld}^b}$ , where  $g$  stands for *good times* and  $b$  for *bad*. The crucial insight is that the workers' outside option is relatively constant, whereas the match value depends more strongly on the shock level.

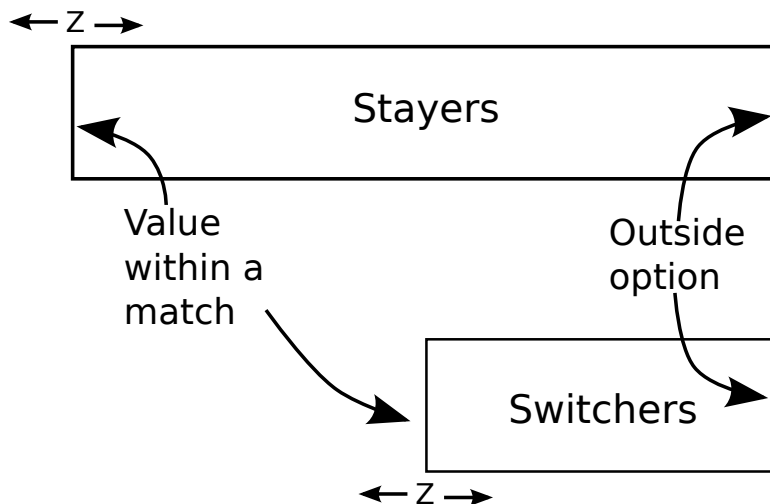


Figure 2.8: The same business cycle shock has a large impact on the surplus of “switcher” markets

## 2.5 Quantitative Strategy

Crucially, workers in the model weigh their attachment to their prior occupation against the forces pushing them away. I will try to match these two forces to the data as precisely and with as much detail as possible. The force attaching workers to their occupation will come from the wage gap between inexperienced and experienced workers in each occupation. The latter force, pushing workers away, will come from the occupation-specific shock processes.

### 2.5.1 Occupation-specific shocks

The shock process described by Equations 2.2-2.4 can be directly estimated if we have information on value-added by occupation, workers per occupation *and their working*

*history*. This final aspect will prove to be the trickiest. The trouble arises from the way we model  $\{\omega_{\ell d}\}$  as a vector of relative productivities. Hence, when workers shift into a new occupation, they affect the observed productivity in that occupation but not the actual shock that hit it. Observing productivity per capita, does not allow me to extract the the primitive shock process, because it is a process that combines these exogenous driving forces and the endogenous movement of workers.

First, I will use the Bureau of Economic Analysis (BEA) data to compute value-added per capita within an industry. This is going to be my fundamental data observation to which I will make the model match. To get a feel for how these shocks look, Figure 2.9 plots the first four industries listed in the BEA data. Like all of the sectors, I removed the mean and linear trend.

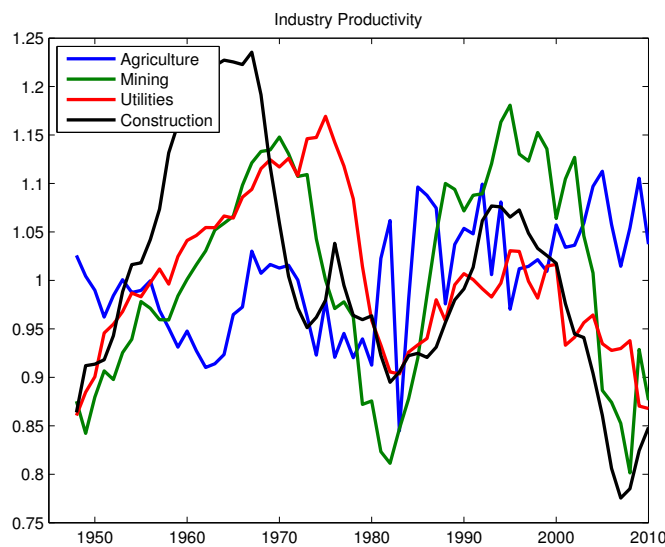


Figure 2.9: A sample of productivity in a few industries

The BEA publishes annual industry accounts that provide the industry-specific value-added and number of workers in terms of bodies and full-time equivalents. The first step to to map from industries to occupations, I pool CPS surveys over the year to compute the portion of workers attached to each occupation working in each industry. For example, in 2000 88% of labor in SOC 31, Health Care Support Occupations, are in the industry code Health Care and Social Assistance and the rest are spread over



other industries. The same year, 22% of those working in Business and Financial Operations Occupations are in the Finance and Insurance industry and there are also high concentrations elsewhere.

Were it not for the productivity differences to experience, I could then attribute value added to the occupation corresponding to each industry in which they work, weighted by the fraction of the workers there. To get value added per worker, I could then divide by the number of workers in that occupation. This gives a notion of the productivity within an occupation, but not one that is consistent with the model's primitive shock.

### **Adjusting for endogenous worker experience**

The problem now is that I treated every worker as equal, whereas in the theory workers of different experience levels will have different average productivity levels in that occupation. The model counterpart to observed output per capita is endogenous and so I can not match productivity shocks in the model to observed output per capita in the data. Also, I cannot adjust the data observation for observed experience because the data is insufficient. In the CPS, I only observe their job experience, but not occupational experience. Even in the SIPP, I observe occupational experience but only their prior occupation if they transitioned during the survey period, which is relatively infrequent given the shortness of the SIPP panel. Further, even if I knew their prior occupation, to be consistent with the model, I would also need to know the tenure in that occupation, to find out if they are providing  $\omega_{0d}$  or  $\omega_{ld}$ .

The model, however, has predictions for the number of workers that will be inexperienced and from whence they came. So, I can make the model analog of observed productivity, in which I can observe this endogenous composition, consistent with the actual observations. I will choose a stochastic process for  $\mathcal{Z}$  such that the output per worker in an occupation is the same in the model and data.

To be specific, there are two major differences between the occupation-level productivity shocks in the model and that which is observed in data:<sup>7</sup> (1) I only observe industry-level productivity and (2) observed productivity in my model is endogenous because the composition of workers determines the output per head.

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<sup>7</sup>A minor difference is that I can only make observations every year, though the model is monthly. I simply estimate the process as if I only observe once every 12 observations.

Notice, that I could relate observed industry shocks,  $z_{i,t}$  to occupation shocks  $z_{d,t}$  if I assume that distributions of types are the same across industries.

$$z_{i,t} = \sum_d w_{i,d} \sum_\ell \omega^{\ell d} x'_{\ell d} z_{d,t} : w_{i,d} = \frac{\Pr[occ \cap ind]}{\Pr[ind]} \quad (2.20)$$

I can get  $w_{i,d}$  from the CPS. However, the object  $\omega^{\ell d} x'_{\ell d}$  is endogenous.  $x'_{\ell d}$  is the density of workers with productivity  $\omega^{\ell d}$ —endogenous and unobservable.

If, however, I pretend  $\omega^{\ell d} = 1 \forall \ell, d$ , then the endogenous experience distribution,  $\mathbf{x}$  does not matter. I go to the data with this false assumption and estimate a process for  $\{\{z_d\}, Z, \mathbf{f}\}$ ,  $\tilde{\mathfrak{Z}}^{data}$  just as described earlier as an “observable” notion of occupational productivity. I parameterize this by the same factor process as described in Equations 2.2-2.4. Hence, the auxiliary model is the dynamic process for productivity, given that  $\omega^{\ell d} = 1 \forall \ell, d$ . I estimate the auxiliary model in the data taking model-generated data with this same assumption, that  $\omega^{\ell d} = 1 \forall \ell, d$ , to find  $\tilde{\mathfrak{Z}}^{model}$ . Then, I choose model parameters for the process in Equations 2.2-2.4 to solve

$$\min LR(\tilde{\mathfrak{Z}}^{data}, \tilde{\mathfrak{Z}}^{model})$$

An alternative way to view this strategy is that I measure output per capita by occupation in both the model and data. To map from industry to occupation, I assign industry output to occupation on the basis of the relative population. Then in the data I have a measure of output per person conditional on occupation and I can compute this same object in the data. The auxiliary model can then be described as the stochastic process for average output per capita within an occupation.

The model does not have a notion of industry, so for equation 2.20 to work, I need to assume that workers from occupations are equally productive in each industry. Otherwise, rather than attributing the output proportional to the workers there, there would need to be some weighting. If I were explicit on industries with specific shocks, one would not expect the productivity distribution to be the same. Just as workers flow in response to occupation shocks, they would also move for industry shocks. However, explicitly considering this would make the model infeasible.

The distance metric I choose is the likelihood ratio rather than the Wald metric for

two reasons. First, there are many parameters in the set of  $\lambda_{f,d}$ ,  $\lambda_{Z,d}$  and weighting them is somewhat fraught, whereas the LR metric gives a natural weighting for observations. Also, the magnitude of the unobservable factors and coefficients is indeterminate; one could multiply each  $\lambda_{f,d}$  by 2 and divide the factors by 2. One can, of course, use a normalization to constrain this degree of freedom, but then that normalization would implicitly affect the weights. By construction, my shock sequence reproduces the data exactly if I were to recompute industry-level shocks using Equation 2.20.

### Specification of the stochastic process

The factor process is explicitly designed to introduce time-varying volatility between occupations. As mentioned, this is a feature explored in Lilien (1982) and Abraham and Katz (1986). More contemporary papers have introduced this into search and matching, notably Schaal (2012). Fernandez-Villaverde and Rubio-Ramirez (2010) discuss several ways to model time-varying volatility. They point out that a finite number of regimes complicates using perturbation techniques to solve the model, the method class I use. Instead, they recommend stochastic volatility. There are a number of shortcomings to modelling occupation specific shocks as they suggest:

$$\begin{aligned} z_{d,t} &= \rho_z z_{d,t-1} + \sigma_t \zeta_{d,t} \\ \log \sigma_t &= \rho_\sigma \log \sigma_{t-1} + \varphi_t \end{aligned}$$

As one might imagine, this process is difficult to estimate precisely on the limited data sample I have. Several methods, indirect inference, GMM and quasi-ML all run into the same basic problem, that estimating a dynamic process for a second moment is essentially using 4th moment information. With only 60 observations on variance from 1947-2007, we end up with quite a wide bound at two standard deviations  $\rho_\sigma \in (0.118, 0.613)$ . Furthermore, the process requires some correlation of the shock structure to have some desirable properties, such as some correlation between  $\varphi_t$  and  $\epsilon$  from Equation 2.2. Without an estimate for  $E[\zeta_{d,t}, \zeta'_{d,t}]$ , we cannot capture the co-movements among occupations, which is an important feature because occupations that tend to experience similar shocks are also similar in skill space. This plays a large role in how “far” workers switch and how much wage they lose.

### 2.5.2 Cost of switching occupations

The relative productivity of inexperienced workers,  $\{\omega_{\ell d}\}_{\ell=0, d=1}^J$  needs to be estimated to match the costs of switching occupations. I use indirect inference to estimate  $\omega$  as a function of the O\*NET skills of the occupation pair. To summarize the method, I quantify occupations' relation to each other by their skill requirements, as published by the US Department of Labor's O\*NET. Then, I assume  $\omega_{\ell d}$  is function of the difference between  $\ell$  and  $d$ . This motivates a regression on the relative wage between  $(\ell, d)$  workers and  $(d, d)$  workers and the difference in O\*NET skills in the two occupations. I then match the coefficients of this regression between model-generated data and observations in the SIPP from 1996-2007.

Were it not for the random utility to choosing occupations changes to  $\{\omega_{\ell d}\}$  would cause discontinuous changes in policies and observable endogenous variables. If in equilibrium workers are making a transition from  $\ell$  to  $d$ , a change to  $\omega_{\ell d}$  by even just an infinitesimal amount will cause the direction of search to change discretely. If these new parameters cause workers to make an  $\ell$  to  $j$  switch, now the observed return to skill will change discontinuously because workers are gaining experience in a different occupation. This is precisely the situation that Smith and Keane (2004) address. Their solution is to modify the discrete choice into a probability, which takes on a similar form as the policy  $g^m$  that convexifies choices in my model.

It should also be noted, that I have assumed occupation stayers experience no wage loss. This restriction can be justified from a modelling perspective, as it focuses the analysis on the additional wage loss for switchers. More importantly, several studies have shown that workers separated but who stay in their occupation have almost no wage loss. Kambourov and Manovskii (2009b) make this point using data from the CPS Displaced Worker Survey and Fujita (2011) corroborates the finding using SIPP data. While Fujita (2011) finds some moderate wage loss for occupation stayers, it is statistically insignificant.

#### O\*NET data

The US Department of Labor's O\*NET database collects data on occupations that can be used to quantify the differences between them. It is the successor to the Dictionary of

Occupational Titles, which classified the types of tasks necessary to work in a particular occupation. The O\*NET expands upon this, providing quantitative information on skills, knowledge, and abilities required to work in a particular occupation. For every occupation each descriptive element gets a score for its “importance” in that occupation and the “level” at which it is performed. It collects survey information from both workers and their supervisors and but publishes only the rescaled means.

To characterize occupations, I use the “skills” measure, because in my model, that which attaches workers to their occupation is learned on the job. O\*NET’s skills are most close to this sort of human capital learned on the job. To process this data, I first combine importance and level scores by a Cobb Douglas with elasticity 0.5, as in Blinder (2009). Next, I reduce the 35 skills down to three principal components. This is because I will eventually have to find coefficients on each skill dimension by a relatively slow global optimization method. But, the dimension reduction is innocuous because they are largely redundant. The first three components explain about 80% of the variation between all of the O\*NET occupations. These occupations, however, are finer than the two-digit SOC code-defined occupations I will eventually work with so I take a simple average over O\*NET occupations within an SOC occupation. Finally, I rescale the measures by replacing the component, with its quantile rank value amongst the occupations. This leaves each occupation with a skill value between zero and one in three categories.

### **The auxiliary model relating occupational skills to productivity**

To map O\*NET data into the model, I assume that the productivity gap between experienced and inexperienced workers is proportional in logs to the difference in skill intensity. More precisely, suppose

$$\omega_{\ell d} = e^{\sum_{i=1}^3 \beta_i (k_{i,d} - k_{i,\ell})}$$

One would expect  $\{\beta_i < 0\}$ , meaning that inexperienced workers will see a larger wage gap if their old job is less intensive in a certain skill than the current one.

Now consider a linear approximation of log wages around the average wage of the experienced worker,  $\bar{w}^{dd}$ . Using the bargained wages in Equation 2.19, this yields a

convenient linear equation relating  $\{\beta\}$  to the wage gap between experienced and inexperienced workers:

$$\log\left(\frac{w^{\ell d}}{\bar{w}^{dd}}\right) \propto \sum_i \beta_i (k_{i,d} - k_{i,\ell}) + \text{const} - \mu\psi_d \quad (2.21)$$

Again, expect  $\beta_i < 0$  as a larger deficiency in skills from the prior occupations means a larger value for  $(k_{i,d} - k_{i,\ell})$  but also a lower  $\log w^{\ell d}$  relative to the average wage in the occupation.

To use this as my auxiliary model, I can just regress the experience premium on the skill difference in both SIPP and model-generated data. Before using wages in the data, I first CPI deflate them and then regress them on sex, age, age squared and college education. I use residual wages because all of these complicating factors in wage determination do not exist in my model, but are quite significant in the data. See A.1 at the end for results of the first stage regression.

Our theory says that in the model, the constant includes information on market tightness and the outside option of workers with experience from occupation  $\ell$ . This implies that the auxiliary model is doubly misspecified. By assumption, the errors are not normal and also there should be  $\ell$  fixed effects.

For the average wage for experienced workers I need to choose who to count as “experienced.” Consistent with the model, I would take workers whose occupational tenure is greater than  $\frac{1}{\tau}$ . Unfortunately, this data operation now depends on calibrated model values and the calibration depends on the results I find this regression. I iterate, first estimating the auxiliary model assuming everyone with any tenure is experienced, then calibrating for  $\tau$  and then using this for the expected duration before becoming experienced in the data. As it turns out, the regressions are almost unaffected by the selection criteria for the experienced workers in constructing  $\bar{w}^{dd}$ .

As seen in Table 2.2, the auxiliary model is quite precisely estimated and skill differences are strong predictors of differences in the wage premium for experience. To interpret negative the coefficients in all of the composite skills, a beginner suffers a larger wage gap in an occupation using a skill much more intensively than his old occupation. Put another way, of those starting in an occupation, the ones paid least are coming from occupations that used skills less than the new occupation. As is often the case

O\*NET elements are quite good predictors for wages. We see that in the auxiliary model' estimation.

	Coefficient	T-statistic	Model	Structural
Skill 1	-0.331	-6.88	-0.35	-0.95
Skill 2	-0.294	-6.20	-0.32	-0.87
Skill 3	-0.186	-4.33	-0.19	-0.52
const	-0.289	-23.98		

Table 2.2: Auxiliary model for the value of occupational skills on productivity

The indirect inference procedure is fairly successful at minimizing the residual between data and model coefficients. The binding function maps larger structural coefficients for skill loss into these regression coefficients, which is again in line with our expectations. Occupational selection means that the wage residuals are truncated from below and so the coefficients are attenuated towards zero.

### 2.5.3 Calibration of the economy

The rest of the model parameters are calibrated using pre-2008 data on both matching and occupational switching behavior. Before listing all of the variables to calibrate, I need to describe functional forms for the matching function and the distribution of disutility shocks.

#### **Heteroskedasticity in the random utility term**

In this paper, I model random deviations in search behavior through exponentially-distributed preference shocks. Because these shocks are scaled by the probability of finding a job in that search direction, which differs across markets, the effective variance is heteroskedastic. My distributional assumption accommodates this while preserving a closed form for the probability of taking a given search direction. Alternatively, if I were to model perturbations from the optimal search direction by individual shocks to the finding rate, I would avoid this issue. These options have slight differences in math and interpretation but, subject to distributional assumptions can be mostly isomorphic.

In my choice I follow a long tradition of partially random match quality back to Boskin (1974) and Miller (1984). In my implementation, the basic interpretation is that

landing a job in some occupations is more pleasant than others. For this framework, we can write the return to searching in direction  $d$

$$p(\theta^{\ell d}) \left( w^{\ell d}(\psi_d) - b + \beta E[U'_{\ell d} - U_{\ell 0}] + \psi_d \right) \quad (2.22)$$

We can separate this into a deterministic and stochastic component because the Nash bargaining assumption makes  $w(\psi)$  linear in  $\psi$ , as in Equation 2.19. I rewrite Equation 2.22 as

$$R_{\ell d} + p(\theta^{\ell d})(1 - \mu)\psi_d$$

This is *almost* like the standard additive random utility model except that the random component is scaled by  $p(\theta^{\ell d})$ . This means that if the variance of  $\psi$  is  $\sigma_\psi^2$  across all choices  $d$ , the effective variance of the shock to return is actually  $(p^{\ell d}(1 - \mu))^2 \sigma_\psi^2$ . Whereas with additive random utility, Boskin (1974) and others use the tractability of Gumbel-distributed shocks, we are now breaking the i.i.d. assumption. If we were to keep Gumbel-distributed errors with heteroskedastic shocks, the direction policy would be chosen according to a heteroskedastic logit, as described in Bhat (1995). While the distribution has a nice interpretation as the first order statistic from a sample of exponentially-distributed utility, it implies policies for  $\{g^{\ell d}\}$  that have no closed form description. In particular, the probability of an individual choosing occupation  $d$  would be

$$\int_{-\infty}^{\infty} \prod_j G \left( \frac{R_d - R_j + ((1 - \mu)p^{\ell d} \sigma_\psi) \psi_d}{(1 - \mu)p^{\ell j} \sigma_\psi} \right) g(\psi) d\psi_d$$

where  $G$  and  $g$  are the CDF and PDF of the Gumbel distribution,  $G(x) = e^{-e^{-x}}$ . Though this is only one integral, rather than 22 without the independence assumption, it is still computationally intensive to evaluate and would considerably increase the computational burden to solve and simulate the model.

With an exponential distribution for  $\psi$ , the probability  $g^{\ell d}$  has a closed form despite the heteroskedasticity. Another likely candidate, the Fréchet distribution is still convenient with heteroskedasticity (as seen in Eaton and Kortum (2002), but only when the average return is zero. To my knowledge, exponentially-distributed shocks have not been used in economics models of discrete choice since Daganzo (1979). In Appendix



A.1 I show that the probability a worker chooses occupation  $d$  takes a closed form:

$$\prod_{j=1}^J \frac{t^{\ell_j}}{t^{\ell_d} + t^{\ell_j}} e^{t^{\ell_d}(R_{\ell_d} - R_{\ell_j})} \quad (2.23)$$

where  $t^{\ell_j}$  is the precision parameter, the inverse of the standard deviation, of shock  $\psi^{\ell_j}$ .

### The matching function

The choice of matching function is actually non-trivial in this model. The most common form is Cobb-Douglas,  $m(u, v) = \phi_0 u^{\phi_1} v^{1-\phi_1}$ , however this has the problem that in many cases,  $v$  rises high enough that matching probability may be greater than one. As is often the case in directed search models with many submarkets in which agents search, this top constraint actually will bind frequently for some submarkets.

Instead of Cobb-Douglas, I follow den Haan et al. (2000) and Hagedorn and Manovskii (2008) using the form  $m(u, v) = \frac{vu}{(v^{\phi_1} + u^{\phi_1})^{1/\phi_1}}$ . This is still homogenous of degree one but has the property that  $p(\theta) < 1 \forall \theta > 0$ . The downside, however, is that this form assumes an elasticity with respect to  $\theta$ . Generally,  $\phi$  is chosen to match the average finding rate and then the level of  $\theta$  implies an elasticity of  $p(\cdot)$  with respect to  $\theta$ . This is problematic because for values of  $\theta$  which are “realistic”<sup>8</sup> this elasticity is too high. By modifying the matching function to

$$m(u, v) = \phi_0 \frac{uv}{(v^{\phi_1} + u^{\phi_1})^{1/\phi_1}}, \quad p(\theta) = \phi_0 \frac{\theta}{(1 + \theta^{\phi_1})^{1/\phi_1}} \quad (2.24)$$

I have both  $\phi_0, \phi_1$  to match both level and elasticity of the job finding rate.

### Separations

For the distribution of disutility to govern shocks, I use a negative-exponential as the tail with a mass point at a disutility of zero. Most workers experience no disutility from

<sup>8</sup>As described in Hagedorn and Manovskii (2008), one can use help wanted listings as a proxy for  $v$  and the entire unemployment pool for  $u$  and generally the economy-wide  $\theta$  is approximately 0.63.

work, but some fraction can, if they stay in the match, experience a great deal.

$$Pr[\xi < x] = \begin{cases} \lambda_0 e^{\lambda_1 x} & \text{if } x < 0 \\ 1 & \text{if } x = 0 \end{cases} \quad (2.25)$$

The form ensures that there are always some separations, as it has infinite negative support, but there is a cap on the separations for a given type. No more than  $\lambda_0$  of any type  $(\ell, d)$  will separate. This contrasts with many other models of this sort which have a lower bound on the number of separations but no upper limit. The reason for this modelling assumption is two-fold. First, it allows me to parsimoniously parameterize a distribution that has both level of separations and elasticity with respect to productivity. Second, the inexperienced workers will have a much higher separation rate, and if it is unbounded on the top, then negative productivity shocks affect inexperienced workers by too much and few workers are able to become experienced. Figure 2.10 plots the distribution in Equation 2.25 to help visualize the distribution and illustrate the magnitudes involved.

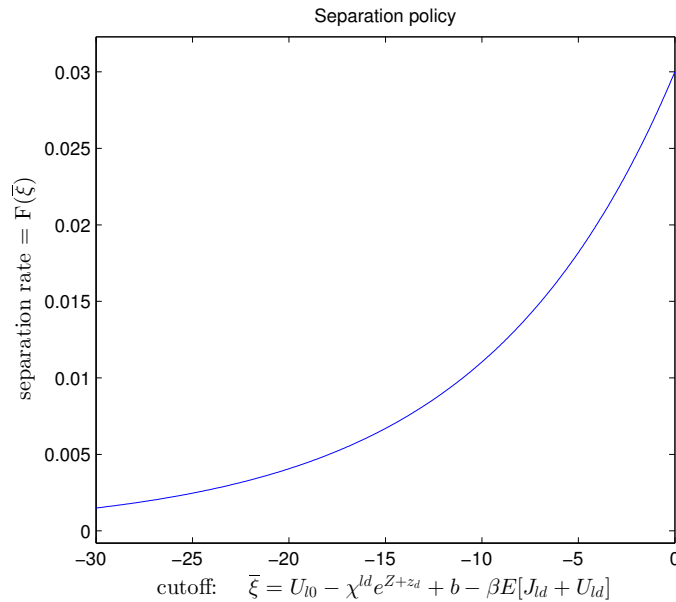


Figure 2.10: The tail of the distribution for disutility

### Choosing targets

The parameters then that we have to match are  $\phi_0, \phi_1, \lambda_0, \lambda_1, \tau, \sigma_\psi$ . Though all the parameters affect all of the targets, there are some heuristic relationships. All of these variables are chosen to match the pre-2008 economy.  $\kappa$  and  $\mu$  also must be set, which I take from the literature.  $\kappa = 0.26$  corresponds to that used in Hagedorn and Manovskii (2008), while the firms' share,  $\mu$  is not easily observable and the literature uses anything in the range of 0.5 to 0.97. I choose a relatively conservative, middle level, 0.66. The results are not particularly sensitive to values anywhere between 0.5 and 0.8, though at very high levels the model becomes difficult to calibrate. The unemployment replacement rate is 40% of the prior working wage, which is approximately average across US states. Rather than targeting the level of separations, the measurement of which suffers from time-aggregation bias as pointed out in Shimer (2012), I choose separations so that the average unemployment rate is 5.5%.

$\tau$ , which governs the speed at which workers become experienced and the wage helps the model match the average returns to occupational tenure. Kambourov and Manovskii (2009b) estimate the five year return using PSID data<sup>9</sup> and correcting for the endogeneity of tenure by instrumenting with average tenure of that occupational stint, a common though imperfect strategy introduced in Altonji and Shakotko (1987). If anything, the returns to tenure are still biased downwards because it may be that unobservable match quality is correlated with labor market experience and tenure is positively correlated with experience. In the context of this model, downwards bias somewhat mitigates the effect of occupational attachment because lower  $\tau$  implies that fewer become experienced and attached.

$\sigma_\psi$ , the standard deviation of occupation-specific preference shocks determines the rate of switching occupations when unemployed. The mapping between this parameter's role in the model and data are not so straightforward, though. For a very low  $\sigma_\psi$ , searchers flock to the single occupation with the largest return and raising it increases the spread of  $g^{\ell d}$  regardless of  $\{z_d\}$ . As described in Section 2.5.3, the standard deviation of shocks, as perceived by workers, actually depends on the finding rate in that occupation. Because the unemployed from some occupations have higher average finding rates than

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<sup>9</sup>They use data from 1968-1993, but the results are not much different when extended to 2006 although changes in the survey make this later data somewhat more suspect.

others, they will actually experience larger standard deviation of finding rate shocks.  $\sigma_\psi$  just acts as a baseline, over which endogenous variables act.

For  $\lambda_1$ , I target the standard deviation of separations across occupations rather than a statistic related to the time-series of the aggregate separation rate. This target means separations are accurate in determining the distribution of unemployed people, which is of primary importance here. To characterize the effect of occupational attachment, we need to have the proper distribution of occupations among unemployed workers. With endogenous separations, when occupation  $d$  suffers a low  $z_d$ , this increases the number of type  $d$  in unemployment through two channels: (1) they have a lower finding rate and (2) they enter unemployment more frequently. Because separations have been made endogenous to get the distribution of unemployed workers correct, I look to the cross-sectional distribution.

### Calibration results

Table 2.3 displays the calibration results. In most dimensions, the model is quite capable of matching the targets. Especially important, parameters of the matching function are matched quite exactly. Of course, these are just average figures and it is up to the model to match facts about the distribution of finding and duration.

Target	Model	Data	Source
Change Probability	0.48	0.46	SIPP 1996-2007 (3 Panels)
Job Finding Rate	0.34	0.33	CPS, 1976-2007
Returns to tenure	0.005	0.006	PSID (monthly rate)
Match Elasticity	0.48	0.48	Barichon (2011)
Separation Rate	0.029	0.028	5.5% unemployment
sd(Separation)	0.01	0.01	CPS, 1976-2007

Table 2.3: Summary of calibration targets

## 2.6 Business Cycle Properties

The model provides insight into how unemployment and duration responds to cycles generally. Given the estimated shock process, it generates counter-cyclical dispersion

of duration and unemployment rates across occupations. Aggregates, the unemployment rate and duration, also fluctuate more over the cycle than a similarly calibrated Mortensen-Pissarides model with homogenous searchers. Summarily, this is because with heterogeneous searchers in a downturn, some are affected more greatly than others and the fall in their finding rate pulls out the whole duration distribution. This is akin to the logic in Figures 2.4 and 2.3, where the negative-sloped finding rate implies duration dynamics that cannot be replicated with homogeneous finding rates.

So, the logic of my results is thus: the finding rate for some occupations falls precipitously and these workers' long duration pulls out the distribution of duration enough to generate realistic levels of long-term unemployment. As discussed in the Section 2.4.7, in a recession, those who stay searching in their own occupation have slow finding and those who try switching also have especially slow finding because wage compression in recessions make unskilled workers particularly unprofitable. This exacerbates counter-cyclical dispersion. With this heterogeneity in recession, the workers from affected occupations constitute a greater part of the tail of the duration distribution.

To turn to heterogeneity in recession, the prior literature has pointed out two mechanisms by which the economy can generate counter-cyclical risk across segments of the economy, as I have discussed. I generalized Abraham and Katz (1986), making occupations differ in their cyclical sensitivity. In this framework, the variance in productivity increases symmetrically for positive and negative aggregate shocks to  $Z$ . Unemployment and duration can be counter-cyclical if the finding rate responds asymmetrically. This asymmetry is built right into the search and matching model through a number of mechanisms. The matching friction implies that hiring in an expansion is slower, while separations are instantaneous in response to a negative shock. In my model, this is exacerbated by occupation-specific skills and occupational attachment. Here, the composition of unemployed workers affects the finding rate because if there are many attached to low productivity occupations this decreases the effective finding rate, even if there are other high productivity occupations. A negative shock to a particular occupation will increase separations and the pool of searchers in a low finding rate occupation. On the other hand, a positive shock, though some occupations will experience a larger increase in their finding rate than others, is dampened because wages also adjust and the separation rate will not vary so much across occupations.

Stat	Model	Data
$\text{corr}(\text{sd}(\log p_{\ell,t}), \log u)$	0.60	0.37
$\text{corr}(\text{sd}(\log u_{\ell,t}), \log u)$	0.63	0.28

Table 2.4: Business cycle properties of the model,  $p_{\ell,t}$  is the finding rate of those coming from occupation  $\ell$  and  $u_{\ell,t}$  is the unemployment rate for occupation  $\ell$

Table 2.4 shows the counter-cyclical dispersion in finding rate and unemployment rate. A reader might find it odd that the finding rate’s dispersion has an even higher correlation with unemployment than in the data. There is no reason that the adjustment asymmetries in the model correspond precisely to those in the data. For instance, the elasticity implied by the form of this particular matching function is higher in slack markets. This increases dispersion’s correlation with average productivity. Alternatively, some complementarity between occupations’ output would also reduce the dispersion across occupations. The important aspect is that the model is very close to the data in the relationship between the dispersion across occupations’ finding rate and the cycle—essential for the recessionary increases in long-term unemployment.

### 2.6.1 Duration and finding rate heterogeneity

The central target of this paper is the heterogeneity in finding rates engendered by occupation specific human capital. This is neatly summarized by the model’s analogue to Figure 2.4, which I plot in Figure 2.11. The finding rate falls from about 36% in the first month to 24% after a year of unemployment. The model misses most in the initial fall in finding rate, where some workers quickly flow out of unemployment but captures the low finding rates of those long in unemployment. This is not to say that none of the searchers in my model find jobs quickly: on average the finding rate for the unattached unemployed, type  $(0,0)$  searching in the most efficient market is 0.47. However, the shocks  $\{\psi_{d,i}\}$  make some of them search inefficiently. These shocks allow the model to match switching behavior for the experienced, attached searchers, but the randomness also affects the unattached searchers who would otherwise focus their attention on easier to find jobs.

The model is fairly successful at matching the expected duration before a match and the cross-sectional standard deviation of duration. For both, the fact that some

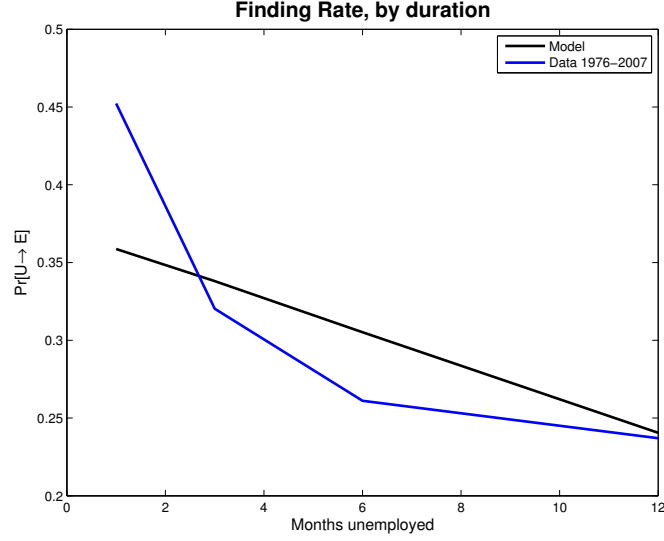


Figure 2.11: Finding rate by duration with occupation-level heterogeneity implied by the model

workers have quite low finding rates at long durations pulls out the moment. At the 10th percentile, the finding rate is only 20%. Essentially, Table 2.5 shows how the model is relatively successful at matching the tail of the duration distribution.

In Table 2.5, I present two other models for contrast, a standard Mortensen-Pissarides model and a “No human capital” version. The Mortensen-Pissarides model is calibrated to match the same average finding rate and is presented in the fourth column. The single finding rate means that the expected duration is just  $\frac{1}{p_t}$ . Because the duration is constrained to be exponentially distributed, its standard deviation is also  $\frac{1}{p_t}$ . The intermediate model is one in which there are multiple occupations but new hires begin at full productivity even if they came from another occupation. That is, the “No HC” column corresponds to  $\omega_{\ell d} = 1 \forall \ell d$ . In this case, because  $var(\psi_d) > 0$  workers still may apply to occupations which are not the highest productivity.

Notice in Figure 2.11 that the hazard falls almost linearly. This is a repercussion of the pure composition effect. The slope is not entirely time independent. To see this, consider the continuous time case, if for each  $i$  groups, the finding rate is  $p_i$  and the initial population when they enter unemployment is  $u_{i,0}$  then the hazard is  $h(t) = \frac{\sum_i u_{i,0} e^{-p_i t} p_i}{\sum_i u_{i,0} e^{-p_i t}}$  and so the derivative of the hazard is  $\frac{-\sum_i p_i^2 u_{i,0} e^{-p_i t}}{\sum_i u_{i,0} e^{-p_i t}} + (h(t))^2$ . But, to make the curve

more convex, as in the data, it would take either more spread in the finding rates or for  $p_i$  to be time-dependent, as in the case of true duration dependence.

Stat	Model	Data	No HC	MP
E(duration)	3.54	3.73	3.30	3.03
sd(duration)	3.91	4.24	3.66	3.03
Fraction $\geq$ 6 mo	0.16	0.16	0.12	0.09

Table 2.5: Duration when matched, implied from CPS 1976-2007

The time series of duration and its cross-sectional variation also matches the data rather well. The correlation between average productivity and average unemployment duration is -0.51, quite counter-cyclical.

## 2.6.2 Cyclical volatility and match efficiency

In my model, the variance of unemployment is quite a bit higher than in many other search and matching models, where low volatility is a common problem that was described in Shimer (2005) and addressed by countless papers. Carrillo-Tudela and Visschers (2013) is quite successful in addressing this critique with a model similar to my own. It generates much of fluctuations from “rest unemployment,” and shows that total unemployment volatility increases when reallocation and matching frictions complement each other. Section 2.4.7 describes why cycles affect some occupations so much worse than others.

The average finding rate fluctuates by more than would be suggested by fluctuations in the average tightness alone. This is because some of the variation comes from changes in the search direction, rather than just congestion. This point is important because it corresponds to findings of Beauchemin and Tasci (2008) and Cheremukhin and Restrepo-Echavarria (2010), who estimate a process for the efficiency of the average matching function and show that it can account for much of the cyclical variation in unemployment rates. My model has endogenous changes in the efficiency of matching because workers may choose their search direction in such a way that reduces their finding chances over



the cycle. I define this effective efficiency as a residual

$$\tilde{\phi}_0 = \frac{p \left( \sum_{l=0, d=1}^J \theta^{\ell d} x_{\ell 0} g^{\ell d} \right)}{\sum_{l=0, d=1}^J p(\theta^{\ell d}) x_{\ell 0} g^{\ell d}}$$

This measure is a very clean way to capture the impact of heterogeneity.  $\tilde{\phi}_0$  is the “match efficiency,” and it incorporates workers choice to search in markets that are more or less likely to yield a match. Its fluctuations capture the allocative efficiency that is endogenous in this model, as with the same aggregates for searchers and vacancies, we may have very different finding rates. As can be seen in Table 2.6, the unemployment and finding rates vary quite a lot over the cycle and much of this is explained by the “efficiency” of the matching function. Clearly,  $\phi_1 \neq 1$  implies that  $\tilde{\phi}_0 \neq 1$  by Jensen’s inequality, but its procyclicality shows that it plays an important role in unemployment fluctuations in the cycle. Beauchemin and Tasci (2008) calculate a strongly procyclical process that is necessary to match unemployment, shown in Table 2.6. This mechanism explains some of it.

	Model	Data	MP	No HC
sd(log $u_t$ )	0.18	0.24	0.021	0.11
sd(log $p_t$ )	0.11	0.21	0.021	0.06
corr( $\tilde{\phi}_{0,t}, E_t[z_{d,t}]$ )	0.439	0.60	0.0	0.11
sd(log $\tilde{\phi}_{0,t}$ )/sd(log $p_t$ )	0.205		0.0	0.08

Table 2.6: Business cycle fluctuations. “Data” for  $\tilde{\phi}_0$  corresponds to the accounting procedure in Beauchemin 2012

Of course, my paper is not the first to show that there is significant variation in the hiring rates across occupations, nor to tie this to shifts in the Beveridge curve. Especially convincing, Hobijn (2012), uses novel vacancy data and shows significant heterogeneity in the hires per vacancy across occupations and that the increase in this heterogeneity during the Great Recession and its aftermath explains a great deal of the shift in the Beveridge curve and slow down in average hiring. Barnichon and Figura (2011) also evaluate

My result is also similar in spirit to the exercise in Sahin et al. (2012), though my

work does not yet directly calculate their measure of “mismatch.” They discuss how allocative efficiency across occupations, locations or industries maps into match efficiency. The difference being that their cyclical volatility is affected by either a random process for posting cost or process for vacancies themselves. In their setup, these components ensure that vacancies will be sufficiently volatile, a dimension of the data that I do not target.

### 2.6.3 Expiring Unemployment Benefits

Now consider an economy in which  $\delta = \frac{1}{5}$ , which is approximately the expiration rate of unemployment benefits during normal times in the US. Workers who are employed expect their benefits to last for 6 months of unemployment.<sup>10</sup> Qualitatively, the effect is to diminish the value of unemployment, lower workers’ outside option and increase the matching rate on average.<sup>11</sup> As was the intuition with switchers’ unemployment duration earlier, a larger surplus with the same size of shocks will imply less variation in the vacancy posting and unemployment rates.

Table 2.7 summarizes the changes to important results in the paper. Workers with yet unexpired benefits change their behavior and also workers whose benefits have expired are more likely to switch occupations and generally appear different. A bit less than one in six unemployed workers has expired benefits and their finding rate is generally higher (holding constant the composition) by 7 percentage points.

Stat	Baseline	6 Mo Expiration	Data
E(duration)	3.54	3.49	3.73
Fraction $\geq$ 6 mo	0.16	0.15	0.16
sd(log $u_t$ )	0.18	0.16	0.24

Table 2.7: The effect of benefits’ expiration

Quantitatively, the change matters. However, it is not obvious that this does not

<sup>10</sup>Note the timing issue here: workers separate at the beginning of the period but do not face expiration risk. They do not enter “expired” status until the next period after unsuccessfully searching and being unemployed for a month. Thus, an expected period of benefits that is 6 months implies an expiration rate of  $\frac{1}{5}$  for workers who enter the period in unemployment.

<sup>11</sup>The change in finding rate goes away because I re-calibrate the model, the average matching rate stays the same

overstate the case of the effect of unemployment benefits expiration. The issue is two-fold: (1) random expiration does not necessarily mimic the experience of workers who know the expiration of their benefits and (2) the fall in consumption due to benefits expiration is significant but not as great as the fall in income would suggest.

Random expiration of unemployment benefits is computationally convenient but for the unemployed their decision always incorporate the risk that next month they may lose benefits. This means that the value of unemployment for short unemployed workers is lower than it would be given a more realistic, deterministic expiration. This point applies to all such models with random expiration back to Fredriksson and Holmlund (2001).

Though the expiration of benefits may entail a significant fall in income, the concomitant fall in consumption may be quite small. Several papers, most canonically Gruber (1997) estimate a fall in consumption expenditures between  $\frac{1}{5}$  to 13 if there were no unemployment benefit. This is significant, but not the same scale as the reduction of income from unemployment benefits to food stamps. Furthermore, Browning and Crossley (2009) show that the composition of expenditures change, i.e. away from durables, and that further reduces the fall in welfare terms.

## 2.7 The Great Recession

The Great Recession is a perfect test of the model out of sample. As has been hopefully made clear, the model's parameters are based entirely on data to 2007. It was successful at generating longer-term unemployed in regular cycles. But how does it fare in the extreme conditions recently observed?

Figure 2.12 (left) plots the dispersion in log-industry productivity. Each industry has its mean and linear trend removed, as in the data fed into the model. Notice that the dispersion in industry-specific productivity is at its highest since the post World War II recessions. In my model, the productivity difference between the best and least productive, the ratio of 90th to 10th percentile, will contribute to the elongation of the tail of the duration distribution.

The fall in average productivity was quite sever, though rather short. However, the

rise in dispersion preceded the recession and continued even afterwards. This observation, that dispersion increases even in 2006 echoes Barnichon and Figura (2011), who find an increase in labor market dispersion that presages the Great Recession.

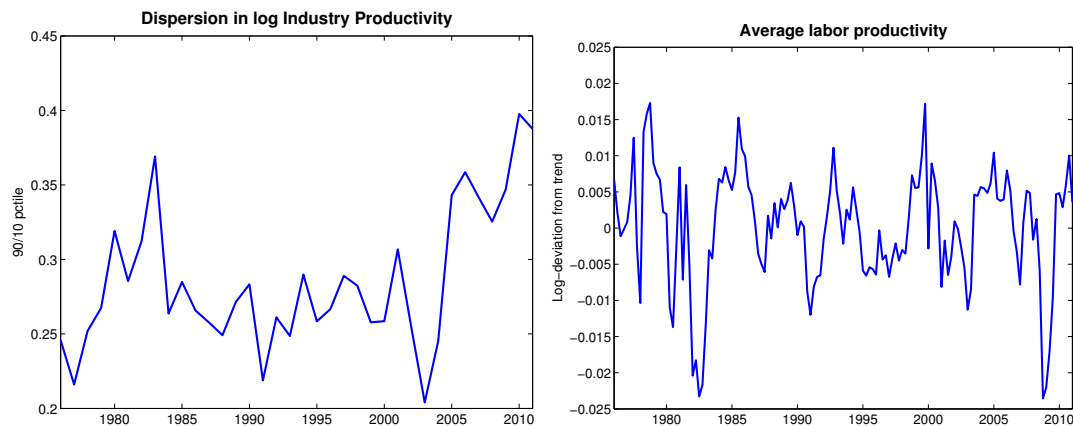


Figure 2.12: The dispersion of industry productivity is peaks in this recession and average productivity hits a nadir

### 2.7.1 Setting up the experiment

My experiment takes from the data the distribution of workers,  $\{x\}$  and the distribution of shocks  $\mathcal{Z}$ . Some manipulations are required to map these observables into model objects because the data on worker experience is not detailed enough and the productivity shocks are only observed through per capita output.

To set up the experiment with  $x$  from the data, distributions of both employed and unemployed are necessary because the distribution of employed will determine the distribution of unemployed as the economy evolves over the Great Recession. The problem is that in the SIPP, I only observe a workers occupation and occupation tenure. I would also need to know the prior occupation to map one for one into the model, but this is unavailable. First, I take the number of experienced workers directly from the data,  $x_{dd}$ . These are workers who have tenure greater than or equal to the average number of months it takes to become experienced in the model,  $\frac{1}{\tau}$ . Then, I have some group of workers observed in occupation  $d$  but who are inexperienced. I assign them to prior occupations  $\ell$  to match the steady state distribution. I set  $\frac{x_{ss,jd}}{x_{ss,\ell d}} = \frac{x_{0,jd}}{x_{0,\ell d}}$ , where  $ss$

means the steady state and 0 is the beginning of the experiment. To set  $x_{00}$ , I take the unemployed workers whose prior occupation tenure was less than  $\frac{1}{\tau}$ .<sup>12</sup>

Next, I need to ensure that the distribution  $x$  from the data is not going to drift on its own because the model's steady-state population in each occupation is different from that in the data. For example, there are some occupations that are very small in the data, but are closer to average size in my model. If I were to just start a simulation with the occupation population from the data, far fewer workers than the model's steady state, there will be a natural drift within the model to attract workers there. I can solve this problem in two ways: (1) I can change the average productivity in each occupation so that the steady state populations correspond between model and data or (2) I can change the size of the population I draw from the data before feeding it into the model. I take the second course. I adjust every occupation's population so that the number I feed into the model is the deviation from its steady state, multiplying by  $\frac{x^{data}_{LR,d}}{\sum_{\ell} x_{ss,\ell d}}$ , the data's long-run average for that occupation's fraction of the labor market over the model's steady state for the same statistic.

To map productivity into the model, I again have to take a structural approach. I can observe output per capita annually and by industry. I take the observations for 2008, 2009, 2010 and interpolate between them. Rather than simple, deterministic interpolations, I sample from the estimated monthly process and trace it out to connect the observed points. I take 100 draws of these 24 month periods. For each history, I solve for the underlying productivity in much the same way as in the other simulations. I require that the model-generated composition of workers and the primitive shock imply observed productivity.

## 2.7.2 Results

Feeding into the model the set of productivity shocks and distribution of unemployed workers I can, indeed recover a large rise in the rate of long-term unemployment and unemployment duration generally. Notice also that the baseline Mortensen-Pissarides model has almost no response. This is because average productivity moved little, as noted by McGrattan and Prescott (2012). But, even though average productivity

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<sup>12</sup>Not every worker reports his prior tenure, so I take the fraction with less than  $\tau$  of those who report a tenure. This assumes that there is no systematic trend in not reporting occupational experience.

moved little, this masks considerable heterogeneity between occupations. In fact, the 90th percentile grew while the median and 10th percentile of occupations' productivity shrank. In particular, the productivity recovery in 2010 occurred largely at the top of the distribution. This change in skewness was dramatic, from 2008 to 2009 Kelly's measure went from 0.15 to  $-0.25$  and then back up to 0.25 by the next year. This third moment behavior is behind some of the large increase in dispersion in the Great Recession period, as shown in Figure 2.12.

In the context of the model, an increase in the spread of productivity creates pressure for workers to reallocate. However, the friction associated with occupation-specific skills interferes. As shown in Table 2.8, average unemployment duration rises in the model, but long-run unemployment is especially prominent as in the data.

	Model	Data	MP	no HC
Expected Duration	3.85	4.36	3.07	3.42
Standard Deviation	4.31	4.60	3.07	3.42
Fraction $\geq 6$ months	0.26	0.30	0.094	0.12

Table 2.8: Unemployment duration during the Great Recession

Notice especially that the model's increase in long-term unemployment nearly keeps pace with the rise seen in the data, but average duration is not as great. Long-term unemployment in the model rose by so much because the spreading of productivity also entailed a spreading of unemployment duration across occupations and the occupations that were affected were affected badly. However, average duration rose by less because at the short end, the finding rate did not fall by much.

Figure 2.13 tells some of this story. As mentioned, the model's finding rate falls by less and is less "kinked" due, in part, to my abstraction from duration dependence. This seems to be the explanation for my model's lower mean duration but relatively high incidence of long-term unemployment. Consider the case in which all of the downward slope were due to duration dependence. Before 6 months, the finding rate was relatively high and after 6 months it went very near zero. This would mean that whomever did not first find a job is now the population of long-term unemployed, and that may be a small number, but the mean unemployment rate is very high. In my model, however, all finding rate heterogeneity comes from differences in the composition of unemployed,

and so even a long durations there are still many who have fairly high finding rates and have merely been repeatedly unlucky.

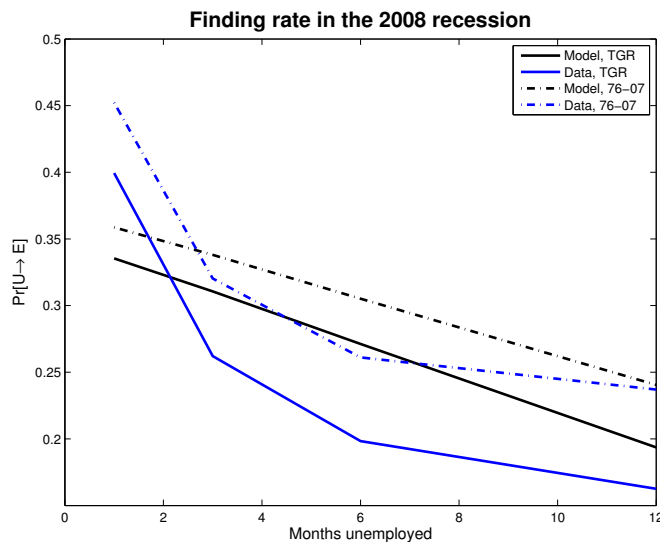


Figure 2.13: The finding rate rotates downward but captures only some of the heterogeneity

### 2.7.3 Time to switch occupations

Crucially, it takes longer to switch occupations in a recession. This holds in the data and in the model. One way to measure and quantify this effect is a simple regression on the data:

$$\text{weeks unemployed} = D_{occ_t \neq occ_{t-1}} + \text{demographics} + \text{const} + \epsilon$$

I include the industry switching dummy for illustrative purposes, to again remind readers that occupations are a useful unit of analysis. Notice that the industry switchers do not have significantly longer durations during the most recession. The crucial coefficients are shown in Table 2.9. Conditional on many demographic factors<sup>13</sup> workers who switch occupations are unemployed for longer than those who do not. For the full regression,

<sup>13</sup>The controls are: race marital status, sex, age, high school and college dummies and an annual trend. The trend is estimated on 1978-2007 and applied to the 2008-2010 data.

see Table A.2.

	1978-2007		2008-2010	
	Coef	Std Err	Coef	Std Err
Data Dummy Occ Switch	7.94	(0.302)	16.16	(0.889)
Model Dummy Occ Switch	6.13		13.74	

Table 2.9: Marginal effect in weeks of an occupation switch

#### 2.7.4 The unemployment rate

The unemployment rate rises less drastically in the model than the data, but by more than would be predicted by a simple search and matching model. This would be suggested by the prior result that unemployment is more volatile in my model than other search and matching models and it is also consistent with the result suggested by Andolfatto and MacDonald (2004). As Figure 2.12 (Right) suggests, there was a large fall in average productivity. In Figure 2.12 (Left) we see this was accompanied by an increase in dispersion that lasted even longer. As seen in Table 2.10 this generates an increase in unemployment rate, though not as large as was actually seen. Consistent with the design of the experiment, unemployment starts at 5.2%, actually below the calibrated steady state, and then we see that it rises considerably. These figures are

Stat	Model	Data
Average $u_t$	6.72	8.23
Peak $u_t$	7.02	10.0

Table 2.10: The effect of benefits' expiration

just about in-line with the upper bound found in Sahin et al. (2012) when they partly endogenize the posting of vacancies.

#### 2.7.5 Unemployment benefits extensions

As discussed in section 2.6.3, expiring unemployment benefits has a sizable impact on the behavior of the model because it affects searchers' outside options. Hence, when the duration of unemployment benefits increases, it non-trivially increases the workers' outside option and encourages them to search more narrowly and for longer. Or, to look



from the other side, it makes it more difficult to pay a worker to switch occupations when his outside option rises.

In the Great Recession, several studies have found that the effect from benefits extension on unemployment is non-trivial. Nakajima (2012) chalks 1.5 percentage points to the extension of unemployment benefits.

One of the key features of a structural model is that I can use it for policy experiments. Here, I look at the effect of the extension of unemployment benefits and perform a counter-factual experiment wherein I do not extend the benefits from 6 to 12 months. The results of this experiment are shown in Table 2.11. Note that, in the new calibration with  $\delta = \frac{1}{5}$ , the unemployment rate goes up considerably when the unemployment benefits are extended to  $\delta = \frac{1}{11}$ .

Stat	Baseline	12 Mo	6 Mo	Data
E(duration)	3.85	3.87	3.76	4.36
Fraction $\geq$ 6 mo	0.26	0.27	0.22	0.30
Average $u_t$	6.72	6.91	6.27	8.23

Table 2.11: The effect of benefits' expiration

## 2.8 Conclusion

The unprecedented rise in unemployment duration during the Great Recession has focused attention onto its causes. One often cited explanation blames a mismatch between skills in demand and those in supply from the unemployed. In this line of thinking, the long-term unemployed are composed of workers with skills in particularly low demand. But, standard theory is ill-suited to quantitatively evaluate this explanation. One needs heterogeneity amongst the unemployed and, more importantly, this heterogeneity must be along workers' skills.

This paper introduces a model with workers who differ by their prior occupation, which summarizes their skills. With discipline from data on the wage premium to occupational experience and the process for occupation-specific shocks, it can quantify the link between unemployment duration and skills. In the model, workers' crucial choice is whether to search in their own occupation where they command a premium

for their experience. But, for workers from hard-hit occupations, searching for jobs in their old occupation will extend their duration in unemployment.

I began with a data exercise, I showed differences across the unemployed in their job finding rates are required for understanding the level and cyclical variation of unemployment duration. In any model in which the rate at which workers find a job is the same and matches aggregate data, the implied duration will be lower and less volatile than in the data. Prior occupation is a useful margin along which to divide searchers. The unemployment rate and average unemployment duration vary substantially across occupations and their dispersion increases during recession. Moreover, other studies have suggested that occupational skills are quite important, enough to motivate these differences.

The model augmented a standard Mortensen-Pissarides model with occupation-specific skills and shocks. This meant that unemployed workers directed their search, balancing the wage upon matching and their probability of finding that job. Because workers might choose to search in relatively low-finding rate occupations, match efficiency was endogenous and, as we showed pro-cyclical. Generally, this model delivered realistic business cycle fluctuations in unemployment duration and the counter-cyclical dispersion across occupation. In particular, the incidence of long-term unemployment was nearly identical between model and data. Finally, I applied the model to the Great Recession. In this experiment, I took as given the distribution of occupational skills amongst the unemployed and the occupation-specific shocks. This was meant to measure the effect of the skills of the unemployed and observed shocks, which spread in the recession. These factors greatly increased long-term unemployment, nearly 70% of the total observed increase.

In the future, the model can be applied to a number of policy experiments. It is a good laboratory to study the effects of targeted interventions. Much of government spending affects certain occupations much more than others, such as building projects that affect construction workers. In this model, unlike models without a notion of occupations, I can assess the effect of such asymmetric intervention on long-term unemployment. The model can also be used on particular policies, such as the Obama administration's answer to long-term unemployment, whereby they encourage employers to hire and train them. In the "Bridge to Work" plan, employers can hire and train

workers without paying them. While this would encourage vacancies to be posted for such workers, workers might not want to apply for such jobs, which is an effect my directed search model incorporate. Its mechanism can help disentangle these effects and assess the policy's effects.

## Chapter 3

# Occupational Skills and Lifetime Earnings

### 3.1 Introduction

How does a workers' choice of occupation affect his lifetime earnings? Why do otherwise similar looking workers earn different amounts in the same occupation? To address this question one must first augment classical human capital theory with a notion of the *allocation* of labor. Just as with physical capital investment, human capital may be deployed in more or less productive ways and so simply counting the resources devoted to investment is insufficient to predict its return. However, the question of lifetime earnings is more complicated than just the effect of static allocative efficiency. Occupational choice affects a worker's wage dynamics. Different occupations have different average wage trajectories, individuals with longer occupational tenure will have greater wage growth, and also individuals within an occupation will have different returns to occupational tenure. This chapter focuses on the last aspect. To put this in context, earlier work has shown convincingly that the growth in one's lifetime earnings can be attributed to the occupation he chooses and how long he stays in this occupation. I take this a step further to show that the quality of one's match with that occupation also determine both the level and growth rate of earnings in that occupation.

In this chapter, I focus the quality of skills match in an occupation, how well a

worker's set of skills corresponds to the skills utilized in his occupation. This is facilitated by a unique pairing of two sets of data. First, for every occupation, the Department of Labor's O\*NET describes the knowledge, skills and abilities (KSA) utilized by an occupation. It uses survey data about the intensity each KSA element is used within an occupation. Second, the National Longitudinal Survey of Youth, a panel data set following a cohort since 1979, includes test scores from the Armed Services Vocational Aptitude Battery (ASVAB). The ASVAB is a set of 10 skills tests originally designed for occupational placement within the US military. Each test examines a different area of skills and it is now in wider use among advanced high school students. The researchers in charge of the ASVAB commissioned a panel of experts to create a mapping between their ten dimensional tests and the KSA space from the O\*NET. I exploit this mapping to compare the workers' test scores and how their occupations utilize them.

I construct a measure of occupational match quality and find that it contributes significantly to earnings in an occupation. Furthermore, it significantly affects the return to occupational tenure. Workers with better match quality earn more after controlling for other standard determinants such as work experience or education and also controlling of occupational tenure and average ASVAB test score. Match quality also contributes significantly to the rate of wage growth within an occupation. That is to say, the return to occupational tenure is significantly higher for workers with a better match quality in that occupation.

This information is particularly important in light of two concurrent trends: just as earnings inequality has drastically risen, so has occupational mobility. It is well documented that earnings have become more dispersed, with difference in real weekly earnings 50% larger than it was 40 years ago. Occupation can explain a great deal of earnings and earnings growth inequality. However workers are increasingly mobile across occupation, affecting how much of the returns to tenure they can enjoy. To link the two, perhaps workers who are poorly matched to their occupation are paid less and switch in response. This is consistent with rising earnings inequality within occupations and the effect of match quality shown herein.

This chapter is organized as follows. After a brief review of the literature, I introduce some data on earnings inequality and occupational mobility. Then, I describe the data and its treatment and present and interpret the main estimation results. After, I build

a model that can motivate this reduced form work. Finally I conclude with a brief description of future work building on these findings.

## 3.2 Related Literature

The return to occupation-specific tenure has gained prominence recently with several high profile papers emphasizing its importance. Kambourov and Manovskii (2009b) use data from the Panel Study on Income Dynamics (PSID) to show quite convincingly that the returns to occupational tenure are significant, especially relative to employer and industry specific experience. Their headline number is that occupational tenure can return wage growth up to 20% over 5 years. The paper takes advantage of a retrospective recoding of occupations in the PSID, which mitigates much of the coding error to occupations and allows for better estimates.

There is a much larger literature on the determinants of wage growth, of which Kambourov and Manovskii (2009b) is a part. Altonji and Shakotko (1987) is also a notable contribution, arguing that the returns to job tenure are fairly small. This paper introduces an instrumenting scheme to get around the endogeneity of observed tenure that we use here. The trouble they identify and address is that a match may continue for a relatively long time because of some unobservable characteristics embodied in the worker-job pair. These characteristics that lengthen the match's duration are also likely to increase the wage during the match and this correlation will spuriously increase the OLS estimate of the returns to tenure. Whereas Altonji and Shakotko (1987) argue that proper instrumenting abrogates the observed returns to job tenure, Topel (1991) influentially disagreed largely based on their IV method and measurement issues. According to Topel (1991), 10 years of job experience leads to 25% higher wages. This figure does not, however, consider how occupation- or industry-specific effects might also be important and, when omitted, contribute to the job returns figure.

Neal (1995) highlights the importance of industry-specific over job-specific experience. To do so, he uses workers displaced from their jobs and compares those who find work in the same industry against those who do not. Workers who stay in their same industry enjoy wages reflecting their past industry experience, whereas switcher's wage losses are much greater if they had more industry experience. As argued in Kambourov

and Manovskii (2009b), this may attribute occupation-specific returns to the industry because of the high correlation between occupation and industry switching.

### 3.3 Earnings and Occupational Mobility

This section will describe facts about the life-cycle for earnings and occupational mobility. First, we will present how occupational mobility evolves over the life-time and then how it relates to earnings. The idea behind studying occupational switching is that a switch likely reveals poor match quality. This chapter is generally showing that the match between occupational skills and individual skills matters for wages and this section shows broadly the ways in which earnings co-move with match quality, proxied by switching.

#### 3.3.1 Occupational mobility

In recent years, one in six workers will switch occupations as defined at the three digit level.<sup>1</sup> Switching is especially concentrated among the young, and then falls quickly through the 20s and 30s. Occupational mobility has risen consistently for almost every cohort until the most recent group whose only labor market experience is in the Great Recession. Occupational switching is quite intertwined with wages. Those with wages far from their predicted rate are more likely to switch, while we also notice vastly different earnings profiles for workers who switch late in life.

Figure 3.1 shows the age profile of the switch rate. It is computed from the Current Population Survey (CPS) by comparing the respondent's primary occupation last year to the current occupation reported. Measuring occupational switches this way avoids much of the artificial switching due to coding error when using chained CPS. Here, a respondent identifies both occupations in a single month's survey. The figure controls for cohort effects, but time effect controls are not noticeably different.

An interesting feature of the data is the distinct trend across cohorts that mirrors the trend in earnings inequality. Younger cohorts switch occupation more frequently than their predecessors. Figure 3.2 plots the cohort average switch rates after controlling for the age profile. An employee born in the 1980s is  $\frac{3}{4}$  more likely to switch occupations

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<sup>1</sup>In this chapter, I use a year-to-year comparable three digit coding system described later.

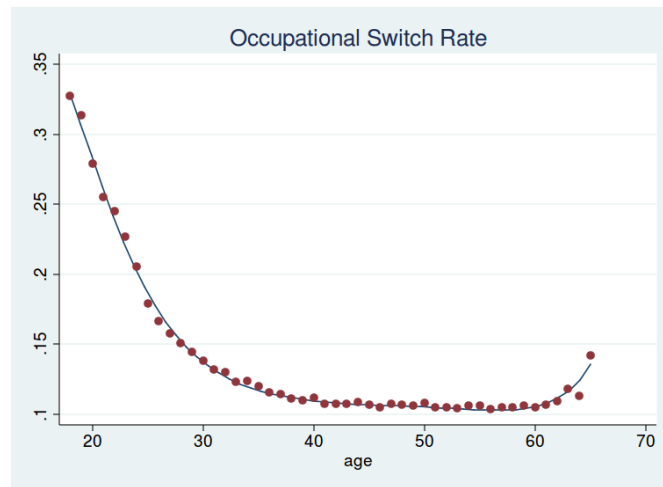


Figure 3.1: The life-cycle profile of occupational switches

than his grandparent. The rise in earnings inequality between cohorts is well documented and basically concurrent. It is this dual trend that Kambourov and Manovskii (2009a) tries to connect. Interestingly, the most recent cohorts seem to switch less. This is showing that those whose only labor market experience is as a young person during the Great Recession switch occupation less frequently than would be expected for their young age group.

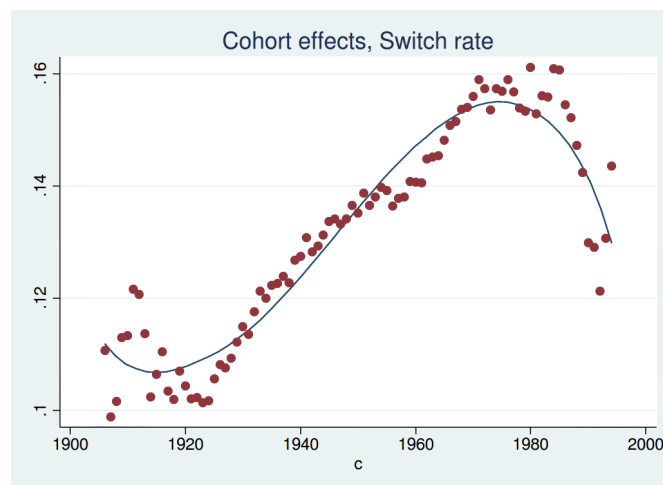


Figure 3.2: The life-cycle profile of occupational switches



### 3.3.2 The connection between earnings and occupational mobility

It is a well known fact that earnings rise of the life-cycle. For reference, the age profile of real wages is shown in Figure 3.3. The rise in earnings corresponds in the life-cycle to the fall in occupational switching. Several studies, Kambourov and Manovskii (2009b) included, show rather convincingly that the rise in wages is due in large part to the rise in occupational tenure. But, then why is there any switching when young? This chapter suggest there are heterogeneous returns, partly due to match quality.

These age profiles are merely age averages. There is much more information in individual wage histories. From Figures 3.1 and 3.3 we can see that the average rate of switching falls just as the average wage is starting to rise, but we will know much more from individual variations in earning and mobility.

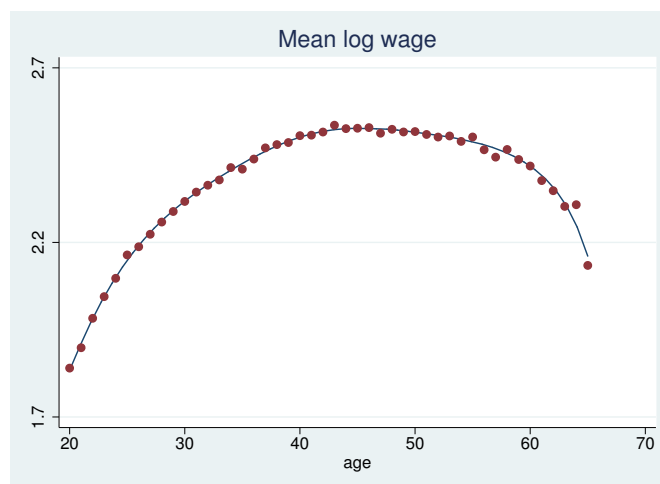


Figure 3.3: The age profile of real wages

How do earnings play into the propensity to switch occupation? There is a simple, negative correlation between earnings and the switching probability. But, the relationship is deeper. With Danish data, Kircher et al. (2009) demonstrate that high and low wage workers (within their occupation) are more likely to switch than those in the center of the distribution. We have found this is also the case for men in the CPS, as seen in Figure 3.4. This is the local linear probability regression of probability to switch on residual wage, where that has conditioned on time, an age polynomial, education and three-digit occupation. Though the figure itself does not imply a causal direction,

it is consistent with workers “learning” from wage data that they are not well matched in their occupation and then switching.

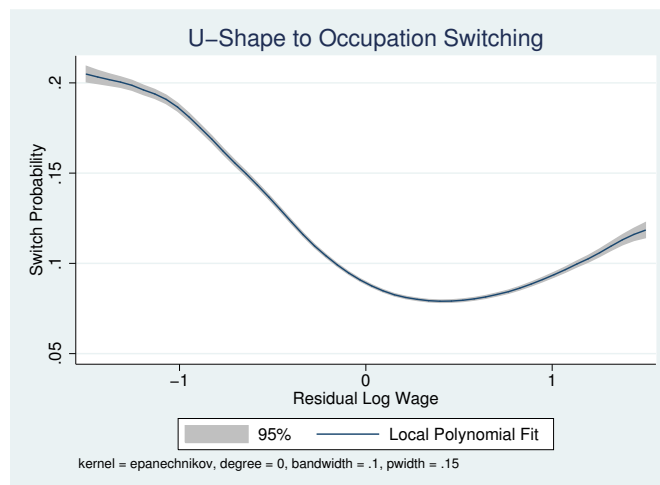


Figure 3.4: Probability of a switch conditional on residual wage

There is also evidence consistent with the effect of switching occupation on the wage of an individual. As chronicled in Kambourov and Manovskii (2009b), the returns to occupational tenure are very important determinants to wages. In Kambourov and Manovskii (2009a), the authors analyze the potential effects on inequality from occupational mobility. But much more directly, there is striking evidence that frequent, late occupation switchers have quite different earnings profiles. Figure 3.5 shows the relative change in wages beginning at age 35 dividing the population between those who switch more than once after 35 and those who do not. It excludes those who switch to become a manager from the switcher group. Those who switch occupations multiple times in middle age, on average, have no wage growth. It is striking evidence of the effect to wages from not finding an occupation.

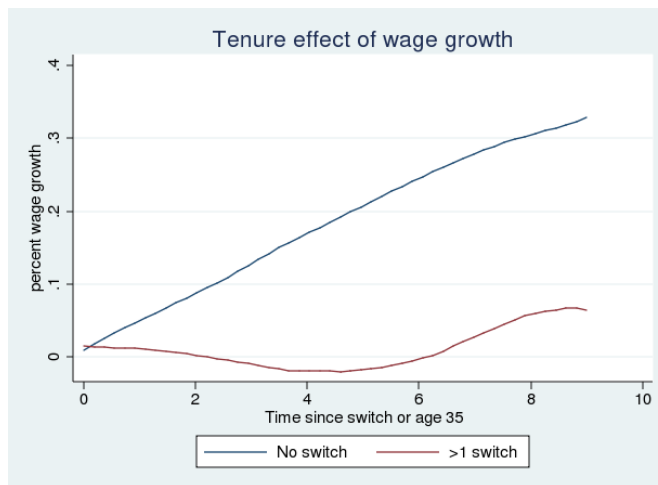


Figure 3.5: Average wage growth after 35

### 3.4 Skills, Abilities and Knowledge Data

This chapter’s innovation is to combine descriptive data on occupations from the O\*NET with the ASVAB test scores in the NLSY79 sample. Other studies have one side; Autor and Handel (2013), for example, have detailed data on the worker’s occupation and many others like Cawley et al. (2000) use data on worker’s skills. As will be seen in the results, data on both matters. With only data on workers, we do not have an exogenous measure of how intensively the worker’s skills are utilized in an occupation and with only occupation-side data we cannot see how well suited an individual is for the type of work.

Table 3.1 summarizes the data on O\*NET and ASVAB. Rather than reporting data on each component score, I present data on the simple sum within occupation or individual. To give a sense of how tightly correlated the elements are, I give the fraction of the variation explained by the first principal component. Figures 3.6 and 3.7 plot the densities of the sum of O\*NET and ASVAB scores.

The following section will detail how the data is treated. The test scores are from a single administration at the beginning of the NLSY sample. Each respondent took the ASVAB and received scores in each of ten dimensions. We use 26 O\*NET KSA descriptors that best correspond to these tests. In each, an occupation receives a score to describe how much it uses that type of knowledge, skill or ability. We transform

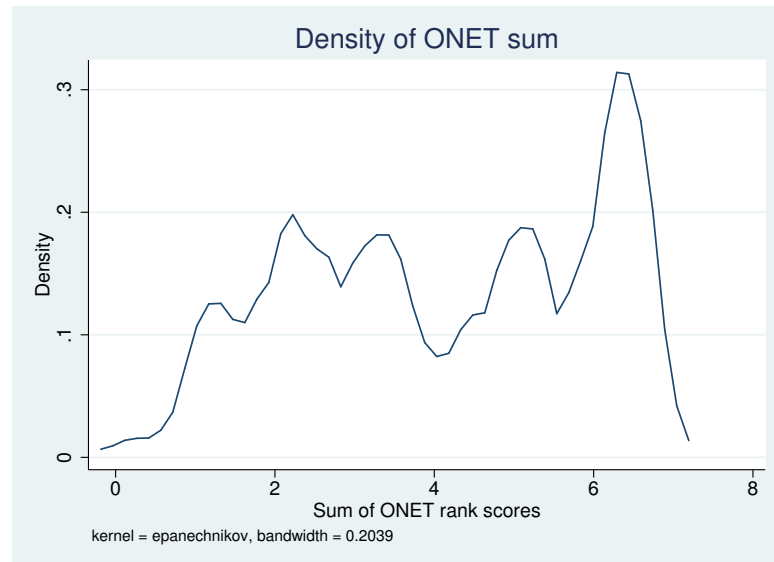


Figure 3.6: Density of the sum of O\*NET Scores

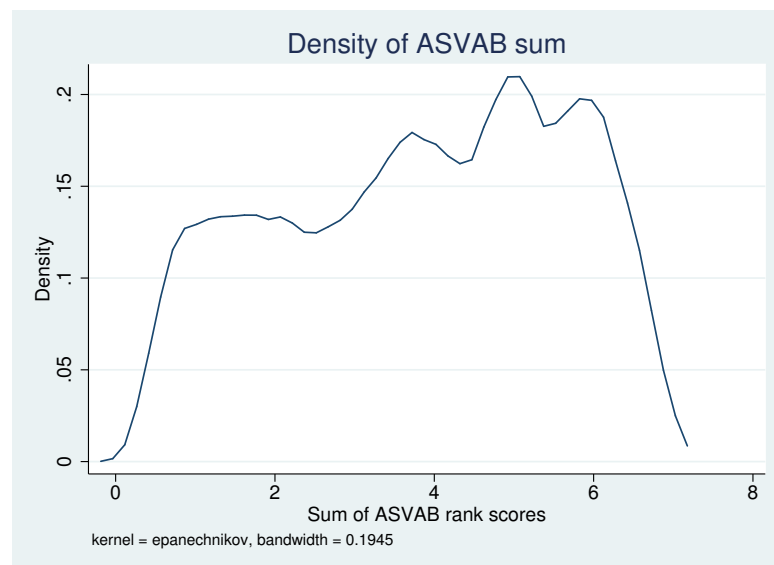


Figure 3.7: Density of the sum of ASVAB Scores

	Mean	St Dev	Kelley	Contribution of first principal component
O*NET	4.14	1.86	-0.15	0.91
ASVAB	3.84	1.78	-0.13	0.76

Table 3.1: Summary statistics of O\*NET and ASVAB scores

both test scores and KSA descriptors into a rank score to norm them and make them comparable.

### 3.4.1 Cleaning the NLSY Sample

#### Sample Selection

In the main estimation, we try to create a fairly homogeneous group, focusing on males between the ages of 18-65. They must be in the labor force and have worked at least 1000 hours. To keep wage rates sane, we drop those who are full time students, in the military or who make less than 2.00 (1984USD) per hour. The lower bound on wage rate drops less than 5% of the sample. We also trim the top 1% of wages.

#### Occupation codes and switches

We use the Minnesota Population Center’s crosswalk to convert respondents’ occupation codes the comparable set they created based upon three-digit 1990 census codes (Occ90). In the NLSY79 raw data, occupations are coded by census three digit code following the 1970 convention until 1994, then the 1990 codes until 2002 when they switched to the 2000-based census codes.

Because O\*NET 4.0 occupations are based upon a more detailed 2000 Standard Occupation Code (SOC), we have to average within these codes to convert to the 2000 Census Codes. This is an unweighted average. There are a few Occ90 codes that have no SOC counterpart, so those respondents with these occupation codes cannot be matched with O\*NET information. For these cases, there was an obviously very similar Occ90 coding that that did match with a 2000 Census Code and so we re-coded these, which affects less than 3% of the sample.

Any time the principal (below we describe how we choose one's chief occupation) occupation does not match from observation to observation we counted that as a switch. The exception is that if occupation changed in one year and then changed right back in the next observation. This smells of a coding error, so we do not count that as a switch and replace the code. This affects about 3% of the total number of switches.

### **Principal Occupation and tenure**

Until 1994, the NLSY records up to 5 jobs for each respondent. Thus, we could either consider this as if there were separate observations for each job or to create a concept of one's principal occupation. We opt for the latter, to avoid potentially perverse weighting issues, as some individuals would count for five times the influence of others and because most of the respondents do have clearly identifiable principal occupation.

A respondent's principal occupation could be either the occupation in which he worked the most hours or the occupation in which he has worked for the longest. We determine both. The code we use for one's occupation corresponds to the occupation with the most hours, however, so long as the respondent worked some time in this occupation we add this year to his tenure clock. Thus, one may have worked in an occupation for X years, switched primary occupations once, but kept working in the other. If his principal occupation switches back, he will still have accumulated tenure in the first occupation during his stint in the other job.

Occupational tenure is computed by us by adding the time since last observation when we do not observe a change in occupation. Though we see the cohort from what is basically the start of their working lives, some have been working before they enter the sample. They report their employer tenure in each year, so we use this number to start counting their occupational tenure.

### **ASVAB scores**

About 94% of the NLSY79 cohort took the Armed Services Vocational Aptitude Battery (ASVAB) form 8a in 1980. This test, by the Defense Manpower Data Center (DMDC) is used for occupational placement within the armed service but has also been

used for general advising outside of the military. The DMDC has collaborated with other government agencies on efforts like OCCU-Find, which merges occupation data to help high school students choose a career.

In the raw NLSY data, they have standardized ASVAB scores, which have a mean of about 50 and standard deviation of about 10. Following Cawley et al. (2000), we regress each score on the respondent’s age when taking the test, run separately by sex and race. We use the standardized residuals from these regressions and assign quantile rank scores. The latter will be used in our analysis.

In the 1980 version of the ASVAB there were 10 tests, General Science, Arithmetic, Word Knowledge, Paragraph Comprehension, Numeric Operations, Coding Speed, Auto and Shop Information, Math Knowledge, Mechanical Comprehension and Electrical Information. We use seven tests Science, Arithmetic, Math Knowledge, Mechanical Comprehension, Electrical Information, Word Knowledge and Paragraph Comprehension.

### 3.4.2 Setting up the O\*NET information

We use the most recent O\*NET 4.0 Analyst database, which was released in 2002 containing information on more than 900 occupations. This database is the successor to the Dictionary of Occupational Titles (DOT), but differs markedly. Whereas the DOT sent out experts with clip boards to generate data about the tasks involved in an occupation, O\*NET takes a random sample of business and then sends questionnaires to workers. Each worker only completes  $\frac{1}{4}$  of the questions. The questions are organized into Ability, Interest, Knowledge, Skills, Tasks, Work Activity, Work Content, and Work Value. The O\*NET website has a cryptic statement that: “Abilities, is completed by occupational analysts using the updated information from incumbent workers.”

We use 26 elements from Knowledge, Skills and Abilities sections for reasons of comparability with ASVAB. In each element, there is an importance and a level score. We use only the Importance score, as recommended by the ASVAB experts, though Firpo et al. (2011) and Blinder (2009) use a Cobb-Douglas of Level and Importance, arbitrarily assigning  $\frac{1}{3}$  weight to level

The scales O\*NET uses are arbitrary, sometimes a 5 point, sometimes a 7 point scale. We rescale everything to be in  $[0, 1]$  by assigning a quantile rank across occupations for each category.

### Merging with ASVAB

To match the O\*NET information with ASVAB we refer to a study by the DMDC for their OCCU-Find program<sup>2</sup>. They were trying to map ASVAB scores to occupation information in the O\*NET so that skills identified in ASVAB tests of non-military high schoolers could be used for career guidance. The research psychologists within the DMDC identified the 26 O\*NET elements from Knowledge, Skills and Abilities categories that might apply ASVAB-tested skills. Then 14 expert judges, 12 PhDs and 2 MAs, judged how related were the ASVAB and O\*NET scores. We use the mean “relatedness” to create O\*NET-based ASVAB categories. We create a weighting matrix  $\Omega$ , in which each row sums to 1, and transform a vector of 26 O\*NET elements  $\mathbf{s}$  to 7 new scores in ASVAB dimensions,  $\mathbf{p} = \Omega\mathbf{s}$ .

### Merging with NLSY79

We have occupation codes in 328 3 digit occupation codes, Occ90 described above. O\*NET uses a SOC code from 2000. The Minnesota Population Center provides a crosswalk to identify each SOC code with an Occ90 code, but there are invariably occupations with several scores now. We take an unweighted average over all of the SOC codes that have the same Occ90 code.

## 3.5 Estimation Results

In this section, I will present results using two measures that combine O\*NET and ASVAB information. The first, simplest is just a dot-product between the vectors of O\*NET and ASVAB rank. This is really a measure of match quality, motivated by a model akin to the “skills weights” model of Lazear (2003). The second, is a mismatch measure that is based on an idea of optimally allocated workers to occupations. In this, we use the Gale-Shapley matching algorithm, Gale and Shapley (1962), to reshuffle workers among their occupations and give a notion of the optimal assignment of workers. Here, optimal means to maximize the dot-product of O\*NET and ASVAB ranks.

<sup>2</sup>[http://www.asvabprogram.com/downloads/Technical\\_Chapter\\_2010.pdf](http://www.asvabprogram.com/downloads/Technical_Chapter_2010.pdf)



The dot-product measure of match quality, called  $q$ , has an attractively simple premise: because both ASVAB and O\*NET ranks are in a zero-one range, a worker maximizes his potential output if he pairs his strengths with an occupation that puts the most intensity on it. To put it more geometrically, the area is maximized if everyone is a “square.”

The advantage of the second measure, the mismatch measure, over the first is in its solution to the “McDonald’s-Le Bernardin” problem. If a worker possesses the skills to cook food, he will be better compensated as a French chef at Le Bernardin instead of a line cook at McDonald’s and with the dot-product measure, everyone is better off by going to an occupation with higher return to skills. Instead, we could hold constant the number of jobs and rearrange workers to increase output. In our implementation of the Gale-Shapley algorithm, employers for each occupation propose to workers to form a match. The final matches are stable in the sense that no (worker, occupation) pair could be better off by finding new partners.

In the following sections we put these two measures into a Mincer equation wage regression framework to see how worker’s skill match quality contributes to wage determination. We will show that match quality robustly affects wages and return to occupational tenure.

### 3.5.1 Dot-product match quality measure

In this section, we present log-wage regressions including the dot-product measure of match quality. We will look not only at how match quality statically affects wages, but also how it interacts with occupational tenure. In particular, does one with a better match between occupational requirements and his own occupational skills have better returns to occupational tenure?

I consider the match quality measure  $q$ . This is calculated as follows. For each individual  $i$ , we take the rank of occupation  $k$  in each O\*NET dimension  $r_{k,j}$  and the individual’s test score in each ASVAB dimension  $s_{i,j}$ . Then  $q_{i,t}$  takes occupation  $k(i,t)$  that worker  $i$  holds at time  $t$  such that

$$q_{i,t} = \sum_j s_{i,j} r_{k(i,t),j} \quad (3.1)$$

The measure has some interesting features. It has quite a right skew to it, though neither the density of  $\sum s_{i,j}$  nor  $\sum r_{k,j}$  is significantly skewed, if not slightly left skewed. Thus, there are relatively few with very highly productive matches, though neither the distribution of occupation or test scores have this property. Table 3.2 summarizes its statistical properties and Figure 3.8 displays the kernel estimate of its density.

Mean	St Dev	Kelley
2.44	1.73	0.28

Table 3.2: Summary statistics of the distribution of dot-product measure of match quality.

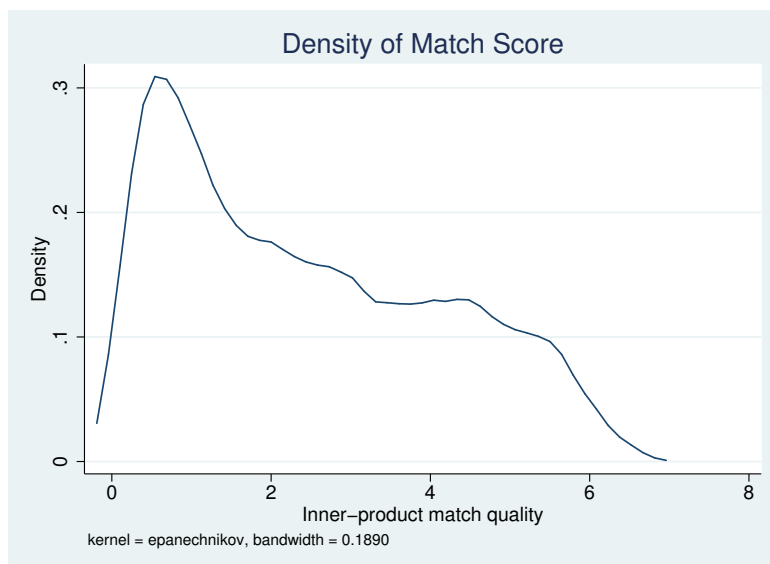


Figure 3.8: Density of the dot-product measure of match quality

For this analysis we build upon the instrumental variables strategy presented in Altonji and Shakotko (1987). The issue is that longer matches (to occupation, or employer) may be due to unobservable characteristics that also increase wages. Hence, a simple OLS regression of wage on tenure length will be biased upwards, reflecting the correlation of both on these unobservables. Altonji and Shakotko (1987) propose a simple, if imperfect, strategy to instrument tenure with its average for that stint. These unobservables will be correlated with the average length during the stint, but not the place within that stint. In other words, if match  $i$  lasts for  $T_i$  years, then the average

tenure observed during this stint is  $\bar{t}_i = \frac{1}{T} \sum_{t=0}^{T_i} t$  (assuming no missing observations) and we will use as an instrument  $t - \bar{t}_i$ . This is the same instrumenting strategy used in Kambourov and Manovskii (2009b) to get at the returns to occupational tenure in the PSID.

In the regression specification, we add demographic controls, such as race and education as well as a quadratic polynomial for occupational tenure, age and employer tenure. The estimation equation will be some form of:

$$\begin{aligned} \log w_{i,t} = & \sum_p \beta_{1,p} \text{EmployerTenure}^p + \beta_{2,p} \text{Experience}^p + \beta_{3,p} \text{OccupationTenure}^p \\ & + \alpha_1 q_{i,t} + \alpha_{2,p} q_{i,t} \times \text{OccupationTenure}^p + \bar{s}_i + \text{Controls} + \epsilon_{i,t} \end{aligned} \quad (3.2)$$

In the instrumental variables versions we assume that employer and occupational tenure and labor market experience are all endogenous and instrument accordingly.  $\bar{s}_i$  is the individual's average test score, to control for individual ability. The controls include one digit industry and occupation dummies, race and education level dummies.

Table 3.3 shows the regression results using this dot-product match quality measure. The first two specifications are from simple OLS regressions and the second two use the IV techniques from Altonji and Shakotko (1987). Specifications (1) and (3) do not include  $\bar{s}$  as a proxy for individual ability and it is added in (2) and (4).

The crucial coefficients are on  $q$  and  $q \times$  occupational tenure. Notice that they are positive and significant in every specification. The interpretation is clear: better match quality is associated with higher wages and higher returns to occupational tenure. It is interesting to see that the interaction term is larger when we instrument with average occupational tenure. In the plain OLS estimation, the coefficients on returns to occupational tenure are biased upwards, and are much larger than the coefficients when using the IV approach. Probably much of the variation due to the interaction between tenure and  $q$  is being associated with the occupational tenure in the OLS version. But, once we instrument and the correlation between unobservable match quality and tenure has been removed, our observable match quality measure has a larger role.

The effect of match quality is almost unaffected by the inclusion of a measure of individual ability.  $\bar{s}$ , though significant in determining wages, does little to affect the

Table 3.3: Dot-product match quality measure regression results

	(1)	(2)	(3)	(4)
q	0.065 (19.20)**	0.037 (8.88)**	0.052 (14.04)**	0.023 (5.25)**
q × occupation ten	0.001 (2.38)*	0.001 (2.41)*	0.003 (8.50)**	0.003 (8.45)**
employer tenure	0.006 (1.85)	0.006 (1.64)	-0.004 (0.81)	-0.003 (0.77)
employer tenure <sup>2</sup>	0.000 (0.04)	0.000 (0.16)	0.000 (1.08)	0.000 (1.01)
occupation tenure	0.031 (6.34)**	0.031 (6.49)**	-0.001 (0.13)	-0.001 (0.18)
occupation tenure <sup>2</sup>	-0.002 (4.13)**	-0.002 (4.18)**	-0.000 (0.94)	-0.000 (0.88)
occupation tenure <sup>3</sup>	0.000 (2.87)**	0.000 (2.85)**	0.000 (0.64)	
experience	0.034 (8.83)**	0.035 (9.21)**	0.055 (13.65)**	0.057 (14.06)**
experience <sup>2</sup>	-0.001 (1.98)*	-0.001 (2.25)*	-0.002 (5.11)**	-0.002 (5.43)**
experience <sup>3</sup>	-0.000 (0.74)	-0.000 (0.57)	0.000 (1.84)	0.000 (2.08)*
$\bar{s}$		0.246 (12.33)**		0.249 (12.25)**
Constant	6.333 (227.77)**	6.314 (226.69)**	6.380 (225.59)**	6.359 (224.90)**
$R^2$	0.28	0.28	0.27	0.27
$N$	36,460	36,460	36,460	36,460

\*  $p < 0.05$ ; \*\*  $p < 0.01$

coefficients on match quality. Hence,  $q$  is not simply a proxy for individual ability. It is instead capturing the importance of the interaction between individual skills and the occupation’s requirements.

### 3.5.2 Gale-Shapley mismatch measure

In this section I present estimation results from a measure that uses the Gale-Shapley algorithm to optimally choose workers for jobs and then compares the existing match to this match. This is meant to incorporate the “demand” side of the labor market, in that not every worker can work in a job that give the highest possible return to his skills. We address the McDonald’s-Le Bernardin problem by fixing the number of jobs available at each institution and then allocating workers to them.

To allocate workers to jobs, I use the Gale-Shapley algorithm to create “stable” matches. They are stable in the sense that, for each worker, job pair, we could not swap any two pairs and benefit both. The mismatch measure is then the value of the dot-product in this optimal match minus the value of the dot-product measure observed in the data. If  $k(i, opt)$  identifies the occupation chosen by Gale-Shapley, and  $k(i, t)$  is the match actually observed. Then our measure is

$$m_{i,t} = \log \left( \sum_j s_{i,j} r_{k(i,opt),j} \right) - \log \left( \sum_j s_{i,j} r_{k(i,t),j} \right) \quad (3.3)$$

Table 3.4 summarizes the features of this measure and Figure 3.9 is the kernel density estimate. First, it is a feature of using the Gale-Shapley algorithm to optimize the matches that the difference between optimal and observed is almost always positive. In fact, only 2.5% are below zero. The distribution is also quite positively skewed. As Kelley’s measure of skewness points out, 30% more of the 90-10 spread comes from the top half of the distribution.

Mean	St Dev	Kelley
0.71	0.65	0.47

Table 3.4: Distribution of the mismatch measure

We insert this mismatch measure into a wage regression with the same specification

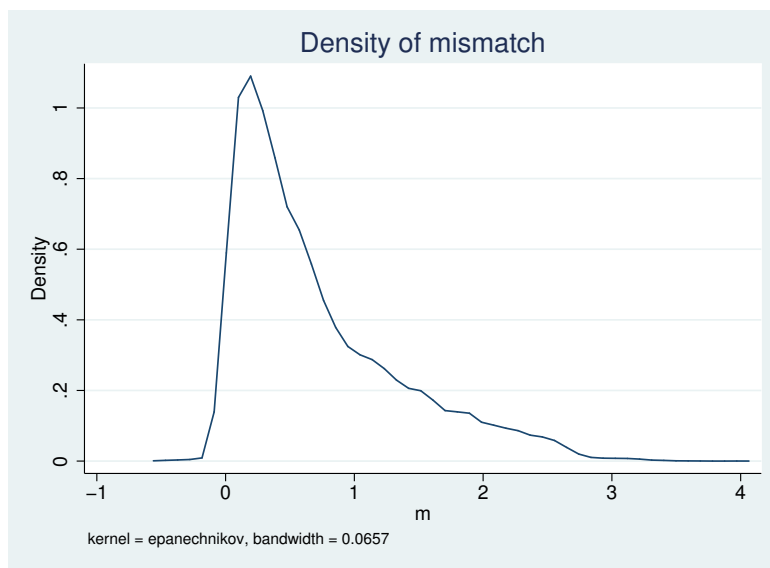


Figure 3.9: Density of the the mismatch measure

as previously in Equation 3.2 but replacing  $q$  with  $m$ . Now the interpretation on the coefficients for  $m$  is slightly different from  $q$ . Whereas  $q$  meant that a worker-occupation pair was well suited, a high value for  $m$  actually means that the worker is *not* well suited for the job. It implies that a much higher dot-product could be achieved with the same skill set.  $m$  is considerably lower for college-educated workers: their mean is only 72% of the mean of high school graduates. This is the opposite for  $q$ , in which the mean of college graduates is 140% of high school graduates. And whereas  $q$  was positively correlated with  $\bar{s}$ , 0.79, that is the opposite for  $m$ , -0.60.

Table 3.5 presents the regression results in the four specifications we ran with the  $q$  measure. Again, the first two are simple OLS regressions and regressions (3) and (4) use the IV strategy. Regressions (2) and (4) include a term for the individual's average test score,  $\bar{s}_i$ .

In every specification, the coefficient on  $m \times$  occupation tenure is significantly negative. Workers whose occupation yields output much worse than they could achieve, i.e. a large value of  $m$ , have poor wage growth in this occupation. They are the worst matched workers and so it makes sense that this should adversely affect their wage

growth. More puzzling is the estimated coefficient on  $m$ . When  $\bar{s}$  is included, this coefficient is significantly negative, but essentially zero when  $\bar{s}$  is omitted. Statistically, the discrepancy between the coefficient in (1) and (3) against (2) and (4) makes sense:  $m$  and  $\bar{s}$  are quite negatively correlated so when  $\bar{s}$  is lumped into the residual, this biases downwards the coefficient. The economic interpretation is more difficult. Why should  $\bar{s}$  have such a strong relationship with mismatch. Further, why does the inclusion of intelligence matter so much, when both specifications also include education dummies?

To interpret the coefficients on  $m$ , recall that it is the log-transformed ratio of optimal and realized matches. Thus in specifications (1) and (3), when the ratio increases by 10%, wages falls by about 1%. But, when we include  $\bar{s}$ , as in (2) and (4), there is no significant relationship between mismatch and wage level. There is, however, always a significant relationship with the returns to occupational tenure. Now, a 10% better match ratio increases the return to occupational tenure by 0.01% per year. Put differently, consider the relative return to a year of occupational tenure in specification (4). It ranges from 0.0001 to 0.011 with plus or minus a standard deviation.

Table 3.5: Gale-Shapley mismatch measure regression results

	(1)	(2)	(3)	(4)
$m$	-0.113 (13.79)**	-0.008 (0.61)	-0.108 (11.66)**	0.014 (1.00)
$m \times$ occupation ten	-0.007 (8.00)**	-0.006 (7.11)**	-0.008 (7.50)**	-0.008 (7.61)**
employer tenure	0.010 (2.67)**	0.009 (2.56)*	0.001 (0.12)	0.001 (0.13)
employer tenure <sup>2</sup>	-0.000 (0.46)	-0.000 (0.43)	0.000 (0.32)	0.000 (0.31)
occupation tenure	0.035 (7.30)**	0.035 (7.30)**	0.011 (1.86)	0.011 (1.87)
occupation tenure <sup>2</sup>	-0.002 (4.01)**	-0.002 (4.13)**	-0.000 (0.91)	-0.000 (0.92)
occupation tenure <sup>3</sup>	0.000 (2.77)**	0.000 (2.87)**	0.000 (0.84)	0.000 (0.85)
experience	0.037 (9.95)**	0.038 (10.06)**	0.059 (14.79)**	0.059 (14.89)**
experience <sup>2</sup>	-0.001 (3.20)**	-0.001 (3.17)**	-0.002 (6.10)**	-0.002 (6.14)**
experience <sup>3</sup>	0.000 (0.44)	0.000 (0.37)	0.000 (2.71)**	0.000 (2.73)**
$\bar{s}$		0.299 (9.82)**		0.333 (10.89)**
Constant	6.635 (238.76)**	6.397 (175.94)**	6.652 (235.00)**	6.383 (173.10)**
$R^2$	0.27	0.27	0.26	0.26
$N$	37,323	37,323	37,323	37,323

\*  $p < 0.05$ ; \*\*  $p < 0.01$



## 3.6 A simple model of occupational choice and learning

In this section I present a simple model of occupations and learning that can be speak to the facts in the previous section of the chapter. It will try to quantify the extent to which workers “know” their abilities and how this uncertainty evolves as they gain labor market experience. In so doing, we can quantify its contribution to earnings inequality over the life-cycle. In other words, our regressions suggest that worse matched workers make less money over their careers. How much is this caused by uncertainty about one’s own skills and how much does this contribute to lifetime earnings inequality?

The model is fairly simple but hopefully incorporates these crucial aspects.

### 3.6.1 Human capital investment and information structure

Workers live for  $T$  periods and have linear, risk neutral utility over their wage. Human capital accumulation very much resembles a multi-dimensional Ben-Porath model. Workers accumulate  $J$  types of human capital, the stock of which is denoted  $h_t^j$  for an individual. In each dimension, individuals choose to invest  $i_t^j$  of their market time to acquiring human capital in the  $j$  dimension. Crucially, there is heterogeneity in learning ability for each dimension,  $A^j$  is an individual-specific parameter. The law of motion for  $h_{t+1}^j$  is:

$$h_{t+1}^j = A^j \left(h_t^j\right)^\gamma \left(i_t^j\right)^\delta \quad (3.4)$$

Individuals, however have imperfect information about each  $h_t^j$  and  $A^j$ . They cannot observe  $A^j$  and the initial human capital  $h_0^j$  and so form working prior beliefs. Each period they only observe  $\tilde{h}_t^j = h_t^j \exp(\epsilon_t^j)$ . The white-noise observation error,  $\epsilon_t^j$  is normally distributed  $\mathcal{N}(0, \sigma_\epsilon^2)$ . So, to tease out the values of  $A^j, h_0^j$  and, thus also  $h_t^j$ , the worker will use Kalman Filtering.

Each  $\epsilon_t^j$  is i.i.d. over time and  $j$ . The former assumption is not really so material, as if there were persistence in these shocks it would simply add a variable to the state in our Kalman Filtering problem. The latter assumption will, when we define the rest of the system play a role in the ease of learning.

Given the structure above, beliefs about  $A^j$  and  $h_t^j$  are log-normally distributed. With the  $t - 1$  information, beliefs about  $h_t^j$  and  $A_t^j$  are  $\hat{h}_{t|t-1}^j$  and  $\hat{A}_{t|t-1}^j$ . The joint

estimation covariance of their log-transformed version is  $\hat{P}_{t|t-1}$ . Hence, the state is distributed

$$\log \mathcal{N} \left( \begin{pmatrix} \hat{h}_{t|t-1}^j \\ \hat{A}_{t|t-1}^j \end{pmatrix}, \hat{P}_{t|t-1} \right)$$

### 3.6.2 Technology and production

Production occurs in  $K$  discrete occupations, each valuing skills differently. Firms hiring workers for an occupation operate in a competitive, frictionless labor market, and so pay workers their marginal product. Firms differ in the weights they place upon each occupation, the so-called skill-weights approach of Lazear (2003). For each firm  $k$ , it uses skill  $j$  with intensity  $p_k^j$ .

Workers choose the occupation in which to work but *before observing*  $\{\epsilon_t^j\}_{j=1}^J$ . Thus, the aged  $t$  individual chooses an occupation based on the priors,  $\{\hat{h}_{t|t-1}^j\}_{j=1}^J$  and  $\{\hat{A}_{t|t-1}^j\}_{j=1}^J$ .

Thus, the realized output and wage for a worker in occupation  $k$  is

$$\left( \sum_j p_k^j h_t^j e^{\epsilon_t^j} \right) \left( 1 - \sum_j i_t^j \right) \quad (3.5)$$

### 3.6.3 Worker's problem

In this subsection we define recursively the worker's problem of occupational choice, investment and learning. Because there is no capital nor diminishing returns, there are no aggregate states nor general equilibrium effects, so we will not define the entire recursive competitive equilibrium. Instead, a worker's state is his age and the set of beliefs,  $\hat{\mathbf{h}}, \hat{\mathbf{A}}$ . where bold face indicates these are vectors in  $J$  dimensions and the hat indicates this is the estimate from the past period, i.e.  $\hat{\mathbf{h}} = \{\hat{h}_{t|t-1}^j\}_{j=1}^J$ .

Note that  $\hat{P}_{t|t-1}$  should generically be a state variable because the uncertainty of the estimate is require to solve for the Kalman gain and, hence, the law of motion on beliefs. However, because of the structure of the problem the uncertainty evolves deterministically and from that we can compute the Kalman gain. This would not be the case if the observable depended upon an endogeneous choice. For instance, if workers only observed their wage, which was a function of  $k$  then forecast uncertainty,

$\hat{P}_{t|t-1}$  would be a function of the history of  $k$  and would hence enter the state.

$$V_t(\hat{\mathbf{A}}, \hat{\mathbf{h}}) = \max_k E[\max_{\mathbf{i}} \mathbf{p}_k^T \tilde{\mathbf{h}}(1 - \mathbf{1}^T \mathbf{i}) + \beta V_{t+1}(\hat{\mathbf{A}}', \hat{\mathbf{h}}')] \quad (3.6)$$

subject to technological constraints below and also the Kalman filtering procedure for the law of motion of the states.

$$\tilde{h}^j = h^j \epsilon^j \quad (3.7)$$

$$\mathbf{1}^T \mathbf{i} \leq 1 \quad (3.8)$$

The state-space model which describes the motion for  $\log(\hat{\mathbf{A}}), \log(\hat{\mathbf{h}})$  is<sup>3</sup>

$$\begin{pmatrix} \log \mathbf{A}' \\ \log \mathbf{h}' \end{pmatrix} = \begin{pmatrix} I & \mathbf{0} \\ I & \text{diag}(\gamma) \end{pmatrix} \begin{pmatrix} \log \mathbf{A} \\ \log h \end{pmatrix} + \delta \begin{pmatrix} 0 \\ \log \mathbf{i} \end{pmatrix}$$

$$\log \tilde{\mathbf{h}} = (\mathbb{O} \quad \mathbf{1}) \begin{pmatrix} \log \mathbf{A} \\ \log \mathbf{h} \end{pmatrix} + \log \epsilon$$

given the Kalman Filtering algorithm, the law of motion for estimated variables is:

$$\begin{pmatrix} \log \hat{\mathbf{A}}' \\ \log \hat{\mathbf{h}}' \end{pmatrix} = \begin{pmatrix} I & \mathbf{0} \\ I & \text{diag}(\gamma) \end{pmatrix} \begin{pmatrix} \log \hat{\mathbf{A}} \\ \log \hat{\mathbf{h}} \end{pmatrix} + G \log \hat{\epsilon}' + \delta \begin{pmatrix} 0 \\ \log \mathbf{i} \end{pmatrix} \quad (3.9)$$

Where  $\log \hat{\epsilon}' = (\log h^j + \log \epsilon^j) - (\log \hat{A}^j + \gamma \log \hat{h}^j + \delta \log i^j)$  is the estimation error times the actual observation error. The Kalman filter gain,  $G$ , depends only upon parameters and time.

Thus, the problem we will solve is the value function in Equation 3.6 subject to the constraints in Equations 3.7,3.8,3.9.

For first order conditions, it is useful to define a function that represents the problem after the realization of  $\epsilon$ .

$$\tilde{V}_t(\hat{A}, \hat{h}, \hat{\epsilon}, k) = p_k^T(\hat{h}, \hat{\epsilon}) + \beta \max_{k'} E \tilde{V}_{t+1}(\hat{A}', \hat{h}', \hat{\epsilon}', k')$$

---

<sup>3</sup> $\log \mathbf{X}$  is the log of each element of the vector  $\mathbf{X}$

with constraints

$$\begin{aligned} \{\lambda^j\} : \quad \log \hat{h}^j \prime &= \log \hat{A}^j + \delta \log i^j + \gamma \log \hat{h}^j + K \log \hat{\epsilon}^j \prime \\ 1 &\geq \sum_j i^j \\ k' &= \phi_{t+1}(\hat{A}', \hat{h}') \end{aligned}$$

To solve this efficiently, we'll have to use first order conditions that hold conditional on an occupational choice. Given  $k, k'$ , the following will allow us to solve for the continuous variables in closed form.

$$\mathbf{p}_k^T \tilde{\mathbf{h}} \frac{i^j}{\delta} = \beta E \left[ \frac{\partial \tilde{V}_{t+1}}{\partial h^j} \hat{h}^j \prime \right] \quad (3.10)$$

$$\frac{\lambda^j}{i^j} = \frac{\lambda^l}{i^l} = \mathbf{p}_k^T \tilde{\mathbf{h}} \quad \forall l, j \quad (3.11)$$

$$\lambda^j = \beta E \frac{\partial \tilde{V}_{t+1}}{\partial h^j} \hat{h}^j \prime \quad (3.12)$$

$$\hat{h}^j \frac{\partial \tilde{V}_t}{\partial h^j} = p_k^j \hat{h}^j \hat{\epsilon}^j (1 - \mathbf{1}^T i) + \lambda^j \gamma \quad (3.13)$$

$$\log \hat{h}^j \prime = \log \hat{A}^j + \gamma \log(\hat{h}^j) + \delta \log(i^j) + G \log \hat{\epsilon}^j \prime \quad (3.14)$$

$$\log \hat{A}^j \prime = \log \hat{A}^j + G \log \hat{\epsilon}^j \prime \quad (3.15)$$

The model is challenging to solve numerically and is still incomplete, in this aspect. However, from the first order conditions a few qualitative features are clear. The learning rates in Equations 3.14, 3.15 show something about the evolution of uncertainty. Because  $G \rightarrow 0$ , they become certain by the end of life. This predicts fewer occupational switches as a worker ages. The idea being that a switch happens because a worker becomes aware that his ability to learn  $A^j$  is actually relatively low in the dimension best rewarded by the occupation.

The model also contains insights into why returns to occupational tenure would be associated with mismatch. From Equation 3.10, one can see that the optimal investment choice is tied to the current wage,  $\mathbf{p}_k^T \tilde{\mathbf{h}}$  and to the perceived return to investment in a particular dimension  $j$ . A worker with an imprecise estimate of ability in dimension  $j$  will invest incorrectly there and also incorrectly choose his occupation. This

means poorly matched workers are also investing unproductively and growing their wages slowly.

### **3.7 Conclusion**

In this chapter, we explored how the match between a worker's skills and the skill requirements of an occupation factor into wages. In particular, we explored how the quality of the skills' match affects the return to occupational tenure. While much evidence suggests that longer occupational experience is an important source of wage growth, we still see that many workers switch occupation. Our evidence showed that the quality of the match plays a large part in the magnitude of the return to occupational tenure.

This is, however, only the beginning of a larger study. We have left quite open how the model maps to data on individual life histories and how it behaves quantitatively in the process of workers learning their match quality affects their switching.

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# Appendix A

## Appendix to Chapter 2

### A.1 Choice probabilities

Exponentially distributed shocks are somewhat non-standard in additive random utility models, like my own. The issue is that, my additive random utility is not strictly iid, because the matching probability makes the shocks heteroskedastic. With heteroskedasticity and non-zero mean, other common distributional assumptions are quite algebraically inconvenient. In this section I derive the distribution in Equation 2.23 by induction. Note that this is not exactly the same as the problem discussed in Daganzo (1979) because the mean is not necessarily zero.

We wish to show that the probability of location  $d$  being optimal given choices  $j \in \{1, \dots, J\}$  where return in  $j$  is  $R_j + \tilde{\psi}_j$  where  $\Pr[\psi \leq \tilde{\psi}_j] = 1 - e^{-\tilde{\psi}_j/\sigma_j}$ . To set notation, let the density of the shock in direction  $j$  be  $f_j(\tilde{\psi}_j)$ . In this proof, I will show that

$$\Pr[d = \operatorname{argmax}_{j \in \{1, \dots, J\}} (R_j + \psi_j)] = \prod_{j=1, \dots, J} \frac{\sigma_d}{\sigma_d + \sigma_j} e^{(R_d - R_j)/\sigma_d}$$

#### Basis step:

Suppose there are two options  $d$  and  $j$  with return  $R_d + \tilde{\psi}_d, R_j + \tilde{\psi}_j$  and distribution parameters  $\sigma_d, \sigma_j$ .

Then

$$\begin{aligned}
\Pr[R_d + \psi_d \geq R_j + \psi_j] &= \int_0^\infty \int_{R_j + \tilde{\psi}_j - R_d}^\infty f_d(\tilde{\psi}_d) f_j(\tilde{\psi}_j) d\tilde{\psi}_d d\tilde{\psi}_j \\
&= \int_0^\infty \frac{1}{\sigma_j} e^{-\tilde{\psi}_j/\sigma_j} \left( e^{-(R_j + \tilde{\psi}_j - R_d)/\sigma_d} \right) d\tilde{\psi}_j \\
&= e^{(R_d - R_j)/\sigma_d} \left( \int_0^\infty \frac{1}{\sigma_j} e^{-\tilde{\psi}_j/\sigma_j} e^{-\tilde{\psi}_j/\sigma_d} d\tilde{\psi}_j \right) \\
&= e^{(R_d - R_j)/\sigma_d} \left( \int_0^\infty \frac{1}{\sigma_j} e^{-\tilde{\psi}_j(\sigma_j + \sigma_d)/\sigma_d \sigma_j} d\tilde{\psi}_j \right) \\
&= e^{(R_d - R_j)/\sigma_d} \frac{1}{\sigma_j} \frac{\sigma_j \sigma_d}{\sigma_d + \sigma_j} \left( \int_0^\infty \frac{\sigma_d + \sigma_j}{\sigma_j \sigma_d} e^{-\tilde{\psi}_j(\sigma_j + \sigma_d)/\sigma_d \sigma_j} d\tilde{\psi}_j \right) \\
&= e^{(R_d - R_j)/\sigma_d} \frac{\sigma_d}{\sigma_d + \sigma_j} \tag{A.1}
\end{aligned}$$

### Induction:

Suppose that for  $j = 1, \dots, J - 1$ , the probability that  $\Pr[d] = \operatorname{argmax}_{j \in \{1, \dots, J-1\}} (R_j + \psi_j)] = \prod_{j=1, \dots, J-1} \frac{\sigma_d}{\sigma_d + \sigma_j} e^{(R_d - R_j)/\sigma_d}$  then for the  $J$  instance

$$\begin{aligned}
\Pr[R_d + \tilde{\psi}_d \geq R_j + \tilde{\psi}_j \quad \forall j = 1, \dots, J] & \tag{A.2} \\
&= \Pr[R_d + \tilde{\psi}_d \geq R_j + \tilde{\psi}_j \quad \forall j = 1, \dots, J - 1] * \Pr[R_d + \tilde{\psi}_d \geq R_J + \tilde{\psi}_J] \\
&= \prod_{j=1, \dots, J-1} \frac{\sigma_d}{\sigma_d + \sigma_j} e^{(R_d - R_j)/\sigma_d} * \Pr[R_d + \tilde{\psi}_d \geq R_J + \tilde{\psi}_J] \\
&= \prod_{j=1, \dots, J-1} \frac{\sigma_d}{\sigma_d + \sigma_j} e^{(R_d - R_j)/\sigma_d} * \frac{\sigma_d}{\sigma_d + \sigma_J} e^{(R_d - R_J)/\sigma_d} \\
&= \prod_{j=1, \dots, J} \frac{\sigma_d}{\sigma_d + \sigma_j} e^{(R_d - R_j)/\sigma_d} \tag{A.3}
\end{aligned}$$

The first line is true because  $\tilde{\psi}$  is independent for each direction.

## A.2 Planner's Problem

To establish efficiency results, I will set up the Planner's Problem, show that it has a unique allocation and then show that the competitive equilibrium with Nash bargained wages solves that. The Social Planner's value function is  $W$  and he chooses search

direction, tightness and separation policy in each labor market.

$$W(x, \mathcal{Z}) = \max_{\{\theta^m, g^m, \xi^m\}_{m \in M}} \sum_{l=0}^J \sum_{d=1}^J x'_{ld1} \omega_{ld} z_d + \left( x_{\ell d1} (1 - \tau \mathbb{I}_{\ell \neq d}) + \tau \mathbb{I}_{\ell \neq d} \sum_{j \neq d} x_{jd1} \right) \int_{\xi^{\ell d1}}^0 \xi h(\xi) d\xi \\ + b_e x'_{l0e} - \sum_m \int_{\psi} g^m a^m (\kappa \theta^m - p(\theta^m) \psi) df(\psi) + \beta E[W(x', \mathcal{Z}')] \quad : \quad (\text{A.4})$$

$$x'_{dd1} = (1 - s^{dd1}) \left( x_{dd1} + \tau \sum_{\ell=0, \ell \neq d}^J x_{\ell d1} \right) + p(\theta^{dd1}) g^{dd1} a^{dd1} + p(\theta^{dd0}) g^{dd0} a^{dd0} \quad (\text{A.5})$$

$$x'_{\ell d1} = (1 - s^{\ell d1}) (1 - \tau) x_{\ell d1} + p(\theta^{\ell d1}) g^{\ell d1} a^{\ell d1} + p(\theta^{\ell d0}) g^{\ell d0} a^{\ell d0} \quad (\text{A.6})$$

$$x'_{\ell 01} = \left( 1 - \sum_d g^{\ell d1} p(\theta^{\ell d1}) \right) \left( (1 - \delta) x_{\ell 01} + s^{\ell \ell 1} \left( x_{\ell \ell 1} + \tau \sum_{j \neq \ell} x_{j \ell 1} \right) \right) \quad (\text{A.7})$$

$$x'_{001} = \left( 1 - \sum_d g^{0d1} p(\theta^{0d1}) \right) \left( (1 - \delta) x_{001} + (1 - \tau) \sum_{d=1}^J \sum_{l=0, l \neq d}^J s^{\ell d1} x_{\ell d1} \right) \quad (\text{A.8})$$

$$x'_{\ell 00} = \left( 1 - \sum_d g^{\ell d0} p(\theta^{\ell d0}) \right) x_{\ell 00} + \delta \left( 1 - \sum_d g^{\ell d1} p(\theta^{\ell d1}) \right) x_{\ell 01}, \quad \ell = 0, \dots, J \quad (\text{A.9})$$

$$1 = \sum_{m \in M_{\ell e}} g^m \quad \forall \ell, e \quad \text{and} \quad g^m \geq 0 \quad (\text{A.10})$$

$$a^m = \begin{cases} x_{\ell 01} + s^{\ell \ell 1} (x_{\ell \ell 1} + \tau \sum_{j \neq \ell} x_{j \ell 1}) & \ell > 0, e = 1 \\ x_{001} + (1 - \tau) \sum_{j=0}^J \sum_{k \neq j} s^{jk1} x_{jk1} & \ell = 0, e = 1 \\ x_{\ell d0} & e = 0 \end{cases} \quad (\text{A.11})$$

And the process for  $\mathcal{Z}$  follows Equations 2.2-2.4

Let the multiplier on the law of motion for  $x_{\ell de}$  be  $v^{\ell de}$ . The first order conditions are:

$$\{\theta^m\} : 0 = -\kappa a^m g^m + p'(\theta^m) a^m g^m \left( v^m - (1 - \delta)v^{n1} - \delta v^{n0} - \int \psi d\tilde{f}(\psi) \right) \quad (\text{A.12})$$

$$\{g^m\} : 0 = p(\theta^m) \left( \psi_d + v^m - (1 - \delta)v^{n1} - \delta v^{n0} + \kappa \frac{\theta^m}{p(\theta^m)} \right) - \gamma^{\ell e} \quad (\text{A.13})$$

$$\{\bar{\xi}^m\} : 0 = \left( x_{\ell d1} (1 - \tau \mathbb{I}_{\ell \neq d}) + \tau \mathbb{I}_{\ell \neq d} \sum_{j \neq d} x_{j d1} \right) h(\bar{\xi}^m) \left( \bar{\xi}^m + v^{\ell 01} - v^m \right) \quad (\text{A.14})$$

$$n1 = (\ell \in m, 0, e \in m), \quad n0 = (\ell \in m, 0, 0)$$

Condition A.12 puts the marginal return to a posting, the expected value of a new match against the cost of posting it  $\kappa$ . Condition A.13 states that, for any locations to which an applicant applies, the marginal value of an application has to be equalized. Of course, this will not generally be the case, given the linearity of the choice  $g^m$ . However, integrating over  $\psi$  will give us a distribution of applications, as in the competitive case. And Condition A.14 gives the condition on separations, which again weighs the marginal value to the planner of a match against the value of a searcher.

### A.3 Efficiency

To show efficiency, I will show that the social planner's policies will be the same as those of the competitive market, conditional on  $\mu = \frac{\theta^m}{p(\theta^m)} \frac{\partial p(\theta^m)}{\partial \theta^m} \forall m \in M$ .

#### A.3.1 Market tightness

The crucial aspect here is to show the two first order conditions for posting are equal:

$$\begin{aligned} \kappa &= p'(\theta^m) \left( v^m - (1 - \delta)v^{n1} - \delta v^{n0} - \int \psi d\tilde{f}(\psi) \right) \\ &= q(\theta^m) \left( \omega_{\ell d} z_d - \int w^m(0, \psi) d\tilde{f}(\psi) + \beta \Pi_{\ell d}(\cdot) \right) \end{aligned}$$

Which we can separate into two pieces. For  $p'(\theta^m) = q(\theta^m)\mu$  I use the beginning assumption. Then, it leaves to be shown that

$$\mu \left( \nu^m - (1 - \delta)\nu^{n1} - \delta\nu^{m0} - \int \psi d\tilde{f}(\psi) \right) = \left( \omega_{\ell d} z_d - \int w^m(0, \psi) d\tilde{f}(\psi) + \beta \Pi_{\ell d}(\cdot) \right)$$

Which is essentially a result of Nash bargaining, where the left hand side is a fraction of the total value of the match to the social planner and the right hand side, because of Nash bargaining is the same fraction of the social value of the match.

### A.3.2 Search direction

For any realized match in market  $m = (\ell, d, 1)$ , let the value of the surplus be  $R_m(\psi_m, z, \omega)$ , it depends on the utility shock  $\psi$ , the long-run productivity  $\omega$  and productivity shock  $z$ . From the previous subsection, we know that separations are efficient so the total value of the surplus is the same whether we consider social planner or competitive settings.

Then for an individual, the first order condition is

$$p(\theta^d)R_w(\psi_d, z_d, \chi^d) = p(\theta^j)R_w(\psi_j, z_j, \chi^j) \quad \forall j, d : g^j, g^d > 0$$

Integrating over  $\psi$ , the search direction decision,  $\bar{g}^m$  is:  $\Pr[p(\theta^m)(R_m + \psi_m) \geq p(\theta^k)(R_k + \psi_k) \quad \forall k \in M_{\ell e}]$  and with Nash bargaining, the probability of applying to market  $m$  becomes  $\Pr[p(\theta^m)\mu(R_m + \psi_m) + W_b \geq p(\theta^k)\mu(R_k + \psi_k) + W_b \quad \forall k \in M_{\ell e}]$  and this simplifies to the same condition.

## A.4 Computation

### A.4.1 Solving the model

In this section I briefly describe the computational methods and considerations to solve the model itself. There are two crucial insights to ease computational burden: 1) without risk aversion, most of the model is linear and 2) the distribution of workers across occupations is not a payoff-relevant state variable for the households or firms. The difficulty is still that all of the shocks,  $\{Z, \{z_j\}, \mathbf{f}\}$ , are required for every problem. Discretization would be infeasible because even with only 2 values per shock, that would

mean that have a total of  $2^{N_d+N_f+1}$  values, where  $N_d$  are the number of occupations,  $N_f$  the number of unobservable factors and there is one more for the average productivity shock,  $Z$ .

Hence, I use a hybrid-approach: a second-order perturbation to approximate the expectations for the value functions and then the actual non-linear decision rules using these approximations. The technique for second-order approximation is described in Lombardo and Sutherland (2007) and the hybrid method is described in Maliar et al. (2011). In the baseline model, I take as dynamic states the total value of the match, that is  $U_w(\ell, d, 1, \cdot) + \Pi_{\ell d}(\cdot)$  and the value of the unemployed worker  $U_b(\ell, 0, e, \cdot)$ . To solve for these approximations, I also need to approximate the policy functions. Once the value functions have been perturbed around their steady state, to perform simulations I need only have the expectation of these values. I take expectations from the approximated versions of  $U_w(\ell, d, 1, \cdot) + \Pi_{\ell d}$  and  $U_w$  and then evaluate the true non-linear decision rules for the simulations.

#### A.4.2 Estimation and calibration

There are six parameters to calibrate,  $\psi_0, \psi_1, \lambda_0, \lambda_1, var(\phi), \tau$ . To estimate, I have to consider the vector of parameters governing  $\{\omega_{\ell d}\}$ ,  $\{\beta_i\}$  and the parameters of the productivity process,  $\rho_Z, \sigma_\epsilon, \{\lambda_{1,j}, \lambda_{2,j}, \lambda_{Z,j}\}_{j=1}^J, \rho_z, \sigma_\zeta, \Gamma, cov(\eta)$ .

I take a three-layer approach to the estimation, using stochastic multi-starts and derivative-free minimizers for the calibration parameters and estimating  $\{\beta_i\}$ . For each set of these parameters, I use an iterative approach to find coefficients of the productivity process. This separation is convenient because there are so many parameters of the productivity process and it would be onerous to estimate the entire Jacobian and the Hessian, which has few exploitable sparsity patterns.

The stochastic multi-start technique is fairly standard. I use a modified version of the multi-stage single-linkage method in which I make a few heuristic adjustments to the prescribed rules for stopping and cluster-size choices. The inner solvers alternate between a Nelder-Mead implementation with a new derivative-free non-linear least-squares method, as described in Zhang et al. (2010).<sup>1</sup>

For the inner-most estimation, the crucial observation is that I can directly estimate

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<sup>1</sup>Zhang graciously provided his Fortran code, which interfaced with my C code flawlessly.



the factor process for per-capita output, ignoring the endogenous productivity that will modify the underlying, unobservable process. Call this  $\tilde{Z}^{data}$ . I use this process as a first guess and simulate the model to get populations that imply productivity. With these populations, I can solve for what should be the underlying productivity process. Maybe not surprisingly, there is relatively little difference between the implied process and the “true” process. I describe the iterative procedure below:

1. From annual industry data, estimate the monthly process  $\tilde{Z}^{data}$
2. Draw  $M$  realized histories from  $\tilde{Z}^{data}$
3. Solve and simulate the model around process  $\tilde{Z}^{data}$  with realized history  $m$ .
4. Solve for  $\{z_{d,t}^1\}$  using

$$z_{d,t}^1 = \tilde{z}_{d,t} \frac{\sum_{\ell} x'_{\ell d}}{\sum_{\ell} \chi^{\ell d} x'_{\ell d}} \quad (\text{A.15})$$

5. Estimate  $\mathcal{Z}^1$
6. Solve and simulate the model around  $\tilde{Z}^1$
7. Return to Step 4 until the likelihood converges
8. Store these coefficients and return to Step 3
9. Average the coefficients

## A.5 Estimation tables

Variables	log(earnings)
age	0.159 (0.00101)
age <sup>2</sup>	-0.00197 (1.20e-05)
college	0.0554 (0.00338)
Female	-0.372 (0.00305)
Constant	5.784 (0.00283)
Observations	2,238,830
R-squared	0.020

Standard errors in parentheses

Table A.1: Initial regression to get residual wage and set up the auxiliary model. Age and age<sup>2</sup> normalized to mean zero

Variables	1978-2008 Duration	2008-2010 Duration
$D_{occ.t \neq occ.t-1}$	7.946*** (0.301)	16.16*** (0.889)
$D_{ind.t \neq ind.t-1}$	4.672*** (0.300)	6.631*** (0.885)
White	-2.974*** (0.145)	-3.803*** (0.413)
Married	-0.981*** (0.136)	-1.783*** (0.394)
Sex	-4.547*** (0.126)	-2.504*** (0.365)
Age	0.311*** (0.00507)	0.334*** (0.0138)
Year	-0.000882 (0.00730)	
College	0.775*** (0.212)	0.0366 (0.512)
high school	0.820*** (0.137)	1.461*** (0.453)
Constant	12.73 (14.52)	11.38*** (0.827)
Observations	139,785	22,698
R-squared	0.095	0.174

Standard errors in parentheses  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A.2: Duration regressions showing the relationship to switching occupations

Occupation	$\lambda_{f,1}$	$\lambda_{f,2}$	$\lambda_Z$
Management	0.020928	0.014669	0.0028246
Business and Financial Operations	0.0065026	0.020844	0.0032932
Computer and Mathematical	0.018718	0.022394	0.0047267
Architecture and Engineering	0.035273	0.024112	0.0040797
Life, Physical, and Social Science	-0.0072506	0.029708	0.008007
Community and Social Services	-0.029922	0.035044	0.012257
Legal	-0.0045351	0.035405	0.0077274
Education, Training, and Library	-0.022472	0.026613	0.0086163
Arts, Design, Entertainment, Sports, and Media	0.019526	0.020907	0.0076848
Healthcare Practitioners and Technical	-0.021383	0.030983	0.013469
Healthcare Support	-0.029418	0.034304	0.01638
Protective Service	-0.019614	0.031706	0.0067835
Food Preparation and Serving Related	0.070791	-0.0032913	-0.0005535
Building and Grounds Cleaning and Maintenance	0.0055642	0.016833	0.0049712
Personal Care and Service	-0.020662	0.028181	0.01227
Sales and Related	0.097902	-0.0092024	-0.012676
Office and Administrative Support	0.019916	0.013054	0.0019693
Farming, Fishing, and Forestry	0.0061461	0.0065009	0.0089745
Construction and Extraction	0.043611	-0.0025576	-0.0065656
Installation, Maintenance, and Repair	0.034796	0.0084809	0.00088448
Production	0.077789	0.016065	0.0080003
Transportation and Material Moving	0.046062	0.0086633	0.0038269

Table A.3: Estimated coefficients on the productivity process