Hiring, Recessions, and Careers: Three Essays in Personnel Economics

by

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B.A., Mills College (2008)

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Abstract

Workers find wage-growth and job-satisfaction by building careers. However a worker's ability to string together a sequence of jobs relies on the availability of appropriate opportunities either within their current firm or in other firms in the market. In this thesis, I investigate how variation in the labor market affects this career building process. In the first chapter, I find that career opportunities are scarce for young workers during recessions, and use theory and evidence to argue that this is due to firms choosing to hire more experienced workers instead. In the second chapter, I find that firms reallocate their employees between occupations during recessions, leading workers to receive lower wages and be employed in lower-quality occupations. In the third chapter, I develop a model to explain why workers change firms when opportunities exist within the firm. I show that heterogeneity in firms' production functions and human capital acquisition are sufficient to generate these movements.

More specifically, in the first two chapters I use data from the CPS to study reallocations over the business cycle. In Chapter 1, I find that during recessions the probability of being hired falls for young workers, while for experienced workers it rises. I develop a model and show this fact can be explained by firms choosing to hire workers with greater work experience when labor markets are slack. My model provides the distinctive prediction that during recessions, young workers will match with lower-quality jobs and receive lower wages while experienced workers will exhibit no change in either dimension. I develop occupational quality indices using O*NET and OES data and find evidence consistent with both predictions, suggesting that firms' hiring behavior actively contributes to negative outcomes for young workers during recessions.

In Chapter 2, I document that occupational mobility is counter-cyclical. I show this is driven by an increase in occupational mobility within firms. I show that these within-firm occupation changers lose ground during recessions, matching with lower-quality jobs and receiving lower wages. Combined with the recessionary increase in within-firm mobility, these results suggest a previously undiscovered cost of recessions borne by employed workers.

Finally, in Chapter 3, I develop a model that demonstrates how career-advancing inter-firm mobility can persist despite the possibility of within-firm mobility. I argue that many of these movements are driven by firm heterogeneity and human capital acquisition and show such a model can capture three key empirical regularities: experienced workers are hired into advanced positions, wages rise more at movements between positions (within and between firms) than at stays in the current firm, and external hires tend to have different qualifications than internal promotees.

JEL Classification: E24, J62, M51

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Chapter 1

Why Don't Firms Hire Young Workers During Recessions?

1.1 Introduction

Recent evidence by Kahn (2010) and Oreopoulos, Von Wachter, and Heisz (2012) demonstrates large and persistent earnings losses for workers graduating college during recessions. While both papers establish the labor market outcomes underpinning these earnings losses,[1] the market-level mechanisms driving these results are unknown. In particular, are young workers disadvantaged because they have the misfortune of searching for employment when labor markets are slack? Or do firms actively change which types of workers they hire during recessions?

A clear understanding of this mechanism is crucial for the design of effective labor market policies. As stubbornly high youth unemployment rates persist throughout the member nations of the OECD (Organisation for Economic Cooperation and Development), governments are increasingly interested in active labor market policies that can improve labor market outcomes for young workers (for instance, see the OECD Action Plan for Youth 2013[2]). Depending on the source of the poor labor market outcomes for youth, these policies will have vastly different direct and indirect impacts; for instance search assistance is only successful inasmuch as there are jobs willing to hire these young workers.

I find evidence that young workers are decreasingly likely to be hired during recessions, while experienced workers are increasingly likely. I show this is consistent with

[1] Specifically, Kahn (2010) shows graduates match with lower-quality occupations during recessions, while Oreopoulos et al. (2012) show graduates match with firms that pay lower wages.

[2] `http://www.oecd.org/newsroom/Action-plan-youth.pdf`

firms choosing to fill vacancies with more-experienced workers. This suggests that young workers are particularly disadvantaged compared with older workers: not only are they more likely to be searching for demographic reasons, but firm hiring behavior makes their search less likely to be successful. To better understand the relationship between the business cycle and firm hiring behavior, I develop a search and matching model and show that firms choosing not to hire young workers during recessions is an equilibrium outcome given conditions that (1) worker productivity increases with experience, and firm production functions exhibit (2) diminishing marginal productivity of labor and (3) fixed operating costs per position. Moreover, if the production function does not exhibit conditions (2) and (3) and wages are flexible, I show that it is optimal for firms to hire all applicants.

My primary empirical innovation is to focus on the effect of recessions on all hiring, not just the typically considered hires from unemployment.[3] Between-firm movements comprise about a third of all hires, while hires from outside the labor force comprise two-fifths and hires from unemployment make-up the balance. In the aggregated sample, the probability of being hired decreases with the state unemployment rate for workers with less than four years of potential experience, while this probability increases for workers with more than nine years of potential experience. I find if I restrict my analysis to hires from unemployment, the effect of recessions on the hiring-rate is negative for all workers. This is consistent with the literature concerning the ins and outs of unemployment, which shows that the hiring rate from unemployment is pro-cyclical (Elsby, Michaels, & Solon, 2009b; Shimer, 2012). My results indicate that the cyclicality of hire rates is quite sensitive to sample restrictions.

The second task of the paper is to reconcile these hiring results with equilibrium models of the labor market. The challenge is to disentangle changes in workers' labor supply decisions from changes in firms' labor demand. I take advantage of the heterogeneity in worker employment status (employed, unemployed, not-in-the-labor-force) to distinguish between potential explanations. I show the pattern of evidence is inconsistent with labor-supply driven changes, such as changes in leisure-labor trade-off, search intensity, or self-selection. I also show that change in the distribution of hiring firms over the business cycle is unlikely to be the primary source of heterogeneity in hiring.

After showing labor supply and composition are unlikely to be the cause of the observed hiring dynamics, I then turn to changes in labor demand. In particular I consider the hypothesis that firms choose to reduce hiring of inexperienced workers during reces-

[3]For instance, Shimer (2012) and others in the ins-and-outs of unemployment literature ignore the role of inflows from non-employment. Elsby, Michaels, and Solon (2009a) is an exception.

sions. Such behavior can easily explain heterogeneous hiring outcomes for young and experienced workers over the business cycle. This hypothesis follows naturally from the cyclical upgrading literature (cf. Reder, 1955; Okun, 1973; and, more recently, Devereux, 2002). These papers argue that when labor markets are slack, firms are able to hire higher-quality workers, as workers will queue for good jobs.

The main drawback to the cyclical upgrading literature is that it relies on strong assumptions limiting firm entry and growth to generate the desired employment dynamics.[4] For instance, Akerlof, Rose, and Yellen (1988) explore changes in employer-to-employer mobility during recessions, but assume firm size is a deterministic function of the aggregate economy. Thus, these papers do not show that changes in hiring is an optimal equilibrium decision for firms. More specifically, by imposing strict limits on firm size, these models cannot provide insight into the firm's decision whether or not to hire less-experienced workers when labor markets are slack.

On the other hand, standard search and matching models (cf. Diamond, 1982, Mortensen, 1982, Pissarides, 1990) are limited in the other direction: these models are unable to capture the possibility that firms might choose not to hire a worker with whom the firm has matched. This is because in most models in this class market distortions are limited to search frictions. Once a worker and firm successfully connect, all matches with positive revenue will be created.[5]

Which distortions in production are consistent with firms ever optimally choosing not to hire a worker with whom they have matched? Candidates include sticky wages, fixed costs of production, and diminishing marginal productivity of labor. Michaillat (2012) shows that diminishing marginal productivity of labor and sticky wages can lead to *rationing unemployment* during economic downturns. When labor is rationed, even if search is costless a firm may optimally choose not to hire additional workers. This is because each additional hire imposes a negative externality on the productivity of other employees. If wages are fully flexible, there are no fixed costs of production, and workers' outside options are zero, the firm and worker can always find a mutually agreeable division of production.[6] However, if any of these distortions bind, there will be a firm size beyond which it is no longer profitable to hire.

In the absence of search costs, each firm will maintain its optimal firm size, which rises

[4] An exception is (McLaughlin & Bils, 2001), which shows that inter-industry mobility exhibits cyclical upgrading and the patterns of mobility are broadly consistent with worker self-selection.

[5] Of course, if the match does not generates positive revenue it will not be created under any circumstance.

[6] Although Michaillat (2012) considers sticky wages, fixed production costs and flexible outside options from heterogeneous firms can also provide the same effect.

and falls with the business cycle. However with the addition of search costs and a finite labor supply, it becomes costly for firms to maintain optimal employment during tight labor markets. Thus, in booms, most unemployment will be driven by search frictions, while in recessions, rationing may dominate.

In order to understand how jobs are distributed during downturns, I extend Michaillat (2012) to allow for heterogeneous workers (low- and high-skill). I show when rationing binds, firms must choose how to distribute their vacancies between applicants. In a simplified one-firm, one-period model, I show that firms will optimally pursue one of two strategies: either hire any worker with whom the firm matches, or only hire high-skill workers. For each individual firm, there is a unique cutoff of the aggregate economic parameter A such that when the economy is sufficiently poor (A below the cutoff) the firm will only hire high-skill workers, and during expansions (A above the cutoff) the firm will hire all matches. This cutoff is decreasing with the cost of posting vacancies, the share of low-skill workers in the economy, and the relative productivity of low-skill workers compared with high-skill workers.

Kahn (2008) and Oreopoulos et al. (2012) find that the persistent wage losses for workers who graduate during recessions can be partially explained by workers matching with lower-paying jobs. In particular, Kahn (2008) finds workers match with lower-quality occupations and Oreopoulos et al. (2012) find that workers match with firms that pay lower average wages. To capture this dynamic, I extend the model to allow for two types of firms and on-the-job search. Consistent with the empirical literature, I model this with an absolute ranking of job quality: all workers are more productive at good firms than bad firms. This is similar to the set-up in Pissarides (1994).[7] For simplicity, only good firms are multi-worker (and hence potentially rationing). Bad firms are of the standard, one-job-per-firm variety, and total employment in such jobs is determined by firm entry. I show that during good states of the economy, the unique steady state equilibrium is for good firms to hire both types of workers, but during recessions, the unique equilibrium is for good firms to only hire high skill workers.

The model is related to that of Barlevy (2002), which shows that recessions can reduce match quality when workers search on-the-job. The key difference is that in Barlevy (2002), worker-firm match quality is idiosyncratic, thus no workers are uniquely disadvantaged by the downturn. The assumption of fixed production costs is very similar to that of sticky wages as in Michaillat (2012) or Hall (2005). Finally, there are many papers that consider search with multi-worker firms, for instance Elsby and Michaels

[7] Acemoglu (2001) considers a similar model to Pissarides (1994) but does not consider on-the-job search.

(2013).

The model predicts that if the economy falls into recession, good firms will stop hiring low-skill workers. This in turn results in low-skill workers matching with lower-quality jobs on average and receiving lower wages.[8] For high-skill workers, job quality and wages may fall or rise depending on the parameters, but will be strictly less than the fall for young workers.

To explore the validity of these predictions, I develop a set of occupational wage indices. I use 2005 wage data from the OES, as well as a set of factor variables derived from O*NET occupation data. These quality indices show that young workers match with lower-quality occupations during recessions, while experienced workers exhibit no significant change. In particular, I find that for a 5% increase in the state unemployment rate, young workers match with occupations that pay on average $0.30 less per hour, with no change for experienced workers. Using CPS wage data I find mixed evidence on the wage predictions. On net, these results are consistent with a broader class of models in which firms choose not to hire young workers during recessions, suggesting that firm hiring behavior actively plays a role in young workers poor labor market outcomes during recessions.

There are a variety of papers documenting the effect of recessions on labor market flows. Fallick and Fleischman (2004) find that mobility between employers are procyclical, also using the CPS. I use the same methodology, so I am able to update and extend their results. Nagypál (2008) finds similar results. Hyatt and McEntarfer (2012) documents the fall in reallocations for the Great Recession in particular. There is a growing literature on churn (see Davis & Haltiwanger, 1999), that is, hiring to offset exiting workers. Lazear and Spletzer (2011) find that during the Great Recession, 80 percent of hiring reduction was due to reduced churn. My results indicate that this fall in churn is likely driven by young workers who are unable to upgrade to better positions. Finally, Kahn and Mcentarfer (2013) find that much of the reduction in gross flow rates can be attributed to a reduction in separation rates from low-wage firms. If young workers are more likely to be employed in low-wage firms, my results on young worker mobility may be capturing the same phenomenon.

The structure of the paper is as follows. In Section 1.2, I describe the data and the empirical strategy. Section 1.3 presents the main empirical results. Section 1.4 develops the model and derives testable predictions. Section 1.5 describes the construction of the occupational quality indices and wage data, and presents further results. I offer

[8]These lower wages are not only driven by lower-productivity matches, but also a diminished outside option, since a whole segment of the job-market is no longer willing to hire.

conclusions in Section 1.6.

1.2 Data Description and Empirical Strategy

My main empirical strategy is to use variation in state unemployment rates to identify the effect of recessions on worker hiring rates. In order to measure worker hiring and movements between firms, I construct a panel from CPS monthly interviews from January 1994 through July 2013. The CPS has the advantages of a very large sample size (approximately 72,000 households per month) and detailed individual-level data. Although the CPS was not explicitly designed as a panel, the sampling strategy involves interviewing the same households eight times, in particular, over four consecutive months, followed by an eight month break, and then another four months of interviews. Using a procedure developed by Madrian and Lefgren (1999), I match individuals using administrative IDs, and confirm matches using sex, race, and age.

Before 1994, employment questions followed independent coding, that is, with no reference to the information the individual provided the previous month. Since less than 3% of workers change employers between months (see Table 1.1), this prevented accurate measurement of true movements between firms, which we now know comprises approximately a third of hires. In 1994, the CPS undertook a major redesign and began asking employed individuals if they still work for the same employer as they did the previous month. At the beginning of the second wave of the survey, which follows an eight month gap in data collection, workers are surveyed with independent coding. Thus each individual has at most six pairs of months for which we are able to observe inter-firm mobility. I restrict my sample to these pairs of months, which leaves me with 17 million pairs.[9]

I use the state monthly unemployment rate as a proxy for local business cycle conditions. There are 51 state unemployment rates per month, for a total of 11,832 unemployment rate observations over the almost 20 year sample. Figure 1.1 shows the frequency distribution of observations by state unemployment rates: the bulk of the observations are from state-months with between two and ten percent unemployment rates.

All regressions include state and month-year dummy variables, to dispose of any state heterogeneity in labor market flows, as well as time trends. Time trends are of particular concern, due to a growing body of literature on the secular decline of mobility

[9]Data from May through August 1995 are missing their longitudinal link ID, which prevents matching months, thus these dates have been excluded.

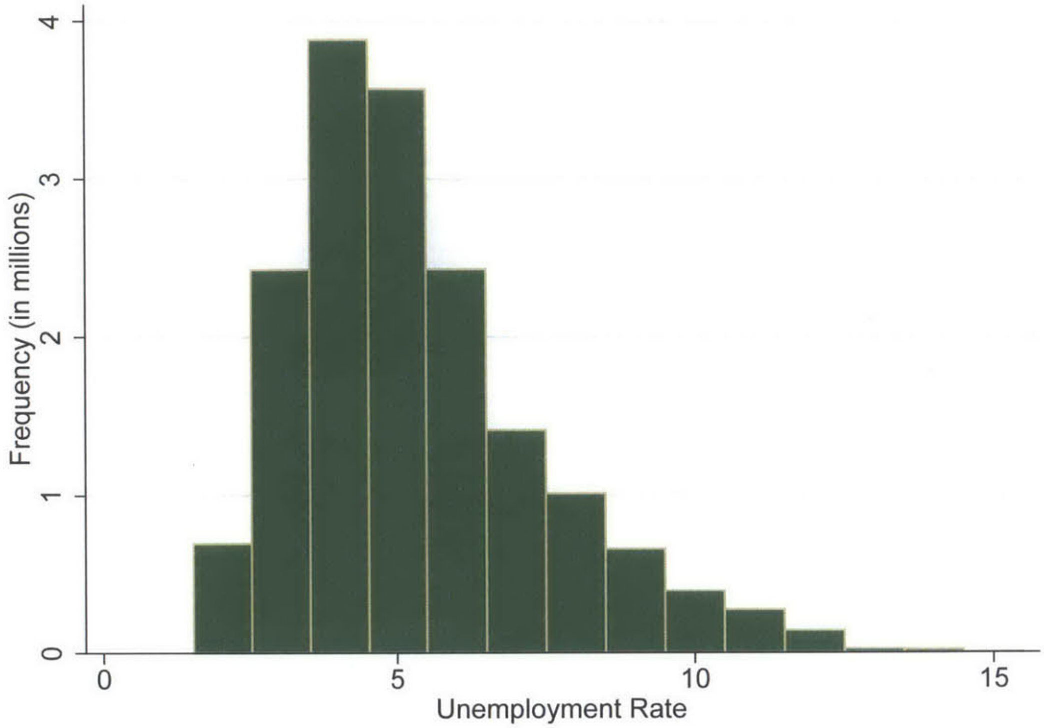


Figure 1.1: Distribution of Observations by State Unemployment Rate

in the United States over the last two decades.[10] Since the first seven years of my sample coincide with a period of sustained economic growth (1994–2001), and the last seven years coincide with the Great Recession and recovery (2007–2013), time trends are particularly likely to be in evidence, which I show is indeed the case. I discuss in detail the role of time trends in the context of specific results.

To capture worker experience, I construct a measure of potential experience, defined as age less years of education less six, the typical age of enrollment in school. This represents the maximum number of years a worker could have been in the labor market. Approximately 1% of the sample is coded as negative potential experience, most likely due to mis-reporting in age or education, although possibly because of early entry into school or early graduation. These workers are very similar to other workers with less than five years of potential experience.

The basic empirical specification is as follows:

$$D_{ikst}^{\text{hired}} = \alpha I_s + \beta I_t + \sum_{k=1}^{K} (\delta_k D_k^{PE} + \gamma_k \times D_k^{PE} \times \text{State Unemp. Rate}_{st}) + \epsilon_{ikst} \qquad (1.1)$$

[10]See Hyatt and Spletzer (2013), Molloy, Smith, and Wozniak (2013)

where D^{hired} is a dummy for whether or not an individual worker i is hired in the second month of his observation, given worker i is in potential experience group k, resides in state s, and is observed in month-years $t-1$ and t. A worker is hired if one of two things happens: (1) he is non-employed in period t and employed in period $t+1$, or (2) he is employed in period t and in period $t+1$ indicates he changed firms. In some specifications I will restrict the sample to particular subsets depending on the worker's labor market status in period $t-1$. ϵ_{ikst} includes any other sources of variation in the worker's probability of being hired. Given the likelihood of correlated mobility within states, I cluster standard errors at the state level. The coefficient of interest, γ_k, measures the responsiveness of hiring probabilities to the state unemployment rate for a worker in potential experience group k. The null hypothesis is that the γ's do not vary by potential experience.

In the main regressions, I interact the state unemployment rate with one-year potential experience bins, allowing the data to reveal the cutoff between young and experienced workers. In most specifications, the inflection point falls between five and ten years of potential experience, which is consistent with the definition of young workers used by Topel and Ward (1992). Table 1.1 describes the characteristics of all workers, workers with less than ten years of potential experience, and workers with more than ten years of potential experience. Young workers comprise 25% of observations. Young workers have slightly fewer years of education and are slightly less likely to be female. These workers are less likely to be employed (60.6% vs. 61.4%) and are more mobile than experienced workers. The overall employer-to-employer mobility of 2.29% is consistent with Fallick and Fleischman (2004) which finds a rate of 2.6%. Finally, young workers are employed in (mostly) lower-quality occupations (as defined in Section 1.5) and receive on average $4 less per hour than experienced workers. These summary statistics are consistent with what we know about young workers: they have higher mobility rates, are more likely to be unemployed, and receive lower wages compared with more experienced workers.

1.3 Hiring Results

It is well known that the total volume of hiring falls during recessions. This is best seen for the U.S. by looking at JOLTS (Job Opening and Labor Turnover Survey) data, which surveys establishments and produces estimates for total hires, job openings, and separations, as well as other statistics. The survey began in late 2000, and so only observed the last two recessions, but the first panel of Figure 1.2 shows substantial reductions in hiring during each recession, with levels as of late 2013 still well below

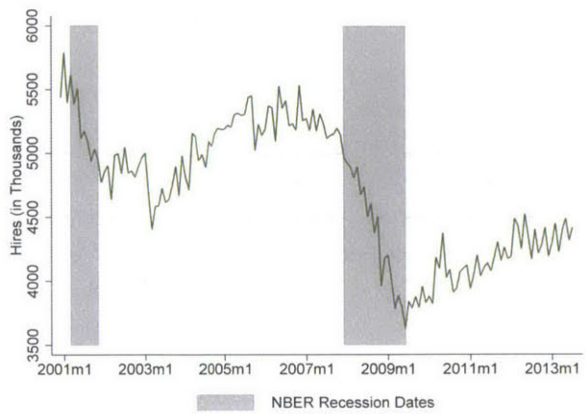
Table 1.1: Data Description

	All	Young	Experienced
Observations	17013532	25.29%	74.71%
Years Potential Experience	25.9	3.69	33.4
Participation Rate	64.8%	66.6%	64.2%
Share Employed	61.2%	60.6%	61.4%
Monthly Employer-to-Employer Mobility	2.29%	3.53%	1.88%
Monthly Employed-to-Non-Employed Mobility	4.14%	6.75%	3.27%
Monthly Unemployed-to-Employed Mobility	24.25%	25.62%	23.29%
Monthly Non-Employed-to-Employed Mobility	2.44%	4.30%	1.33%
Age	44.8	22.4	52.4
Years Education	13.0	12.7	13.1
Female	52.4%	50.9%	53.0%
Non-White	15.8%	19.1%	14.7%
Occ. Quality Factor 1 (mean 0, SD 1)	-.046	-.191	.006
Occ. Quality Factor 2 (mean 0, SD 1)	-.381	-.578	-.310
Occ. Quality Factor 3 (mean 0, SD 1)	.271	.333	.249
Occupational Wage Index	16.90	14.77	17.66
Wage Observations	1174875	385704	789171
Hourly Wage	\$ 12.97	\$10.11	\$ 14.36

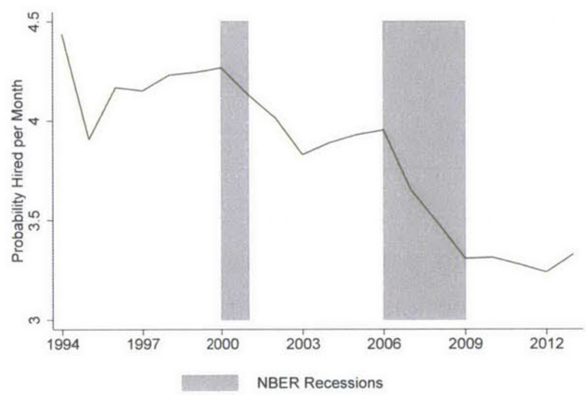
the peak in 2000. In the second panel of Figure 1.2, I plot the share of workers hired each month in the CPS (see Section 1.2 for data definition), averaged across each year to smooth out volatility. I use the percent of individuals hired rather than raw hiring numbers to reduce sampling variation. This plot is consistent with the aggregate hiring patterns we see in the JOLTS: large drops during each recession, with weak recoveries.

In the third panel in Figure 1.2, I divide workers into young workers (those with less than ten years potential experience) and experienced workers (those with more than ten years potential experience), and graph the percentage of each group hired each month. This graph shows that the bulk of the fall in hiring appears to be borne by young workers. Not only do experienced workers appear to be much less affected by the cyclical decline in hiring, they also demonstrate no perceptible secular trend in hiring rates.

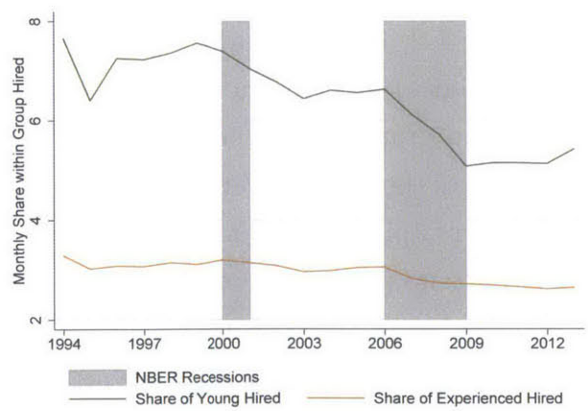
Figure 1.3 plots the fraction of workers hired per month against the state unemployment rate. The first graph shows that young workers are substantially more likely to be hired, but this rate is decreasing with the state unemployment rate. More experienced workers, in general, are hired at a lower frequency, and this rate changes little with the unemployment rate. The second graph separates out hires of workers who are already employed. Here we see the mobility of workers with low potential experience drops dramatically with the unemployment rate, approaching the mobility rates of more-



(a) Seasonally Adjusted Monthly Hiring Flows, JOLTS

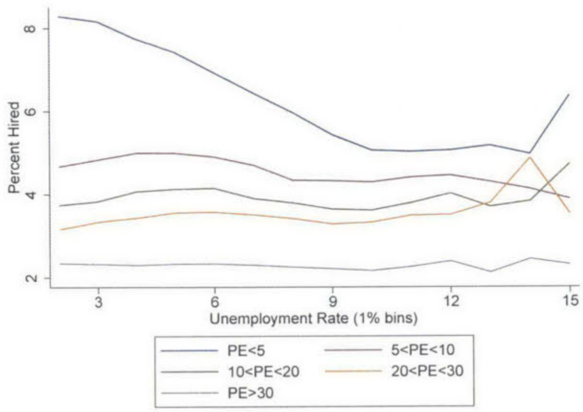


(b) Fraction Hired per Month, CPS

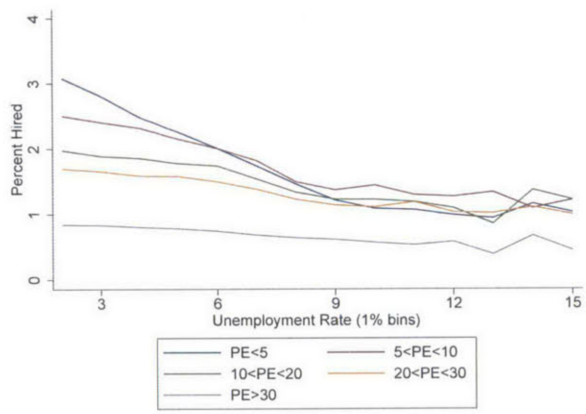


(c) Fraction Hired per Month, CPS

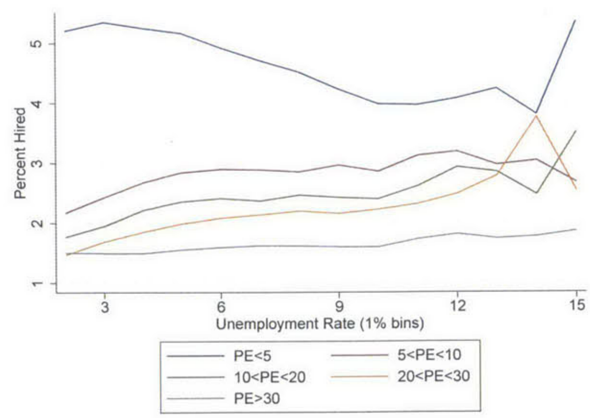
Figure 1.2: Hiring Over the Business Cycle



(a) Hire Rate, All Hires

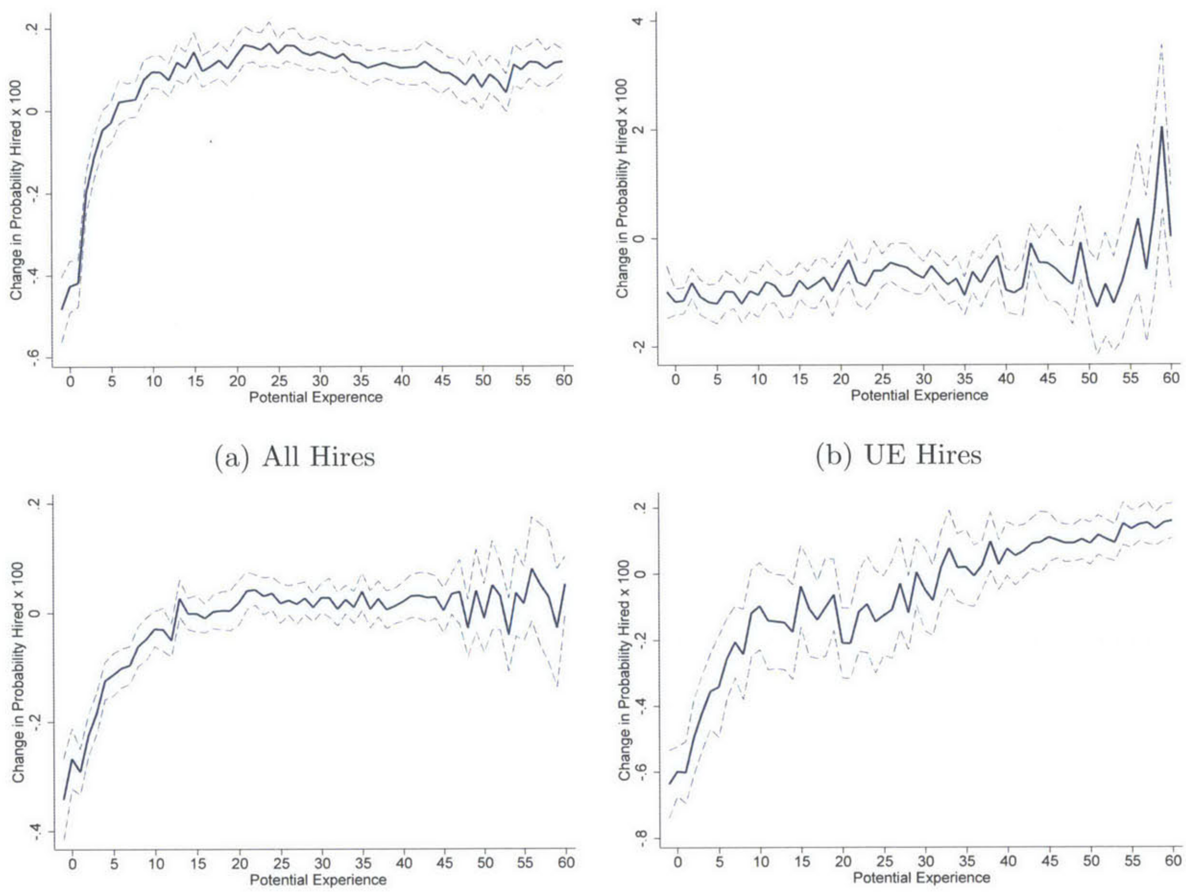


(b) Hire Rate from Employment



(c) Hire Rate from Non-Employment

Figure 1.3: Hiring Rates by State Unemployment Rate



(a) All Hires

(b) UE Hires

(c) EE Hires

(d) NILFE Hires

Figure 1.4: Coefficients from regressing probability of hire on the state unemployment rate for one year potential experience bins, partialling out main effects and state and month-year fixed effects. Figures include 95% confidence intervals.

experienced workers. In the third panel it appears that for most workers the probability of being hired from non-employment is increasing with the business cycle, but this is not true for workers with less than five years of potential experience.

Table 1.2 contains the main empirical results, as described in Equation 1.1 and illustrated in Figure 1.4. Column (1) includes all individuals, while Column (2) restricts the sample to individuals who were unemployed in the first month, Column (3) restricts to individuals who were employed in the first month, and column (4) restricts to workers not in the labor force (NILF). In Panel (A) we see that in aggregate, the probability of being hired is increasing with the state unemployment rate, after controlling for state and date fixed effects. This positive aggregate result in contrast to the negative estimate from (Fallick & Fleischman, 2004); however, those authors do not include date fixed-effects. Moreover, when I select the sample on the workers' previous state (unemployed, employed, not-in-the-labor-force(NILF)) I find negative point estimates.

In Panel (B), I split the state unemployment rate into interactions with potential experience bins. For less than ten years of pòtential experience, I include bins for every year of potential experience, including a bin for less than zero. For above ten years of potential experience, I include five-year bins. Figure 1.4 displays point-estimates for each one-year bins up to sixty years.

In contrast to Panel (A), we see that for young workers the probability of being hired is negative, and remains so when hires from employment, unemployment, and NILF are considered separately. For workers with enough potential experience, these relationships flip and are positive. For aggregated hires, the inflection point is somewhere between four and nine years of potential experience. For hires from employment the sign changes between ten and twenty years of potential experience, and for hires from non-employment it changes between nine and twenty-five years. These levels of experience are roughly consistent with the (Topel & Ward, 1992) definition of young workers as those with less than ten years of potential experience.

Hires from unemployment behave quite differently than hires from employment and NILF. For these workers, we do not see a statistically significant change by potential experience in the probability of hire. Although historically, many analyses of hiring only include hires from unemployment, there are two drawbacks to this specification. First, individuals' membership in the labor force varies over the business cycle, so the sample will vary systematically with the unemployment rate. Second, a non-negligible fraction of hires come from outside the labor force. In my sample I find about two-fifths of hires are workers who were not classified as being in the labor force during the previous month, and about a third are hired from employment. Table 1.2 shows that all unemployed workers' are less likely to be hired the higher the state unemployment rate, although this falls by more for young workers than for experienced workers. This indicates that an analysis excluding either employer-to-employer moves or hires from outside the labor force would fail to capture the hiring dynamics apparent in the unrestricted sample.

In Table 1.3, I collapse the potential experience categories into two groups, young (those with less than ten years potential experience) and experienced, for easier interpretation. We can soundly reject the null hypothesis that the effect of the state unemployment rate is equal across potential experience categories. If we consider a 5% increase in the state unemployment rate, these results predict that young workers will see a half-percentage point fall in mobility between firms, which corresponds to one-sixth of the mean (3.53% per month). Experienced workers see an increase in mobility of two-fifths of a percentage point, which corresponds to one-fifth of the mean (1.88%). For hires from non-employment, young workers see a decrease of about one-third from the mean (6.74%), while experienced workers see an increase of one-half of the mean (3.27%).

For hires from unemployment, although the difference is slight, we are able to reject that there is no change in hiring probability. Thus, even for hires from unemployment, we see that young workers' probability of hire falls by more than it does for experienced workers.

As a back-of-the-envelope calculation using 2012 employment numbers, 243 million individuals are in the civilian non-institutional population. Extrapolating from my sample, about 60 million of those workers should have less than ten years potential experience in 2012. My estimates that predict a 5% increase in the state unemployment rate across all states would result in 200 thousand fewer employer-to-employer moves for young workers and 600 thousand fewer hires from non-employment. At the same time, these results predict 800 thousand additional moves between firms for experienced workers and 1.2 million additional hires from non-employment.

1.3.1 Sensitivity Analysis

Next I explore the robustness of the finding that experienced workers' probability of hiring rises during recessions. Figure 1.2 illustrates the potential confound: the hiring rate has been steadily falling over time, in addition to the sharp drops occurring with each recession. Since my sample begins in 1994, most of the observations with high unemployment rates come from late in the sample. Regressions taken without time fixed effects show a negative relationship between the probability of being hired for all workers and the state unemployment rate, but with fixed effects we see a positive relationship

Table 1.2: Hiring Over the Business Cycle: Detailed Potential Experience Categories

Outcome:	Pr(Hired)*100	Pr(UE)*100	Pr(EE)*100	Pr(NILFE)
	(1)	(2)	(3)	(4)
	Panel A			
State Unemp. Rate	0.0468***	-0.867***	-0.0275**	-0.0654**
	(0.0122)	(0.0968)	(0.00941)	(0.0213)
	Panel B			
PE< 0 × U. Rate	-0.484***	-0.997***	-0.342***	-0.637***
	(0.0409)	(0.248)	(0.0378)	(0.0522)
0 ≤PE< 1 × U. Rate	-0.429***	-1.179***	-0.268***	-0.598***
	(0.0324)	(0.121)	(0.0284)	(0.0383)
1 ≤PE< 2 × U. Rate	-0.420***	-1.158***	-0.291***	-0.601***
	(0.0293)	(0.122)	(0.0212)	(0.0477)
2 ≤PE< 3 × U. Rate	-0.199***	-0.831***	-0.224***	-0.496***
	(0.0252)	(0.144)	(0.0193)	(0.0574)
3 ≤PE< 4 × U. Rate	-0.109***	-1.088***	-0.183***	-0.421***
	(0.0267)	(0.168)	(0.0193)	(0.0575)
4 ≤PE< 5 × U. Rate	-0.0461	-1.184***	-0.124***	-0.356***
	(0.0248)	(0.163)	(0.0175)	(0.0582)
5 ≤PE< 6 × U. Rate	-0.0289	-1.213***	-0.114***	-0.342***
	(0.0251)	(0.186)	(0.0199)	(0.0784)
6 ≤PE< 7 × U. Rate	0.0214	-0.989***	-0.101***	-0.257***
	(0.0270)	(0.198)	(0.0181)	(0.0617)
7 ≤PE< 8 × U. Rate	0.0248	-0.999***	-0.0958***	-0.207***
	(0.0214)	(0.154)	(0.0177)	(0.0555)
8 ≤PE< 9 × U. Rate	0.0279	-1.218***	-0.0614**	-0.244**
	(0.0217)	(0.173)	(0.0185)	(0.0698)
9 ≤PE< 10 × U. Rate	0.0757**	-0.982***	-0.0477*	-0.119
	(0.0244)	(0.192)	(0.0199)	(0.0667)
10 ≤PE< 15 × U. Rate	0.0975***	-0.977***	-0.0166	-0.141*
	(0.0153)	(0.134)	(0.0112)	(0.0560)
15 ≤PE< 20 × U. Rate	0.115***	-0.854***	-0.0000752	-0.0900*
	(0.0152)	(0.145)	(0.0109)	(0.0436)
20 ≤PE< 25 × U. Rate	0.152***	-0.675***	0.0332**	-0.155***
	(0.0169)	(0.152)	(0.0112)	(0.0435)
25 ≤PE< 30 × U. Rate	0.146***	-0.550***	0.0184	-0.0755
	(0.0144)	(0.112)	(0.0114)	(0.0450)
30 ≤PE< 35 × U. Rate	0.132***	-0.716***	0.0191	-0.001000
	(0.0134)	(0.113)	(0.0107)	(0.0350)
35 ≤PE< 40 × U. Rate	0.110***	-0.699***	0.0180	0.0336
	(0.0141)	(0.126)	(0.0118)	(0.0304)
40 ≤PE< 45 × U. Rate	0.107***	-0.743***	0.0270*	0.0788*
	(0.0179)	(0.128)	(0.0133)	(0.0362)
45 ≤PE< 50 × U. Rate	0.0832***	-0.548**	0.0166	0.100***
	(0.0195)	(0.195)	(0.0147)	(0.0259)
PE≥ 50 × U. Rate	0.103***	-0.550**	0.0251	0.143***
	(0.0166)	(0.172)	(0.0137)	(0.0246)
N	17013532	624613	10407753	5981166
R-sq	0.049	0.260	0.027	0.069
Sample	All	Unemployed	Employed	NILF

Standard errors in parentheses, clustered at the state level * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Estimates include main effects and state and month-year fixed effects.

Table 1.3: Condensed Hiring Results

Outcome:	Pr(Hired)*100	Pr(UE)*100	Pr(EE)*100	Pr(NILFE)
	(1)	(2)	(3)	(4)
PE$\leq$ 10 $\times$ U. Rate	-0.131***	-0.575***	-0.115***	-0.479***
	(0.0167)	(0.157)	(0.0139)	(0.0314)
PE> 10 $\times$ U. Rate	0.185***	-0.0772	0.0810***	0.130***
	(0.0177)	(0.195)	(0.0152)	(0.0262)
Wald test: $\beta_1 = \beta_2$	404.96 ***	48.99***	373.34***	373.34***
R-squared	0.045	0.258	0.026	0.058
N	17013532	624613	10407753	5981166
Sample	All	Unemployed	Employed	NILF

Standard errors in parentheses, clustered at the state level * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Estimates include main effects and state and month-year fixed effects.

for experienced workers. In order to verify the robustness of this result, I regress the hiring rate without date fixed effects on five sub-samples: pre-2001 recession, during the 2001 recession, between the 2001 and 2007 recessions, during the 2007 recession, and post-2007 recession. I include state and month fixed effects to remove variation within state and month of the year. Table 1.4 shows the results.

Within each sub-sample, the positive relationship between the unemployment rate and the hiring rate of experienced workers is robust. The relationship for young workers is generally negative but less significant. I perform a Wald test of equality between the coefficients for young workers and experienced workers, which is firmly rejected in all sub-samples. This indicates that the result that hiring decreases more for young workers during recessions is present across my sample and is not an artifact of a particular period of time.

1.3.2 Alternative Specifications

Next I investigate alternative specifications. Other groups, such as worker with low levels of education and minorities, are also known to be particularly sensitive to the business cycle (Hoynes, Miller, & Schaller, 2012), so one might wonder how hiring varies for these groups. Figures 1.5a 1.5c show the raw hiring probabilities for young and experienced workers, split into low-education (high school graduate or less) and high-education categories. Figures 1.5d–1.5f show equivalent figures, broken into white and minority (non-white) categories. These figures show the striking pattern that, across education categories and race categories, levels and slopes are nearly identical within potential experience groups. This is especially true for the high-potential-experience

Table 1.4: Hiring Without Time Fixed Effects

Outcome: Pr. Hired	(1)	(2)	(3)
PE$\leq$ 10 $\times$ U. Rate	-0.110*	0.0220	-0.0229
	(0.0477)	(0.108)	(0.0418)
PE$>$ 10 $\times$ U. Rate	0.134***	0.371***	0.168***
	(0.0158)	(0.0636)	(0.0230)
Wald test: $\beta_1 = \beta_2$	24.94***	7.24***	11.54**
N	5765005	592915	5632317
R-squared	0.009	0.009	0.007
Sample	Feb 94–Mar 01	Apr 01–Nov 01	Dec 01–Dec 07
Outcome: Pr. Hired	(4)	(5)	
PE$\leq$ 10 $\times$ U. Rate	-0.149***	-0.0745**	
	(0.0307)	(0.0241)	
PE$>$ 10 $\times$ U. Rate	0.0260*	0.102***	
	(0.0129)	(0.0130)	
Wald test: $\beta_1 = \beta_2$	24.01***	29.41***	
N	1371187	3652108	
R-squared	0.005	0.004	
Sample	Jan 08–Jun 09	Jul 09–Jul 13	

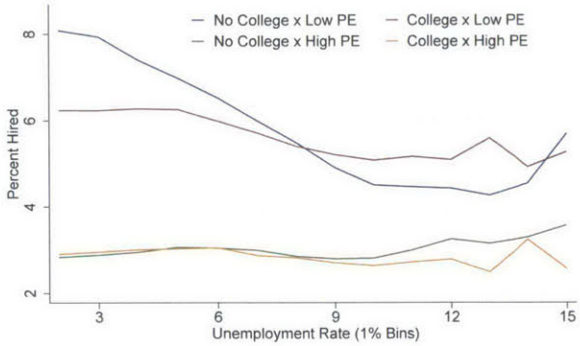
Standard errors in parentheses, clustered at the state level * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Estimates include main effects and state and month fixed effects.

groups: the levels and slopes are quite similar across education and race categories. For low-potential-experience workers, we see some separation, but largely similar trends.

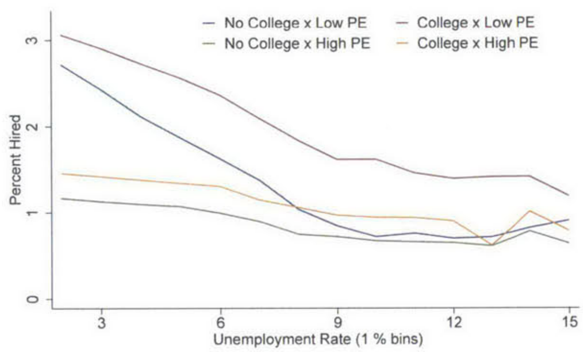
To solidify the interpretation in the above figures, in Table 1.5, I split each demographic variable into two groups (no college, college+; minority, white; female, male) and further split each group into low or high potential experience. I then have four demographic categories, which I interact with the state unemployment rate. In all three panels, we see negative coefficients for young workers and positive coefficients (except for in minority EE), for experienced workers, although not all coefficients are precisely estimated. This pattern of results strongly suggests that experience is a fundamental driver of the heterogeneity in the cyclical changes in hiring rates.

1.3.3 Exits

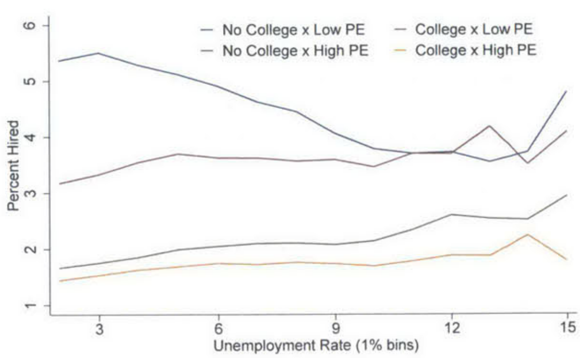
Although my primary interest is in hiring, an analysis of cyclical mobility would be incomplete without a consideration of exits, shown in Table 1.6. Exit rates are higher for young workers, but their change with the state unemployment rate is broadly similar across potential experience categories, increasingly slightly and occasionally significantly.



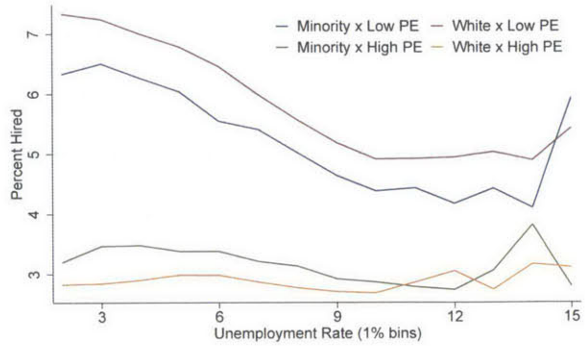
(a) All hires: Potential Experience × Education



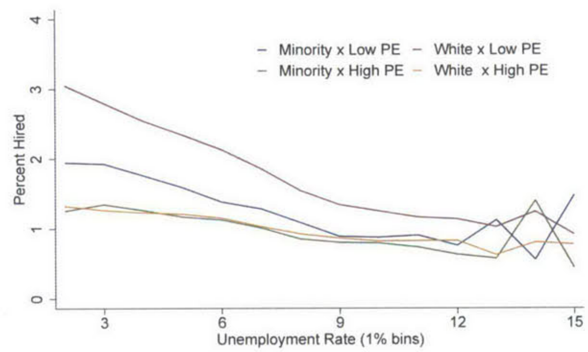
(b) EE Hires: Potential Experience × Education



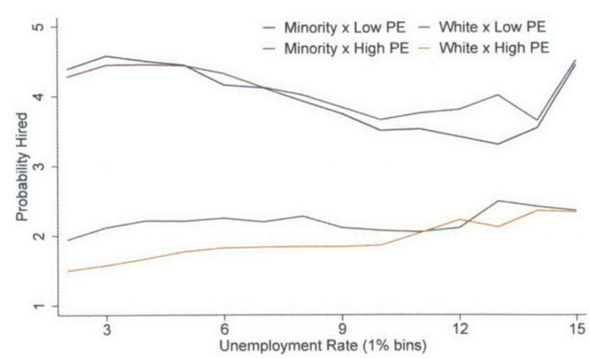
(c) NE-E Hires: Potential Experience × Education



(d) All Hires: Potential Experience × Race



(e) EE Hires: Potential Experience × Race



(f) NEE Hires: Potential Experience × Race

Figure 1.5: Hiring by Education and Race

Table 1.5: Hiring: Alternative Specifications

Outcome:	Pr(Hired)*100	Pr(EE)*100	Pr(NEE)
	(1)	(2)	(3)
Panel A: Education			
PE$\leq$ 10 $\times$ Educ.$\leq$ 12 $\times$ U. Rate	-0.322***	-0.232***	-0.533***
	(0.0225)	(0.0150)	(0.0372)
PE$\leq$ 10 $\times$ Educ.$>$ 12 $\times$ U. Rate	-0.0254	-0.109***	-0.437***
	(0.0154)	(0.0109)	(0.0506)
PE$>$ 10 $\times$ Educ.$\leq$ 12 $\times$ U. Rate	0.139***	0.00927	0.325***
	(0.0180)	(0.0105)	(0.0404)
PE$>$ 10 $\times$ Educ.$>$ 12 $\times$ U. Rate	0.102***	0.0230*	0.193***
	(0.0118)	(0.00975)	(0.0282)
R-squared	0.046	0.027	0.081
Panel B: Race			
PE$\leq$ 10 $\times$ Non-white $\times$ U. Rate	-0.164***	-0.131***	-0.289***
	(0.0223)	(0.0139)	(0.0426)
PE$\leq$ 10 $\times$ White $\times$ U. Rate	-0.170***	-0.163***	-0.522***
	(0.0148)	(0.0113)	(0.0370)
PE$>$ 10 $\times$ Non-white $\times$ U. Rate	0.0407*	-0.0195	0.0816*
	(0.0184)	(0.0144)	(0.0400)
PE$>$ 10 $\times$ White $\times$ U. Rate	0.132***	0.0247*	0.291***
	(0.0135)	(0.00940)	(0.0331)
R-squared	0.046	0.027	0.078
Panel C: Gender			
PE$\leq$ 10 $\times$ Female $\times$ U. Rate	-0.188***	-0.153***	-0.445***
	(0.0161)	(0.0131)	(0.0379)
PE$\leq$ 10 $\times$ Male $\times$ U. Rate	-0.168***	-0.170***	-0.542***
	(0.0174)	(0.0128)	(0.0349)
PE$>$ 10 $\times$ Female $\times$ U. Rate	0.0920***	0.0152	0.219***
	(0.0130)	(0.0105)	(0.0309)
PE$>$ 10 $\times$ Male $\times$ U. Rate	0.151***	0.0222*	0.323***
	(0.0140)	(0.00964)	(0.0368)
R-squared	0.046	0.027	0.078
N	17013532	10407753	6534953
Sample	All	Employed	Non-Employed

Standard errors in parentheses, clustered at the state level * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Estimates include main effects and state and month-year fixed effects.

Table 1.6: Employment Exits Over the Business Cycle

Outcome:	Pr(Exit Emp.)*100	Pr(Exit to U)	Pr(Exit LF)*100
	(1)	(2)	(3)
E< 0 × U. Rate	0.0109	0.0347	-0.0217
	(0.109)	(0.0357)	(0.0968)
0 ≤PE< 1 × U. Rate	0.0553	0.0685***	-0.0138
	(0.0559)	(0.0187)	(0.0512)
1 ≤PE< 2 × U. Rate	0.0327	0.0853**	-0.0534
	(0.0441)	(0.0246)	(0.0463)
2 ≤PE< 3 × U. Rate	0.0486	0.0465**	0.00245
	(0.0380)	(0.0173)	(0.0333)
3 ≤PE< 4 × U. Rate	0.119**	0.0563**	0.0626*
	(0.0403)	(0.0191)	(0.0305)
4 ≤PE< 5 × U. Rate	0.0786*	0.0604**	0.0159
	(0.0376)	(0.0194)	(0.0242)
5 ≤PE< 6 × U. Rate	0.109***	0.0761***	0.0349
	(0.0251)	(0.0157)	(0.0195)
6 ≤PE< 7 × U. Rate	0.115**	0.0653**	0.0489*
	(0.0340)	(0.0212)	(0.0185)
7 ≤PE< 8 × U. Rate	0.113***	0.0893***	0.0237
	(0.0246)	(0.0118)	(0.0192)
8 ≤PE< 9 × U. Rate	0.0987***	0.0590***	0.0401
	(0.0233)	(0.0127)	(0.0204)
9 ≤PE< 10 × U. Rate	0.0888***	0.0779***	0.0109
	(0.0227)	(0.0129)	(0.0184)
10 ≤PE< 15 × U. Rate	0.0980***	0.0833***	0.0149
	(0.0170)	(0.00717)	(0.0154)
15 ≤PE< 20 × U. Rate	0.0916***	0.0736***	0.0189
	(0.0174)	(0.00665)	(0.0147)
20 ≤PE< 25 × U. Rate	0.0967***	0.0716***	0.0256
	(0.0171)	(0.00749)	(0.0145)
25 ≤PE< 30 × U. Rate	0.0976***	0.0789***	0.0184
	(0.0172)	(0.00704)	(0.0133)
30 ≤PE< 35 × U. Rate	0.0988***	0.0750***	0.0236
	(0.0183)	(0.00840)	(0.0144)
35 ≤PE< 40 × U. Rate	0.0521**	0.0520***	-0.000411
	(0.0178)	(0.00717)	(0.0149)
40 ≤PE< 45 × U. Rate	0.0360	0.0615***	-0.0261
	(0.0246)	(0.00909)	(0.0206)
45 ≤PE< 50 × U. Rate	-0.138***	0.0440***	-0.182***
	(0.0292)	(0.0116)	(0.0278)
PE≥ 50 × U. Rate	-0.340***	0.0258*	-0.366***
	(0.0573)	(0.0124)	(0.0544)
N	10407753	10407753	10407753
R-squared	0.064	0.015	0.054

Standard errors in parentheses, clustered at the state level * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Estimates include main effects and state and month-year fixed effects.

1.3.4 Explaining the Fact Pattern

Next I consider possible explanations for the main empirical result: that young workers' probability of being hired is decreasing with the state unemployment rate while experienced workers' probability is increasing. I first consider four market-clearing hypotheses: change in workers' labor supply decision, change in workers' search intensity, worker self-selection, and change in the distribution of vacancies. After showing that none of these explanations is likely to fully explain the hiring result, I introduce my preferred explanation, that firms optimally choose to reduce hiring of inexperienced workers during recessions.

Labor Supply: A possible explanation for increased unemployment during recessions is that workers value employment less during recessions and choose to forgo employment. If this affects young workers more than experienced workers, this could explain why youth hiring from non-employment falls during recessions. However since I also observe a reduction in mobility for currently employed workers, labor market participation decisions alone cannot explain the results.

Self-selection: This explanation was advanced by McLaughlin and Bils (2001) as a potential explanation for cyclical upgrading across industries. In a frictionless world, workers should flow between jobs as the relative rate of return to different activities fluctuates. If young and experienced workers have different productivity profiles across jobs, and the distribution of returns across jobs changes with the business cycle, then worker flows between jobs may vary by age. However since we also see large variations in flows from non-employment to employment, self-selection is unlikely to be the primary driver of the heterogeneity we observe in hiring between young and experienced workers.

Search Intensity: Similarly to the labor supply argument, young workers could put forth less effort at search during recessions or become less effective at searching compared with experienced workers. Since I do not have data on job applications or contact rates, I cannot rule out this explanation. However, we do see youth hiring rates fall for unemployed workers (who self-report to be searching) as well as for employed workers (who have successfully found employment in the past). Since employed workers have already demonstrated their competency at search, this is unlikely to be the primary driver of changes in hiring rates.

Although labor-supply decisions, self-selection, and search intensity cannot individually explain the mobility results, it is possible that a combination of these effects could be jointly at work. I revisit this in Section 1.5, where I introduce evidence on occupation

Table 1.7: Youth Share of Hires

Outcome: $Pr(young|hired)$	(1)	(2)	(3)
State Unemp. Rate	-0.360***	-0.389**	-0.348***
	(0.0758)	(0.125)	(0.0704)
N	653067	238750	414317
R-squared	0.012	0.014	0.016
Sample	All in LF	Employed	Non-employed

Standard errors in parentheses, clustered at the state level * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Estimates include main effects and state, month-year, occupation, and industry fixed effects.

quality and wages, and show that the evidence is not consistent with a supply-driven explanation.

Composition of Vacancies: If the firms that are most likely to be expanding during recessions are those at which experienced workers are more productive, it is possible that the change in hiring rates could be driven by the composition of firms rather than a behavior change. To address this, I test to see if industry and occupation fixed effects remove the cyclical variation in the youth share of hires. Table 1.7 shows that the youth share of hires is decreasing with the state unemployment rate even after controlling for variation in the composition of hiring jobs. The CPS does not include further information on job characteristics, so I cannot rule out variation in composition on other dimensions, such as firm size or average wages. However, it is unlikely that these characteristics alone could explain the variation in hiring rates.

If none of these market-clearing explanations can account for the flow results, what can? An old literature on cyclical upgrading holds promise: these papers argue that firms are able to hire higher-quality workers during recessions (cf. Reder, 1955; Okun, 1973). This is consistent with case study evidence; for instance, Bewley (1999) reports that applicant quality and hire quality both rose for firms during the recession of the early 1990s.

In the classic literature, firm size is assumed to be fixed, thus firms cannot endogenously respond to lower wages by increasing employment. To more fully capture the equilibrium dynamics, I build on this idea, but endogenize the firm size decision, which allows for the characterization of conditions such that firms would not hire young workers. I find the key components are that inexperienced workers must be less productive, firm production functions must exhibit diminishing marginal productivity of labor, and firms must pay a fixed cost per position.[11] I show that in the absence of these three conditions, firms will always hire all applicants. In the next section, I describe and solve the model, and derive testable predictions to bring back to the evidence.

1.4 Model

In order to understand how firms' optimal choice of hiring strategy may vary over the business cycle, I develop an equilibrium search and matching model in which workers are of either low- or high-skill, the stock of workers of each type is fixed, and low-skill workers produce a fraction of what high-skill workers produce. The model is in discrete time, and workers and firms are infinitely lived. Each period, firms must choose how many vacancies to post.

1.4.1 An Example

Consider the one-period hiring decision of a single good-quality firm, holding fixed the rest of the market. The firm must decide how many vacancies to post given the aggregate state of the economy, A, the probability each vacancy matches with a worker, $q(A)$, and the share of job seekers that are low-skill, δ. $q(A)$ is strictly decreasing in A. Production $g(.)$ depends on the effective units of labor employed, N, where each low-skill worker produces share $\gamma < 1$ of what a high-skill worker produces. The production function is strictly increasing in N at a weakly decreasing rate, and strictly increasing in A. Firms must pay a fixed operating cost k per worker employed. Thus, the firm solves following problem:

$$\max_{N_L, N_H} g(A, \gamma N_L + N_H) - N_L(k + w_L) - N_H(k + w_H) - C(q(A), N_L, N_H) \tag{1.2}$$

where N_L and N_H are the numbers of low- and high-skill workers employed, and $C(.)$ is a function describing the cost of hiring which depends on the total number of vacancies posted. The timing consists of four stages: (1) the firm chooses how many and what type of vacancies to post; (2) the firm and workers match; (3) for each worker, the firm decides whether to extend an offer and bargains over wages; (4) the worker produces and is paid.

In principle, firms can hire workers in three ways. First, the firm can post unrestricted vacancies and hire any worker to whom it matches. Alternatively, the firm can post

[11] This may occur, for instance, if there is congestion in technology, so only one worker at a time can use a machine.

restricted vacancies, such that the firm designates the vacancy as for high- or low-type workers, and only hiring matched workers of the correct type. Since low-skill workers are less productive but require the same fixed cost k, firms will always weakly prefer to hire a high-skill worker. This allows us to rule out low-type exclusive vacancies.

Since search is frictional, the firm must post additional vacancies to hire a targeted number of hires. In particular, to hire H_L low-skill workers, the firm must post

$$V_L = \frac{H_L}{q(A)\delta}$$

vacancies, and to hire H_H high-skill workers, the firm must post

$$V_H = \frac{H_H}{q(A)(1-\delta)}$$

vacancies. Thus we can reformulate the firm's problem as a choice of how many unrestricted (V_A) and high-skill restricted vacancies (V_H) to post.

Following the convention of other search papers with multi-worker firms and diminishing marginal productivity of labor, including Michaillat (2012) and Elsby and Michaels (2013), I assume firms and workers bargain over wages, as if each worker was the marginal worker. This is an application of the Stole and Zwiebel (1996) bargaining solution. In this case, with worker bargaining power β and outside option 0, so we can write wages:

$$w_L = \gamma\beta\frac{\partial g}{\partial N}(A, N) - \beta k \tag{1.3}$$

$$w_H = \beta\frac{\partial g}{\partial N}(A, N) - \beta k \tag{1.4}$$

where all workers of the same type are paid equal wages.

Finally, the cost of hiring is given by a constant cost c for each vacancy posted. Now we can write the firm's problem,

$$\begin{aligned} &\max_{V_A, V_H} g(A, \gamma N_L + N_H) - N_L(w_L + k) - N_H(w_H + k) - c \times (V_A + V_H) \\ &\text{such that} \quad N_L = q(A)\delta V_A, \quad N^H = \frac{1-\delta}{\delta}(\delta q(A)V_A) + (1-\delta)q(A)V_H, \\ &\qquad w_L = \gamma\beta\frac{\partial g}{\partial N}(A, N) - \beta k \text{ and } w_H = \beta\frac{\partial g}{\partial N}(A, N) - \beta k \end{aligned} \tag{1.5}$$

The first-order conditions are as follows:

$$V_A: (1-\beta)\frac{\partial g}{\partial N}(N^*) - \beta N^* \frac{\partial^2 g}{\partial N^2}(N^*) \leq \frac{(1-\beta)k}{1-\delta+\gamma\delta} + \frac{c}{q(A)(1-\delta+\gamma\delta)} \tag{1.6}$$

$$V_H: (1-\beta)\frac{\partial g}{\partial N}(N^*) - \beta N^* \frac{\partial^2 g}{\partial N^2}(N^*) \leq (1-\beta)k + \frac{c}{q(A)(1-\delta)} \tag{1.7}$$

Assumption 1 $(1-\beta)\frac{\partial g}{\partial N}(N^*) - \beta N^* \frac{\partial^2 g}{\partial N^2}(N^*)$ *is strictly decreasing in* N.

Since

$$\frac{\partial g}{\partial N}(N) < 0$$

by construction, a sufficient condition is $\beta < \frac{1}{2}$ and

$$\frac{\partial^3 g}{\partial N^3}(N) \geq 0.$$

For simplicity, I will use this restriction, but it can be weakened by imposing further constraints on the third-derivative of $g(.)$.[12] In addition, to rule out multiplicity of solutions, I will impose that when the firm is indifferent, it does not discriminate between workers.

Lemma 1 *The optimal hiring strategy is to either hire all workers* ($V_H = 0$), *or only hire skilled workers* ($V_A = 0$).

Lemma 1 follows directly from the first-order conditions. Both conditions have the same left-hand-side, which represents the marginal profits from hiring. The right-hand-side of each condition is the marginal cost of hiring another worker. The firm optimally chooses the hiring strategy that yields the smaller marginal cost. Thus, we can characterize the optimal hiring decision by defining the cut-off $\hat{A}$ such that the marginal costs are equal. Since $q(A)$ is strictly decreasing with A by assumption, we have the firm will hire all workers if

$$A \geq \hat{A} \text{ such that } \frac{1}{q(\hat{A})} = \frac{1-\gamma}{\gamma}\frac{k(1-\delta)(1-\beta)}{c} \tag{1.8}$$

and otherwise, the firm will only hire high-skill workers. This cut-off weakens the closer the productivity of low- and high-skill labor (γ), the smaller the fixed cost of hiring (k), the larger the share of low-skill labor in the market (δ), and the more costly it is to post a vacancy (c).

[12]In particular, that $\frac{\partial^3 g}{\partial N^3} > \frac{-2}{N}\frac{\partial^2 g}{\partial N^2}$.

Lemma 2 *If there is no fixed cost per position ($k = 0$), the firm's optimal decision is to hire all workers. If there is no hiring cost ($c = 0$), the firm's optimal decision is to only hire high-skill workers.*

When there is no fixed cost per position, the cost per unit of output of high- and low-skill workers equalizes. Since only hiring high-skill workers is more costly (as the firm must post more vacancies), this will never be optimal. Conversely, if it is costless to post vacancies and $k > 0$, the firm will choose to hire only high-skill workers.

In this simplified example, we see that the firm's optimal hiring decision depends directly on the state of the aggregate economy. Low-skill workers are more costly to employ in terms of cost per unit of output, but are cheaper to hire. When the A is above the cutoff, low-skill workers are sufficiently productive to outweigh the additional cost. As A falls, the fixed cost k becomes increasingly salient, until the firm switches to only hiring high-skill workers. In a full equilibrium model, the share of low-skill workers δ and the hiring friction q are endogenous, depending on past and present hiring decisions by all firms in the economy.

1.4.2 Model Description

Returning to the full model, there is now a fixed measure M firms of the type described in the above example, which I will now refer to as good firms. Each firm is small in the labor market, thus optimizes as if the set of searching workers and vacancies were fixed. In addition, there is an endogenous set of bad firms, at which each worker is less productive than at a good firm. These firms have constant marginal productivity of labor and no fixed cost, thus without loss of generality, we can assume each firm is comprised of a single worker. The stock of bad firms is endogenous, such that new firms will enter as long as the expected benefit exceeds the cost of vacancy posting. Finally, I will later explicitly derive conditions such that bad firms are less productive in all states of the economy, to ensure workers will always seek to move from bad firms to good firms.

Matching Process

Contacts between workers and firms are given by the matching function $x(N^V, N^S)$, where N^V is the total number of vacancies, and N^S is the total number of workers searching. The matching function represents the congested process by which workers and firms encounter one another. The number of vacancies consists of the good (N^{VG}) and bad (N^{VB}) vacancies. Since workers search on the job, N^S is not only the stock of unemployed, but also of workers who are matched with bad firms and are searching for a match at a good firm. Search is costless for workers but vacancy posting is costly for firms. In particular, I will use the following functional form:

$$x(N^V, N^S) = \frac{N^V N^S}{N^V + N^S} \tag{1.9}$$

which satisfies the usual properties of matching functions: homogeneous of degree one, increasing and concave in both arguments, and bounded by the minimum of its arguments.

The probability that a worker of type i finds a match at a firm of type j during a particular period is given by

$$p_{ij} = \frac{N_{Vj} I_{ij}}{N_S + N_V} \tag{1.10}$$

where I_{ij} is an indicator for whether a worker of type i and a firm of type j will choose to produce upon matching. I will focus on symmetric equilibria, so I_{ij} will be constant across firms of type j.

Similarly, each firm of type j's probability of filling a vacancy with a worker of type i is given by

$$q_{iB} = \frac{N_{Ui}}{N_S + N_V} \tag{1.11}$$

$$q_{iG} = \frac{N_{Si}}{N_S + N_V} \tag{1.12}$$

where Equation 1.11 reflects the fact that only workers at bad firms search on-the-job, and will only change firms if the offer strictly dominates the current offer. In equilibrium, this implies that the only workers changing firms are those employed by bad firms who match with a good firm. In addition, since search is costless, I assume all workers at bad firms always search on-the-job, regardless of good firms' hiring strategies.[13] Finally, the accounting equations for the number of workers and vacancies of each type are as follows:

$$N_S = N_{SL} + N_{SH} \tag{1.13}$$

$$N_{Si} = N_{Ui} + N_{Bi}, \text{ for } i = \{L, H\} \tag{1.14}$$

$$N_V = N_{VB} + \sum_{j=1}^{M} N_{VGjt} \tag{1.15}$$

[13]This simplifies the analysis, but could be endogenized by including heterogeneity in good firms' such that there are always some firms willing to hire low-skill workers.

Worker Dynamics

The total labor force is normalized to size 1, with share δ low-skill. Employed workers separate from jobs with exogenous probability s, returning to the pool of unemployed.

In order to characterize how workers move between unemployment and employment, we can write the worker flows recursively. The number of workers in a state in any period is given by the share of workers who remain in the state from the previous period, plus the new entrants into the state. Thus we can write,

$$N'_{UL} = (1 - p'_{GL} - p'_{BL})N_{UL} + s(N'_{BL} + N'_{GL}) \tag{1.16}$$
$$N'_{UH} = (1 - p'_{GH} - p'_{BH})N_{UH} + s(N'_{BH} + N'_{GH}) \tag{1.17}$$
$$N'_{BL} = (1 - s - p'_{GL})N_{BL} + p'_{BL}N_{UL} \tag{1.18}$$
$$N'_{BH} = (1 - s - p'_{GH})N_{BH} + p'_{BH}N_{UH} \tag{1.19}$$

where x' indicates the next period's value. Since the total number of workers is fixed, we can express the stock of workers in good jobs in terms of the stock of unemployed workers and workers in bad jobs,

$$N_{GL} = \delta - N_{UL} - N_{BL} \tag{1.20}$$
$$N_{GH} = 1 - \delta - N_{UH} - N_{BH} \tag{1.21}$$

Using the expressions for the probability of a worker matching with a vacancy (p_{ij}) from Equation 1.10, we can rewrite Equations 1.16–1.19 in terms of the number of vacancies and the number of workers in each state. This yields the law of motion of worker flows, which are the first four equilibrium conditions.

Bad Firms' Entry and Wages

Bad firms behave like typical firms in search and matching models. Firms decide whether or not to enter by evaluating the cost of entry c_b against the probability of matching with a worker q_{ji} and the expected return for such a match J_{ji}. Firms and workers discount the future at rate $1 - r$. We can write the asset value of each state of a job as follows:

$$V_B = -c_b + q_L(J_{BL} - V'_B) + (1 - r)q_H(J_{BH} - V'_B) \tag{1.22}$$
$$J_{BL} = A\gamma F^B - w_{BL} + (1 - r)(1 - s)(1 - p'_{GL})J'_{BL} + (1 - r)(s + (1 - s)p'_{GL})V'_B \tag{1.23}$$
$$J_{BH} = AF^B - w_{BH} + (1 - r)(1 - s)(1 - p'_{GH})J'_{BH} + (1 - r)(s + (1 - s)p'_{GH})V'_B \tag{1.24}$$

By free entry, each period V_b is driven to zero, thus we can re-write Equation 1.22 as

$$c_b = q_L J_{BL} + q_H J_{BH} \tag{1.25}$$

Wages are determined via bargaining. Following Pissarides (1994), I restrict analysis to short-term (one-period) contracts, in which the firms and workers follow Nash bargaining over the marginal product with worker bargaining power β. Thus, for a worker of type i, wages w_{iB} will solve the following equation

$$(1-\beta)(E_{Bi} - U_i) = \beta J_{Bi} \tag{1.26}$$

where U_i and E_{Bi} are the asset values of unemployment and employment at a bad firm at time t. These asset values can be written recursively:

$$U_i = (1-r)(1-p'_{Bi} - p'_{Gi})U'_i + (1-r)p'_{Bi}E'_{Bi} + (1-r)p'_{Gi}E'_{Gi} \tag{1.27}$$
$$E_{Bi} = w_{Bi} + (1-r)(1-s)(1-p'_{Gi})E'_{Bi} + (1-r)(1-s)p'_{Gi}E'_{Gi} + (1-r)sU'_i \tag{1.28}$$
$$E_{Gi} = w_{Gi} + (1-r)(1-s)E'_{Gi} + (1-r)sU'_i \tag{1.29}$$

Combining and rearranging Equations 1.27 and 1.28 yields

$$E_{Bi} = U_i + w_{Bi} + (1-r)((1-s)(1-p'_{Gi}) - p'_{Bi})(E'_{Bi} - U'_i) - (1-r)p'_{Gi}s(E'_{Gi} - U'_i) \tag{1.30}$$

which combined with the bargaining equation yields expressions for wages

$$w_{BL} = \beta A\gamma F^B + \beta(1-r)p'_{BL}J'_{BL} + (1-\beta)(1-r)p'_{GL}s(E'_{GL} - U'_L) \tag{1.31}$$
$$w_{BH} = \beta A F^B + \beta(1-r)p'_{BH}J'_{Bh} + (1-\beta)(1-r)p'_{GH}s(E'_{GH} - U'_H) \tag{1.32}$$

The wage expressions depend on the workers' share of current output, but also his outside option which is a function of the probability he matches with another firm, as well as the expected output in the new match.

In steady state, these expressions simplify considerably, and we can write bad firms' free entry condition as a function of the stocks of searching workers (N_{UL}, N_{UH}, N_{BL}, and N_{BH}) and the stocks of vacancies N_{VB} and N_{VG}, all as a function of the aggregate state parameter A.

$$J_{BL} = \frac{(1-\beta)A\gamma F^B - (1-\beta)(1-r)p_{GL}s(E_{GL} - U_L)}{1-(1-r)(\beta p_{BL} + (1-s)(1-p_{GL}))} \tag{1.33}$$

$$J_{BH} = \frac{(1-\beta)AF^B - (1-\beta)(1-r)p_{GH}s(E_{GH} - U_H)}{1-(1-r)(\beta p_{BH} + (1-s)(1-p_{GH}))} \tag{1.34}$$

This yields the fifth equilibrium condition. In order to determine the share of these vacancies posted by good firms, we turn to good firms' optimization problem, which will provide the sixth and final equilibrium condition.

Good Firms' Hiring and Wages

Good firms post multiple vacancies per period, thus must decide how many of each type of vacancy to post. As in the example in Section 1.4.1, firms will only post one of two types of vacancies: vacancies that will hire any type of worker and vacancies that only hire high-skill workers. Firms must choose each vacancy's strategy before posting. In addition, firms must choose whether or not to dispose of labor. Let V^A and V^H refer to the quantity of vacancies posted, and F^L and F^H refer to the number of workers fired. Each good firm solves

$$\max_{\{V_A, V_H\, F_L, F_H\}_{t=0}^{t=\infty}} \sum_{t=0}^{\infty} (1-r)^t \Big[g(N_t) - (w_{Lt}+k)(N_{Lt}) - (w_{Ht}+k)(N_{Ht}) - c(V_{At}+V_{Ht})\Big] \tag{1.35}$$

such that

$$\begin{aligned}
N_t &= \gamma N_{Lt} + N_{Ht}, \\
N_{Lt+1} &= q_{LGt}V_{At+1} + (1-s)N_{Lt} - F_{Lt+1}, \\
N_{Ht+1} &= q_{HGt}V_{At+1} + q_{HGt}V_{Ht+1} + (1-s)N_{Ht} - F_{Ht+1} \text{ and} \\
V_{At} &\geq 0,\ V_{Ht} \geq 0,\ F_L \geq 0,\ F_H \geq 0
\end{aligned}$$

Where $g(N)$ is increasing and concave in N, and strictly increasing in A.

As in the example, I will impose that wages are determined by bargaining over the marginal product, where each worker is potentially marginal. In keeping with the standard notation, I will define the value of a firm hiring a worker of type j as follows:

$$J_{GL} = \gamma \frac{\partial g(N^t)}{\partial N} - k - w^{GL} + (1-r)(1-s)J'_{GL} \tag{1.36}$$

$$J_{GH} = \frac{\partial g(N^t)}{\partial N} - k - w^{GH} + (1-r)(1-s)J'_{GH} \tag{1.37}$$

and thus the bargaining condition is

$$(1-\beta)(E_{Gj} - U_j) = \beta J_{Gj} \tag{1.38}$$

Using Equations 1.36, 1.37, and 1.38, we can express wages in terms of E_{Gj} and U_j, that is, the net present value of employment in a good firm and unemployment, respectively. So we have

$$w_{GL} = \gamma \frac{\partial g(N^t)}{\partial N} - k - \Omega_L \tag{1.39}$$

$$w_{GH} = \frac{\partial g(N^t)}{\partial N} - k - \Omega_H \tag{1.40}$$

where

$$\Omega_L = \frac{1-\beta}{\beta}(E_{GL} - U_L) + (1-r)(1-s)\frac{1-\beta}{\beta}(E'_{GL} - U'_L)$$

$$\text{and } \Omega_H = \frac{1-\beta}{\beta}(E_{GH} - U_H) + (1-r)(1-s)\frac{1-\beta}{\beta}(E'_{GH} - U'_H)$$

Now we can solve the maximization problem in Equation 1.35, yielding the following optimality conditions:

$$\frac{\partial}{\partial V_{At}} : -\frac{\partial^2 g(N_t)}{\partial N_t^2}(\gamma N_{Lt} + N_{Ht}) - (1-r)(1-s)\frac{\partial^2 g(N_{t+1})}{\partial N_{t+1}^2}(\gamma N_{Lt+1} + N_{Ht+1}) = \frac{c - q_{LGt}(\Omega_{Lt} + (1-r)(1-s)\Omega_{Lt+1}) - q_{HGt}(\Omega_{Ht} + (1-r)(1-s)\Omega_{Ht+1})}{\gamma q_{LGt} + q_{HGt}} \tag{1.41}$$

$$\frac{\partial}{\partial V_{Ht}} : -\frac{\partial^2 g(N_t)}{\partial N_t^2}(\gamma N_{Lt} + N_{Ht}) - (1-r)(1-s)\frac{\partial^2 g(N_{t+1})}{\partial N_{t+1}^2}(\gamma N_{Lt+1} + N_{Ht+1}) = \frac{c - q_{HGt}(\Omega_{Ht} + (1-r)(1-s)\Omega_{Ht+1})}{q_{HGt}} \tag{1.42}$$

As in the example in Section 1.4.1, both constraints cannot bind simultaneously, thus the optimal choice of strategy is to either post all non-restricted vacancies (hire whichever type matches), or to post all restricted vacancies. We can define the cutoff as follows: if

$$\frac{1}{q_{GHt}} \geq \frac{\gamma\Omega_{Ht} - \Omega_{Lt} + (1-r)(1-s)(\gamma\Omega_{Ht+1} - \Omega_{Lt+1})}{\gamma c} \tag{1.43}$$

the firm will choose to only post non-restricted vacancies, otherwise the firm will only hire high-skill workers.

Thus, given the current state of the economy A, the existing stocks of workers $N^{ULt}, N^{UHt}, N^{BLt}, N^{BHt}$, and the number of vacancies posted by other firms, a firm will choose to post unrestricted vacancies if Equation 1.43 holds. Since this depends on the vacancies posted by other firms, these may be strategic complements, leading to multiple equilibria.

Now we can define equilibrium.

Definition 3 *Given initial conditions* $\{N_{UL0}, N_{UH0}, N_{BL0}, N_{BH0}\}$*, and aggregate state of the economy* A*, a symmetric equilibrium is a collection of paths of the stocks of workers* $\{N^{ULt}, N^{UHt}, N^{BLt}, N^{BHt}\}_{t=0}^{\infty}$ *that satisfy bad firms' free entry condition (Equation 1.25), the good firms' optimization problem (Equation 1.35), and the laws of motion for worker flows (Equations 1.16–1.19).*

1.4.3 Steady-State Equilibrium

To show equilibria exist, I will focus on the steady-state. For every state of the world A, there are two possible symmetric steady-state equilibria: either good firms post unrestricted vacancies or good firms only hire high-skill workers.

Proposition 1 *There are two cutoffs,* $\bar{A}_A$ *and* $\bar{A}_H$*, such that for every* A *outside the interval,* $[\min\{\bar{A}_A, \bar{A}_H\}, \max\{\bar{A}_A, \bar{A}_H\}]$*, there is a unique symmetric steady-state equilibrium. In particular, for values of* A *below the interval, good firms only hire high-skill workers, and for values of* A *above the interval, good firms hire all workers.*

To prove this, first observe that in steady state, the cutoff equation (Equation 1.43) becomes:

$$\frac{1}{q_H} \geq \frac{1-\beta}{\beta} \frac{(1+(1-r)(1-s))^2(\gamma J_{GH} - J_{GL})}{\gamma c} \tag{1.44}$$

We will proceed by showing that there always exists some A where the cutoff is crossed. First, we will consider the left-hand-side of the equation.

Lemma 4 q_H *is strictly decreasing with* A*.*

To see this, recall the free entry condition governing job creating by bad firms:

$$c_b = q_L J_{BL} + q_H J_{BH} \tag{1.45}$$

The value of job creation, J_{BL} and J_{BH} are both strictly increasing in the state of the economy A, thus firms create new vacancies until the equality is maintained, driving down the probability that each firm hires a worker of type i, q_i.

By Lemma 4, we have that the left-hand-side of the equation is strictly increasing with A. It will be sufficient to show the right-hand-side of the equation is non-increasing in A. First, consider the simplified single period case. How does $\gamma \hat{J}_{GH} - \hat{J}_{GL}$ vary with

A? Under the bargaining assumptions, we have

$$\hat{J}_{GL} = (1-\beta)\gamma g(N^*) - (1-\beta)k \tag{1.46}$$

$$\hat{J}_{GH} = (1-\beta)g(N^*) - (1-\beta)k \tag{1.47}$$

Thus when we calculate $\gamma\hat{J}_{GH} - \hat{J}_{GL}$, we get $(1-\gamma)(1-\beta)k$ which is independent of A. The intuition is that since the operating cost k does not scale with the relative productivity of the low-skill worker (γ), it is cheaper to hire γ units of labor from a high-skill worker than a low-skill worker. In this simplified case, the difference in cost is constant across the quality of the economy A. In the dynamic model, this is more complicated, since transition probabilities also depend on the state of the economy A. However the principle of the result goes through.

Lemma 5 *If the rest of the good firms in the economy play a symmetric equilibrium,*

$$\frac{1-\beta}{\beta}\frac{(1+(1-r)(1-s))^2(\gamma J_{GH} - J_{GL})}{\gamma c}$$

is strictly decreasing in A.

The last step to proving existence is ensuring the equilibrium is well defined on both sides of the cutoff. To be precise, I will use a specific functional form for good firms' production function: $g(N) = F_G AN - F_G\frac{x}{2}N^2$, which is increasing and concave in N. We need the following conditions:

Assumption 2 *To insure wages are higher at good firms, we need*

$$A > \frac{2x+k}{F_G - F_B}.$$

In addition, provided $\gamma < F_G - F_B$, there are A above the first cutoff, but in which good firms will not hire low-skill workers.

By the conditions in Assumption 2, q_H is continuous in A. Thus, the cut-off exists and is well-defined, completing the proof of Proposition 1.

1.4.4 Comparative Statics and Testable Predictions

In order to understand the effect of good firms' hiring strategy, I next explore comparative statics. Since I have characterized steady-state equilibria, I will compare between otherwise identical economies with different long-run values of A. In particular, let $\bar{A}$

be in the region in which good firms hire all types of workers by Proposition 1, and let $\underline{A}$ be in the region in which good firms only hire high-skill workers. How do the transition probabilities compare in two economics in the $\bar{A}$ equilibrium and $\underline{A}$ equilibrium respectively?

We can express the probability of a worker of type i being hired as:

$$\Pr(\text{EE mobility} \mid \text{employed worker type } i) = \frac{p_{Gi} N_{Bi}}{N_{Bi} + N_{Gi}} \tag{1.48}$$

$$\Pr(\text{hired} \mid \text{nonemployed worker type } i) = p_{Gi} + p_{Bi} \tag{1.49}$$

For low-skill workers, since p_{GL} is zero in the $\underline{A}$ economy, all mobility is reduced compared with the $\bar{A}$ equilibrium. For high-skill workers, p_{GH} falls with A, but the distribution of employment between good and bad jobs may go either way, depending on

Lemma 6 *Between firm mobility falls to zero for low-skill workers when the A falls from $\bar{A}$ to $\underline{A}$. High-skill workers may see a fall in mobility, depending on the distribution of vacancies between good and bad jobs.*

The mobility results are consistent with the flow results in Section 1.3.

The model predicts additional implications for job quality and wages that can be brought back to the data and tested.

Proposition 2 *When A falls from $\bar{A}$ to $\underline{A}$, unskilled workers are only hired by bad firms, thus average occupation quality and wages decline. Skilled workers may see a change in the hiring distribution, but it always contains some good jobs, and wages always fall strictly less than the wage losses for young workers.*

1.5 Evaluating Model Predictions

The model predicts that if we observe the youth share of hires fall with the business cycle, we should also observe young workers are hired by lower-quality jobs, while there should be little or no change for experienced workers. In addition, all young workers should receive lower wages, while again there should be little or no change for experienced workers. Although this model provides an equilibrium explanation of how demand may change the youth share of hiring over the business cycle, there are potentially other models that could arrive at the same results. Any cyclical upgrading model, in which firms hire high-skill workers during recessions, will provide the similar job quality predictions.

In order to evaluate the validity of these predictions, I return to evidence. To measure the quality of jobs, I construct several measures of occupation quality. First, I generate a wage index, following the methodology of Acemoglu (1999). I use wage data from the OES (Occupational Employment Statistics) survey. The OES surveys 1.2 million non-farm establishments every 3 years. Each establishment reports worker wages within detailed SOC categories, which should, in principle, represent a more accurate source of occupational wages than the self-reported wages in the CPS. I use median occupational wages from the May 2005 OES release, which includes data from 2002–2005. These are reported using SOC 2000 codes, thus I use U.S. Census Bureau occupation crosswalks to assign a 2005 wage index, i.e. a median hourly wage, for each occupation in the CPS. The wage index ranges from \$6.60 to \$80.25.

As another source of occupation quality, I use O*NET data on occupational characteristics. O*NET replaces the Dictionary of Occupational Titles (DOT) as the national taxonomy of occupational characteristics. While the DOT was primarily organized around tasks, O*NET follows a content model, including data on characteristics such as abilities, skills, and activities. This includes 483 variables in total, on which I perform principal component analysis to condense the matrix into the three most important factors (eigenvectors). These can be thought of as a statistical representation of the latent variables underlying variation in occupational characteristics. These factor variables form a concise description of occupational characteristics, and jointly explain 60% of the total variance in the O*NET data. The factors are described in Table 1.8.[14] In order to associate the factors with occupation quality, I use the CPS extract to find the correlation between each factor and the age, education, and experience of workers. I find Factor 1 and Factor 2 indicate "high-skill" occupations, with age, education, and experience all positively correlated, while Factor 3 is "low-skill". These quality interpretations are consistent with the titles of occupations that receive high scores: for instance CEOs receive high scores in Factor 1 and electricians receive high scores in Factor 2. In addition, the occupational characteristics these factors weight highly are consistent with the quality ranking: Factor 1 includes characteristics such as communication skills and judgment, Factor 2 includes characteristics such as troubleshooting. Occupations that score high ranks in Factor 3 include flight attendants and correctional officers, and the factor is associated with lower-level service sector tasks such as assisting others. I normalize the factors to mean 0, standard deviation 1. O*NET uses SOC 2010 occupation classifications, so I again use the Census Bureau crosswalks to assign scores to each occupation in my dataset.

Table 1.9 shows how the quality of occupations into which workers are hired varies over the business cycle. The regressions are performed at the individual level, with the

[14]This methodology is also employed by Poletaev and Robinson (2008) and Abraham and Spletzer (2009), who use the DOT and O*NET, respectively.

Table 1.8: Generating Occupational Quality Indices

	Occupations with High Scores	Top Characteristics	Correlations	
Factor 1	CEOs	Speaking ability	Experience	0.0518
	Neurologists	Written expression ability	Years Ed.	0.5273
	Lawyers	Judgment and decision-making ability	Age	0.1541
Factor 2	Ship and Boat Captains	Inspecting equipment ability	Experience	0.0753
	Electricians	Mechanical ability	Years Ed.	0.1144
	Robotics Technicians	Troubleshooting ability	Age	0.0971
Factor 3	Correctional Officers	Assisting others important	Experience	-0.0323
	Flight Attendants	Working with public important	Years Ed.	-0.0592
	Acute Care Nurses	Dealing with aggressive people	Age	-0.0436

sample limited to individuals who are hired and have valid occupational information. All specifications include state and date fixed effects, as well as education, race, and gender fixed effects to remove compositional variation. For Columns (1) through (3), occupational quality is increasing with the variable (Wage Index, Factor 1, and Factor 2). For Column (4), however, occupation quality is decreasing with Factor 3 (see Table 1.8). In Panel A, for each column I regress a different occupational quality index on the state unemployment rate. Here we see that although the point estimates indicate occupational quality is decreasing with the state unemployment rate, the magnitudes are small and not significant. In Panel B I interact the unemployment rate by worker potential experience (young versus experienced). Here we see that for the first three columns, occupational quality is declining for young workers, which is significant, while for experienced workers the coefficients are small and not significant. The wage index indicates that for each additional percentage point of state unemployment, young workers are hired into occupations that pay six cents less per hour in 2005 median wages. So, for instance, given a five percentage point increase in the state unemployment rate, a young hire could expect on average to receive 30 cents less per hour. Sustained over a year, this adds up to approximately $600 in foregone earnings.

In Panel C, I split the potential experience categories more finely. Here we see that the negative effect of the state unemployment rate on occupational quality is significant through six years of potential experience for the wage index, and through 9 years of potential experience for Factor 2. The magnitude of the effect of a five percentage point increase in the state unemployment rate on the wage index ranges between seven and eleven cents per hour, or between $700 and $1100 per year of foregone earnings.

These results are consistent with the first prediction of model: that when the youth share of hires falls, the average occupational quality for hires falls for young workers, but not for experienced workers. This is also consistent with evidence in (Kahn, 2010) which shows that a key source of missing wages for youths who graduate college during recessions is due to matching with lower-quality occupations. My evidence shows this result holds more broadly for young workers of different education levels. However my results also show the extent of this result: hires with more than ten years of potential experience do not exhibit any recessionary change in average occupational quality.

The second prediction from the model is that if we observe the youth share of hiring falling during recessions, these workers should receive lower wages. To see if there is evidence of this prediction, I use hourly wage data from the CPS. Wage information is only collected in the fourth and eighth months of the survey, so this cuts the available sample by two-thirds. I exclude imputed and top-coded values. Table 1.10 shows the results. In Panel A, I regress log wages on the state unemployment rate with state, date, and demographic (education, race, and gender) fixed effects. In Panel B I split the state unemployment rate into young and experienced portions, to see the variation by potential experience. In Panel C I provide flexible potential experience categories to allow for a more nuanced investigation of variation by potential experience.

In Column (1) I include all workers and show, on average, that wages fall by 0.006 log points for each percentage point increase in the state unemployment rate. Panel B shows this holds for both young and experienced workers, although the magnitude is twice as large for young workers. Column (2) restricts the sample to individuals who are hired, which cuts the sample to 57,000 observations. Here we see young workers' log wages fall by 0.006 log points for each percentage point increase in the state unemployment rate, while experienced workers see no change. I further break the sample into hires from non-employment, column (3), and hires from employment, column (4). These results indicate that the main driver of the fall in wages at hiring appears to be reductions in the wages of workers hired from employment. Finally, column (5) shows wage changes for continuing workers. Since the vast majority of workers are not new hires, these estimates are nearly identical to column (1), again showing that young workers wages fall by 0.01 log points compared with 0.006 for experienced workers.

Using the average wages from Table 1.1, I estimate a five percentage point increase in the state unemployment rate is associated with a decrease of about 50 cents per hour for young workers from an average wage of \$10.11. In contrast, experienced workers would see a larger fall in dollar terms: a decrease of 86 cents per hour from a wage of \$14.36.

Finally, panel (C) breaks the results out by fine potential experience bins. Here we see that the 0.01 log point decrease in wages appears to be relatively robust across workers with less than 10 years potential experience, and only disappears once we get to the older categories.

These results do not provide clear evidence in support of or against the model. Youth

Table 1.9: Occupational Quality of Hires over the Business Cycle

Outcome:	Wage Index	Factor 1	Factor 2	Factor 3
	(1)	(2)	(3)	(4)
Panel A				
State Unemp. Rate	-0.00655	-0.00190	-0.00128	0.000119
	(0.0104)	(0.00126)	(0.00167)	(0.00130)
R-squared	0.255	0.298	0.157	0.029
Panel B				
PE$\leq$ 10 $\times$ U. Rate	-0.0581***	-0.00552***	-0.00780***	-0.000775
	(0.0114)	(0.00137)	(0.00220)	(0.00153)
PE$\leq$ 10 $\times$ U. Rate	0.0169	-0.0000420	0.00172	0.00118
	(0.0130)	(0.00147)	(0.00159)	(0.00144)
Wald test: $\beta_1 = \beta_2$	23.67***	13.23***	22.17***	22.17
R-squared	0.271	0.301	0.174	0.033
Panel C				
PE< 0 $\times$ U. Rate	-0.0298	-0.00325	-0.00278	0.000823
	(0.0267)	(0.00285)	(0.00472)	(0.00328)
0 <PE$\leq$ 1 $\times$ U. Rate	-0.0992***	-0.0117***	-0.0113**	-0.00274
	(0.0157)	(0.00204)	(0.00350)	(0.00257)
1 <PE$\leq$ 2 $\times$ U. Rate	-0.0797***	-0.00754***	-0.00839*	-0.00216
	(0.0152)	(0.00207)	(0.00319)	(0.00205)
2 <PE$\leq$ 3 $\times$ U. Rate	-0.0716**	-0.00411	-0.00901*	-0.00149
	(0.0216)	(0.00253)	(0.00372)	(0.00239)
3 <PE$\leq$ 4 $\times$ U. Rate	-0.102***	-0.00498*	-0.0156***	0.00300
	(0.0221)	(0.00214)	(0.00355)	(0.00269)
4 <PE$\leq$ 5 $\times$ U. Rate	-0.114***	-0.00161	-0.0159***	-0.00161
	(0.0275)	(0.00362)	(0.00351)	(0.00270)
5 <PE$\leq$ 6 $\times$ U. Rate	-0.0787**	-0.00515	-0.0150***	0.000163
	(0.0261)	(0.00347)	(0.00406)	(0.00254)
6 <PE$\leq$ 7 $\times$ U. Rate	-0.0560	-0.00292	-0.00936*	0.00444
	(0.0316)	(0.00274)	(0.00366)	(0.00270)
7 <PE$\leq$ 8 $\times$ U. Rate	-0.0299	0.00277	-0.0117**	0.00356
	(0.0368)	(0.00277)	(0.00411)	(0.00337)
8 <PE$\leq$ 9 $\times$ U. Rate	-0.0165	0.00277	-0.00820	0.00460
	(0.0325)	(0.00319)	(0.00444)	(0.00307)
9 <PE$\leq$ 10 $\times$ U. Rate	0.0158	0.00132	-0.00686	0.000841
	(0.0334)	(0.00279)	(0.00522)	(0.00320)
10 <PE$\leq$ 20 $\times$ U. Rate	0.0137	0.00185	0.0000819	0.00302
	(0.0156)	(0.00167)	(0.00173)	(0.00167)
20 <PE$\leq$ 30 $\times$ U. Rate	0.00731	-0.00246	0.00146	0.000222
	(0.0192)	(0.00248)	(0.00216)	(0.00159)
30 <PE$\leq$ 40 $\times$ U. Rate	0.0366*	-0.00103	0.00325	0.000826
	(0.0172)	(0.00173)	(0.00163)	(0.00183)
PE$\geq$ 40 $\times$ U. Rate	0.0315	0.00151	0.00596*	-0.00138
	(0.0166)	(0.00170)	(0.00260)	(0.00259)
R-squared	0.276	0.304	0.185	0.034
N	598417	581638	581638	581638

Standard errors in parentheses, clustered at the state level * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Estimates include main effects and state, month-year, education, race, and gender fixed effects.

wages do fall more than experienced workers' wages in percentage terms, but not in dollars lost. The primary driver of wage loss appears to be wages lost by continuing workers, which is consistent with falling real wages during recessions, as raises do not keep up with inflation. More broadly, these results are consistent with the results of Oreopoulos et al. (2012), who show that a major source of missing wages for youths graduating college during recessions is matching with lower-paying firms.

1.5.1 Reconciling Evidence and Theory

These occupational mobility results are consistent with firms hiring more-experienced workers during recessions, but cannot distinguish between the proposed model and other models of cyclical upgrading. What about labor supply explanations? In Section 1.3.4, I show the hiring pattern is unlikely to be driven by self-selection between jobs, since we also observe large fluctuations in workers entering the labor force as well. The occupation quality and wage results make these results even more unlikely, since it would require young workers to choose to match with lower paying occupations and receive lower wages while experienced workers do not make such choices.

The occupation quality results provide even stronger evidence against changes in search intensity or other changes in the frequency with which a young worker matches with a firm. Although this can explain the fall in the frequency of hiring for young workers, it would predict that conditional on being hired, young and experienced workers should be hired by a similar mix of jobs. This is inconsistent with the evidence that young workers match with lower quality occupations during recessions.

While I cannot rule out that these different channels play a role in the observed variation in hiring, occupational quality, and wages by potential experience over the business cycle, on balance, I conclude the most plausible explanation is demand-side changes in hiring.

1.6 Conclusions

In this paper, I show that workers' labor market experiences over the business cycle vary dramatically by potential experience. During recessions, young workers are decreasingly likely to be hired, and, when hired, will match with lower-quality occupations. Experienced workers actually grow more likely to be hired during recessions, and do not experience any change in occupation quality. All workers are more likely to become non-employed during recessions, and average wages fall. I show this fact pattern is in-

Table 1.10: Log Hourly Wages over the Business Cycle

Outcome: Log Wages	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A			
State Unemp. Rate	-0.00615**	-0.00125	0.00399	-0.00411	-0.00340	-0.00612**
	(0.00182)	(0.00188)	(0.00333)	(0.00252)	(0.00252)	(0.00190)
R-squared	0.285	0.287	0.290	0.280	0.304	0.282
			Panel B			
PE$\leq$ 10 $\times$ U. Rate	-0.0101***	-0.00611**	-0.00106	-0.0102**	-0.00548*	-0.0103***
	(0.00238)	(0.00215)	(0.00312)	(0.00320)	(0.00266)	(0.00246)
PE$>$ 10 $\times$ U. Rate	-0.00425*	0.0000588	0.00342	-0.0000561	-0.00261	-0.00415*
	(0.00172)	(0.00202)	(0.00334)	(0.00295)	(0.00297)	(0.00179)
Wald test: $\beta_1 = \beta_2$	22.48***	10.06**	3.34	8.73**	1.14	25.90***
R-squared	0.362	0.346	0.357	0.341	0.349	0.357
			Panel C			
PE$<$ 0 $\times$ U. Rate	-0.00766**	-0.00184	0.00467	-0.00311	-0.00454	-0.00845**
	(0.00277)	(0.00316)	(0.00716)	(0.00760)	(0.00542)	(0.00287)
0 $<$PE$\leq$ 1 $\times$ U. Rate	-0.00987***	-0.00543*	-0.00404	-0.0161***	-0.00235	-0.0103***
	(0.00272)	(0.00248)	(0.00397)	(0.00459)	(0.00301)	(0.00287)
1 $<$PE$\leq$ 2 $\times$ U. Rate	-0.00994***	-0.00413	0.00169	-0.00792*	-0.00403	-0.0106***
	(0.00248)	(0.00249)	(0.00431)	(0.00382)	(0.00297)	(0.00257)
2 $<$PE$\leq$ 3 $\times$ U. Rate	-0.0132***	-0.00846**	-0.00340	-0.00967	-0.0126**	-0.0137***
	(0.00290)	(0.00287)	(0.00467)	(0.00524)	(0.00371)	(0.00299)
3 $<$PE$\leq$ 4 $\times$ U. Rate	-0.0156***	-0.0141***	-0.0129*	-0.0209***	-0.00646	-0.0155***
	(0.00238)	(0.00357)	(0.00542)	(0.00550)	(0.00475)	(0.00239)
4 $<$PE$\leq$ 5 $\times$ U. Rate	-0.0123***	-0.0110*	-0.00470	-0.0212*	-0.00272	-0.0122***
	(0.00269)	(0.00446)	(0.00641)	(0.00869)	(0.00431)	(0.00271)
5 $<$PE$\leq$ 6 $\times$ U. Rate	-0.0137***	-0.0138**	-0.0118	-0.0109	-0.0204**	-0.0135***
	(0.00277)	(0.00463)	(0.00723)	(0.00781)	(0.00710)	(0.00275)
6 $<$PE$\leq$ 7 $\times$ U. Rate	-0.0121***	-0.00530	-0.00194	-0.00863	0.00333	-0.0125***
	(0.00245)	(0.00448)	(0.00638)	(0.00761)	(0.00887)	(0.00255)
7 $<$PE$\leq$ 8 $\times$ U. Rate	-0.0106***	-0.00429	-0.00132	0.00211	-0.0104	-0.0111***
	(0.00234)	(0.00378)	(0.00632)	(0.00692)	(0.00865)	(0.00243)
8 $<$PE$\leq$ 9 $\times$ U. Rate	-0.0111***	-0.0149**	-0.00712	-0.00601	-0.0199	-0.0110***
	(0.00227)	(0.00535)	(0.00776)	(0.00699)	(0.00989)	(0.00232)
9 $<$PE$\leq$ 10 $\times$ U. Rate	-0.0110***	-0.00764	-0.00399	-0.0130	0.00400	-0.0110***
	(0.00273)	(0.00415)	(0.00761)	(0.00849)	(0.00754)	(0.00289)
10 $<$PE$\leq$ 20 $\times$ U. Rate	-0.00749***	-0.00354	0.00148	-0.00290	-0.00662	-0.00742***
	(0.00166)	(0.00226)	(0.00316)	(0.00369)	(0.00401)	(0.00172)
20 $<$PE$\leq$ 30 $\times$ U. Rate	-0.00473**	0.000631	0.00353	0.000588	0.000713	-0.00464**
	(0.00162)	(0.00256)	(0.00442)	(0.00423)	(0.00382)	(0.00167)
30 $<$PE$\leq$ 40 $\times$ U. Rate	-0.00252	0.00361	0.00572	0.00710	-0.00292	-0.00258
	(0.00199)	(0.00321)	(0.00482)	(0.00455)	(0.00589)	(0.00204)
PE$>$ 40 $\times$ U. Rate	0.00406	0.00436	0.00692	0.00801	-0.000601	0.00415
	(0.00215)	(0.00356)	(0.00640)	(0.00633)	(0.00528)	(0.00224)
R-squared	0.388	0.365	0.375	0.364	0.361	0.383
Sample:	All Workers	All Hires	UE	EE	NILF-E	Non-Hires
N	1174198	89034	25878	31837	31319	1085164

Standard errors in parentheses, clustered at the state level * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Estimates include main effects and state, month-year, education, race, and gender fixed effects.

consistent with standard labor supply explanations, but is consistent with firms taking advantage of slack labor markets by hiring more-experienced workers.

My results support and extend the studies of Kahn (2010) and Oreopoulos et al. (2012), who find persistent effects from graduating college during a recession. Although I am unable to document persistence due to the type of data I employ, I find flow, occupation, and wage evidence that are consistent with Kahn (2010) and Oreopoulos et al. (2012)'s results, and show these effects are present for workers with up to ten years of potential experience. I also show that these results are not specific to college graduates, but extend to all workers with low levels of labor market experience. In fact, I find the simultaneous cyclical reduction in hiring of young workers and increase in hiring of experienced is remarkably robust across demographic groups, suggesting that labor market experience is particularly relevant to hiring firms during slack labor markets. In light of the results of Kahn (2010) and Oreopoulos et al. (2012), it is also likely that the costs of reduced mobility during recessions and being employed in lower-quality jobs will have persistent effects on young workers, resulting in substantial earnings losses over subsequent years.

A key limitation on this project is the lack of data on actual firm-worker contacts. Such data would allow for direct tests of whether firms choose to hire different workers during recessions, and would provide further information about the mechanism at work. In addition, since the CPS is a worker-level survey, it lacks detailed information about firms. Matched employer-employee datasets such as the LEHD may provide clearer information about how these hiring dynamics vary across firms, and is a fruitful direction for future work.

Chapter 2

The Hidden Cost of Recessions: Career Effects of Occupational Reassignment inside Firms

2.1 Introduction

A worker's ability to build a career is closely linked to the quality of the labor market. When young and searching for the right career path, the worker relies on the availability of appropriate job opportunities. When more established and settled into a stable, productive job, the worker relies on the indefinite continuation of the position. And if the worker acquires skills that make him suited for a promotion or a higher-skilled occupation, the worker relies on a market that demands his services in these positions.

During recessions, many of these opportunities disappear. Firms reduce hiring, jobs are less stable, and the chance of being hired falls. A growing body of evidence suggests that even temporary exposure to poor labor markets can have long term effects on workers' employment, earnings, and job quality. Kahn (2010) and Oreopoulos et al. (2012) have documented persistent earnings losses from graduating college during a recession. Not only did these workers earn lower wages, they also were employed in lower quality occupations (Kahn, 2010) and employed by firms with lower average wages (Oreopoulos et al., 2012).

Topel and Ward (1992) show that a major source of wage growth for workers is movements between firms, and most of workers' firm changes occur for workers with less than 10 years of potential experience. In Chapter 1 of this dissertation, I show these workers are particularly vulnerable during recessions: not only are they less likely to make moves between firms, they earn lower wages. Another way workers advance their careers is by changing jobs, either within their current firm or between firms. Just like moves between firms, job changes are more likely for young workers (Neal, 1998).

Authors have long realized that job mobility is an important facet of career development and wage growth (cf. Parnes, 1954). From a theoretical perspective, there are three reasons why workers may benefit from job mobility. First, jobs may be experience goods (Jovanovic, 1979). In this framework there is an idiosyncratic match component of the quality of the employment relationship, but this can only be revealed through actually forming the match. In this case, workers will switch jobs until they find one that fits "just right". Second, workers could build careers through the sequence of jobs, a process Jovanovic and Nyarko (1997) call "stepping-stone mobility". In this case, workers gain skills from each job, which prepares them for the next step in the career. Finally, a worker may know a match is subpar but accept it as an interim job while continuing to search. This process is common in macroeconomic models of on-the-job search, such as Pissarides (1994) and Barlevy (2002).

The first two models both predict decreasing hazard of separation with job tenure and age. In the first, the longer a worker has remained in a job the more likely he has found his best match. For the second, the longer the worker has been in the labor market the higher the probability he has found his best match. In the case of occupational mobility, Kambourov and Manovskii (2008) find that occupational mobility declines with age and the hazard rate of occupational mobility falls with occupational tenure. Topel and Ward (1992) found that most of a worker's employer changes occur during the first ten years of their careers, and Neal (1998) finds that once a worker has changed employers within the same type of job (in his case, industry), the worker is substantially less likely to make future job changes.

On the other hand, finding the right match is not the whole story. Shaw (1984) first demonstrated the role of occupational tenure in earnings, a fact that Kambourov and Manovskii (2008) confirmed. In fact, these authors found that occupational tenure plays a larger role in earnings than either employer or industry, with displaced workers who must change occupations experiencing larger wage losses than displaced workers who are able to be re-employed in the same occupation.

In summation, it appears the benefits of mobility depend on where the worker is in his career. Among workers that have not found their chosen profession, or are still accumulating human capital in order to qualify for their chosen profession, we will observe workers choosing to change occupations and receiving higher wages by doing so. On the other hand, the longer an individual is employed in an occupation, the smaller the net benefit they may obtain by switching to another occupation, even if it may be a better fit.

In this paper, I use data from the CPS to measure variation in occupational mobility over the business cycle. By focusing on occupations, this allows us to better understand how worker careers evolve over the business cycle, both within and between firms. This complements the results in Chapter 1 regarding cyclical employer mobility. I find that in net, occupational mobility rises during recessions, however this is driven by increases in the frequency of occupation change within firms.

Two other papers (Kambourov & Manovskii, 2008; Moscarini & Thomsson, 2007) have previously documented facts relating to the cyclicality of occupational mobility. Kambourov and Manovskii (2008) find that net occupational mobility is counter-cyclical using the PSID. Moscarini and Thomsson (2007) use the CPS and show that national occupational mobility appears to be pro-cyclical. I also use CPS data, but I am able to move away from time series trends by using state unemployment rates as a proxy for local economic conditions. This also allows me to include month-year and state fixed effects, distinguishing secular trends from movements that are closely linked to the unemployment rate.

Once I have established the cyclical changes in mobility, I move on to the cost of these movements. I find that the average quality of occupations workers move to inside the firm falls during recessions, and the wages these moving workers earn fall as well. Workers moving between firms during recessions do not experience this same effect, nor do workers hired from unemployment.

These results are consistent with a deterioration of workers' bargaining position during recessions. When job opportunities are scarce and the expected duration of employment lengthens, the cost of job loss rises, making workers more willing to comply with unfavorable firm personnel policies. What we cannot know from this data is whether or not these are moves that are intended to be temporary responses to the recession, or if they are permanent changes. A temporary reallocation is consistent with the idea of labor hoarding, in which firms resist reducing their labor forces for short-run downturns to avoid losing talent and paying hiring costs in the future. To answer such questions will require a longer panel than is available from the CPS.

2.2 Methodology

I use monthly Current Population Survey (CPS) survey data from January 1994 through December 2013. The CPS is a large national survey of U.S. households, which provides cross-sectional data for national employment statistics. Although its primary purpose is as a cross-sectional dataset, the CPS is in fact designed as a panel, where each household is surveyed multiple times. Before 1994, the CPS used independent coding, that is, each month the survey treated respondents as new participants. This led to a great deal of noise in the coding of occupations and industries, and did not allow any measurement of mobility between employers.[1] With the major survey re-design in 1994, individuals were asked if they still worked for the same employer and if their duties and activities had changed, allowing a cleaner observation of occupational mobility. Perhaps more crucially, this allows us to observe whether or not an individual has changed firms, which will prove to be fundamental to understanding occupational mobility.

The CPS is structured as a rotating panel, wherein each household is surveyed for four consecutive months, takes an eight month break, and then is surveyed for four more months. This allows us to match individuals across pairs of months and observe labor market changes. In particular, I use a procedure developed by Madrian and Lefgren (1999) to match individuals using administrative IDs, and confirm matches using sex, race, and age. As the fifth month of the survey returns to independent coding, there is only mobility information for six pairs of months for each individual, which leaves approximately 17 million pairs.[2]

Measurement of occupational mobility follows different procedures depending on the type of accompanying labor-market mobility. For employed individuals, the sequence of questions is as follows:

1. LAST MONTH, IT WAS REPORTED THAT YOU WORKED FOR (EMPLOYER'S NAME). DO STILL WORK FOR (EMPLOYER'S NAME) (AT YOUR MAIN JOB)?
2. HAVE THE USUAL ACTIVITIES AND DUTIES OF YOUR JOB CHANGED SINCE LAST MONTH?
3. LAST MONTH YOU WERE REPORTED AS (A/AN) (OCCUPATION) AND YOUR USUAL ACTIVITIES WERE (DESCRIPTION). IS THIS AN ACCURATE DESCRIPTION OF YOUR CURRENT JOB?

I use the first question to capture direct employer-to-employer mobility. If either the second question is answered affirmatively or the third question is answered negatively, the surveyor returns to independent coding.

[1]See (Moscarini & Thomsson, 2007) for a detailed exploration of this problem

[2]Although in practice one could match all eight months of an individual's history in the survey, few participants can be matched for all eight months, so this would dramatically reduce the sample size.

Table 2.1: Occupational Quality Index

Occupations with High Scores	Top Characteristics	Correlations	
CEOs	Speaking ability	Experience	0.0518
Neurologists	Written expression ability	Years of Ed.	0.5273
Lawyers	Judgment and decision-making ability	Age	0.1541

For individuals who have changed firms (e.g., who answer "No" to the first question) occupational data is collected using the standard open-ended questions (e.g., "WHAT KIND OF WORK DO YOU DO, THAT IS, WHAT IS YOUR OCCUPATION?"). This means that the rates of occupational mobility cannot be directly compared between firm-changers and stayers. A key identifying assumption will be that the *rate* of occupational coding errors is independent with the business cycle metric, after partialing out geographic and time fixed effects.

For individuals who are not currently employed, only a subset have past employment data to identify occupation-changers. If the individual is classified as unemployed (e.g., actively looking for work) and has been unemployed for less than one year, he is asked about his last occupation. Thus an important caveat to understanding this paper's results for unemployed workers' occupational mobility is this limitation on data collection.

To measure the quality of jobs, I use two metrics constructed in Chapter 1 of this thesis. The first metric is a wage index, constructed from the 2005 OES (Occupational Employment Statistics) survey. This survey collects administrative wage data from 1.2 million establishments with fine occupational gradation. Using the median wages for each occupation, this provides a single index of occupational quality, ranging from \$6.60 to \$80.25.

The second occupational quality metric is derived from O*NET data on occupational characteristics. I perform principal component analysis on O*NET's 483 occupational categories, and use the factor that explains the largest fraction of the total variation in its data,[3] normalized to mean zero and standard deviation one. This variable is summarized in Table 2.1.

Wage information is only collected during the fourth and eighth months of the CPS survey. As discussed above, between the fourth and fifth months of the sample, the surveyors "forget" dependent coding. Thus the survey does not provide the data to connect wage changes with firm mobility information. For this reason, in this paper I only use second period wage data (e.g., month pairs 3-4 and 7-8).

[3] In Chapter 1 I use the first three factors.

Table 2.2: Employed Worker Skill by Mobility Status

Dependent Variable	Years Potential Experience		Years of Education	
	(1)	(2)	(3)	(4)
Employed in 2nd Period	2.296***	2.325***	1.120***	1.127***
	(0.115)	(0.115)	(0.0185)	(0.0193)
Employer Change	-4.213***	-1.427***	-0.335***	-0.0975***
	(0.140)	(0.0688)	(0.0139)	(0.0257)
Occ. Change Between Firms		-4.466***		-0.389***
		(0.140)		(0.0272)
Occ. Change Within Firm		3.350***		0.0934
		(0.204)		(0.0530)
Constant	25.42***	25.42***	12.52***	12.52***
	(0.132)	(0.132)	(0.0449)	(0.0449)
N	10500150	10500150	10500150	10500150
R-sq	0.003	0.004	0.007	0.007

Standard errors in parentheses, clustered at the state level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
All specifications include state and month-year fixed effects.

2.3 Results

2.3.1 Understanding Worker Mobility

The first task is to understand which workers are mobile, which will have bearing on our interpretation of the reasons for mobility. First I focus on worker skill, using years of potential experience and years of education as proxies. Table 2.2 shows how employed workers changing firms and/or occupations differ on average from non-movers. In column (1) we see that workers that change employers have on average 4.2 years less of potential experience than those that stay at the same firm. In column (2) we break this out by occupational change. Here we see that occupation-changers within-firms have the highest average potential experience: 31 years, compared with 27.8 years for non-occupation changers within the firm, 26.3 years for non-occupation changers that change firms, and 21.9 years for occupation-changing firm-changers. We see a similar pattern for years of education: column (3) shows firm-changers have on average 1/3 of a year less education than stayers. Column (4) indicates that occupation-changers within-firms have an average of 13.7 years of education, compared with 13.6 years for non-changers within-firms, 13.5 years for non-changers between-firms, and 13.2 years for occupation-changing firm-changers. These results suggest that the selection process for occupation-changers between firms is quite different than that for within-firms: workers who change occupations simultaneously with changing firms are the least skilled workers on average, while occupation changers within firms are the most skilled.

We can do the same exercise with unemployed workers. For these workers we measure

Table 2.3: Unemployed Worker Skill by Mobility Status

Dependent Variable	Years Potential Experience		Years of Education	
	(1)	(2)	(3)	(4)
Hired	-2.182***	1.095***	-0.000103	-0.0626
	(0.102)	(0.145)	(0.0285)	(0.0681)
Hired into New Occupation		-4.791***		0.0914
		(0.122)		(0.0620)
Constant	24.97***	24.97***	12.53***	12.53***
	(0.182)	(0.182)	(0.0402)	(0.0402)
N	575435	575435	575435	575435
R-sq	0.005	0.011	0.000	0.000

Standard errors in parentheses, clustered at the state level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
All specifications include state and month-year fixed effects.

occupation change if the occupation into which they are hired is different from their last reported occupation. Table 2.3 shows the average years of potential experience and education for these hires. Column (1) shows that unemployed workers with less potential experience comprise a disproportionate share of hires. Column (2) indicates that unemployed workers who do not change occupations have 4.8 years additional potential experience than those that change occupations. These numbers lead to totals of 26.1 years of potential experience for hires that do not change occupations and 21.3 years for those that do change occupations. These numbers are very similar to the average potential experience of employed workers changing firms (26.3 and 21.9 respectively). For years of education, however, we see no significant variation by hiring status and occupational change. The average of 12.53 years of education indicates that the average unemployed worker has less education than the average employed worker, but this is not correlated with whether or not he is hired.

Table 2.4 shows the differences in initial occupational quality for workers by mobility. This allows us to see if workers that change occupations begin in different types of occupations than non-changers. Columns (1) and (3) show that individuals who change firms begin in lower quality occupations. These occupations pay \$2.21 less per hour in median wages, and score about 1/5 of a standard deviation less in occupation quality. Columns (2) and (4) show the a similar pattern in the ranking of occupation quality between types of movers as we saw in Table 2.2. In particular, the workers who stay at the same firm but change occupations start in the highest quality occupations on average (\$18.88, .048), then firm stayers that don't change occupations, (\$17.45, 0.005), then firm changers that don't change occupations (\$16.30, -.115), and finally firm changers who also change occupations (\$14.65, -.232).

What about occupation experience of hires from unemployment? Table 2.5 shows

Table 2.4: Occupational Quality of Labor Force Participants by Mobility Status

Dependent Variable	Occupational Wage Index		Occupational Quality Index	
	(1)	(2)	(3)	(4)
Employed	3.730***	3.736***	0.376***	0.378***
	(0.0572)	(0.0578)	(0.00553)	(0.00552)
Employer Change	-2.206***	-1.155***	-0.193***	-0.120***
	(0.0572)	(0.0555)	(0.00680)	(0.00756)
Occ. Change Between Firms		-1.654***		-0.117***
		(0.0775)		(0.00843)
Occ. Change Within Firm		1.421***		0.0430**
		(0.107)		(0.0133)
Constant	13.72***	13.72***	-0.373***	-0.373***
	(0.0686)	(0.0686)	(0.0115)	(0.0115)
N	9629623	9629623	9322279	9322279
R-sq	0.007	0.007	0.007	0.007

Standard errors in parentheses, clustered at the state level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
All specifications include state and month-year fixed effects.

Table 2.5: Occupational Quality of Labor Force Participants by Mobility Status

Dependent Variable	Occupational Wage Index		Occupational Quality Index	
	(1)	(2)	(3)	(4)
Hired	-0.441***	-0.408***	-0.0566***	-0.141***
	(0.0538)	(0.0953)	(0.00591)	(0.00848)
Hired into New Occupation		-0.0485		0.123***
		(0.0832)		(0.00677)
Constant	14.18***	14.18***	-0.439***	-0.439***
	(0.110)	(0.110)	(0.0163)	(0.0163)
N	546463	546463	529760	529760
R-sq	0.001	0.001	0.001	0.002

Standard errors in parentheses, clustered at the state level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
All specifications include state and month-year fixed effects.

no statistically significant difference in the occupation wage index between hires that change occupations and those that do not, however occupation changers appear to be from occupations that score about 1/8 of a standard deviation higher than individuals that do not change occupations.

In sum, the process that selects occupation changers inside the firm appears to operate very differently from the process that selects occupation-changers between firms and from unemployment. The within-firm occupation changers are more experienced, more educated, and employed in higher quality occupations than all other categories of workers, while the between-firm occupation changers are the least experienced, least educated, and employed in the lowest quality occupations than the other categories of workers.

2.3.2 Cyclical Mobility Patterns

Next we look at how the frequency of occupational mobility changes with the business cycle. To do this, I run two complementary sets of specifications. First, in Table 2.6 I run a set of linear probability models, with an indicator for whether or not a worker changes occupations as the dependent variable. This shows how the frequency of occupational change varies over the business cycle for different types of movements. In Tables 2.7 I run a set of multinomial logit models, in order to see more clearly how the distribution of worker movements varies cyclically.

In Table 2.6, I include all individuals in the labor force with valid occupational information in the first month who are employed in the second month.[4] In particular, I run the following specification:

$$D_{ist}^{\text{occchange}} = \alpha I_s + \beta I_t + \gamma \times \text{State Unemp. Rate}_{st} + \epsilon_{ist} \tag{2.1}$$

where $D^{\text{occchange}}$ is a dummy for whether or not an individual worker i changes occupations in the second month of his observation, given worker i resides in state s, and is observed in month-years $t-1$ and t. In columns (1) and (2), I show that the rate of occupational mobility is increasing with the state unemployment rate. In column (1) I do not include fixed effects, but in column (2) I include state and month-year fixed effects, to show that the result is not driven by time-series variation or heterogeneity between states.

In columns (3) and (4) of Table 2.6, the labor force is divided into three component parts: firm-stayers, employer-changers, and hires from unemployment. When we look at the main effects, we see that about 74% of workers hired from unemployment are hired into new occupations, as well as 69% of workers hired between firms. In contrast, within firms only about 1% change occupations each month. As discussed in the methodology section, some of this is due to differences in how the survey is conducted with regards to firm-stayers and new hires. Moscarini and Thomsson (2007) find similar numbers using the same dataset through 2006: 64% of firm-changers and 1.26% of firm-stayers change occupations. Much of that article is devoted to cleaning up missing and suspicious data in the CPS. Although these issues are unlikely to affect estimates of the change with the state unemployment rate, especially after controlling for state and date fixed effects, it is reassuring that my average mobility estimates are not too far off from Moscarini and Thompsson's.

When we consider the relationship between occupational mobility and different types

[4]This is the same definition of occupational mobility used in Moscarini and Thomsson (2007) and Kambourov and Manovskii (2008).

of employer mobility, we see that for workers being hired to new firms, either from unemployment or between firms, the share changing occupations decreases by about one percentage point for each percentage point increase in the state unemployment rate. At the bottom of Table 2.6, I report results from Wald tests on the coefficients, which show that the total effect of the unemployment rate for individuals who begin unemployed or who change firms is negative and significant at the less than one percent level. Although these estimates are quite significant, the effect is somewhat small compared with the effect on the average occupational mobility levels for hires: a five percentage point increase in the state unemployment rate leads to about a six percent decrease in the mobility rate.

For workers remaining at the same firm, the probability of changing occupations increases with the state unemployment rate; however, the magnitude and significance is sensitive to the inclusion of fixed effects. Still, even with state and date fixed effects, the estimate is significant at the five percent level. A five percentage point increase in the state unemployment rate corresponds to an increase in mobility with in the firm of between a third and 1.5 percentage points, which amounts to an increase of at least 25 percent increase in the mobility rate.

These results indicate that while the aggregate probability of occupational mobility is increasing during recessions, workers hired into new firms are less likely to change occupations. The increase in occupational mobility is driven by workers changing occupations within the firm; these workers experience a large increase in their probability of changing occupations, although their total occupational mobility remains significantly below the mobility rates for workers changing firms.

Although Table 2.6 shows that the rate of occupational mobility is increasing for individuals that stay at the firm and decreasing for those moving between firms, we might be concerned that this is driven by variation in the denominator rather than the numerator. Thus it is illustrative to show how the distribution of moves vary jointly, which we can see graphically in Figure 2.1. Reassuringly, we see large increases in the share of workers changing occupations inside the firm, and decreases in the share changing occupations and firms at the same time.

To formalize this, I run a multinomial logit specification. The set of possible moves are 0: stay, 1: change occupations within employer, 2: change employers within occupation, 3: change both employer and occupation, 4: exit to unemployment, and 5: exit the labor force.

In the first specification, I use the unadjusted state unemployment rate. In the second specification, I use the residual unemployment rate, which is derived by partialing out state and month-year fixed effects. In parentheses is the overall distribution of moves;

Table 2.6: Probability Workers in the Labor Force Change Occupations

Outcome: Pr. Change Occupation	(1)	(2)	(3)	(4)
State Unemp. Rate	0.274***	0.115***	0.321***	0.0610*
	(0.0286)	(0.0279)	(0.0297)	(0.0265)
Unemp. Rate × Unemployed			-1.149***	-1.140***
			(0.109)	(0.111)
Unemp. Rate × Emp. Change			-1.328***	-1.318***
			(0.168)	(0.170)
Unemployed Worker			72.66***	72.67***
			(0.710)	(0.714)
Employer Change			67.78***	67.78***
			(1.104)	(1.110)
Constant	3.383***	4.151***	0.762***	1.204***
	(0.129)	(0.234)	(0.135)	(0.226)
N	10209051	10209051	10209051	10209051
R-sq	0.001	0.002	0.302	0.304
State and Date Fixed Effects	No	Yes	No	Yes
Wald Test: State Unemp. Rate + Unemp. Rate × Unemp.= 0			77.66***	106.08***
Wald Test: State Unemp. Rate + Unemp. Rate × Emp. Change= 0			44.20***	58.46***

Standard errors in parentheses, clustered at the state level. $^{*}\ p < 0.05$; $^{**}\ p < 0.01$; $^{***}\ p < 0.001$.
All specifications include state and month-year fixed effects.

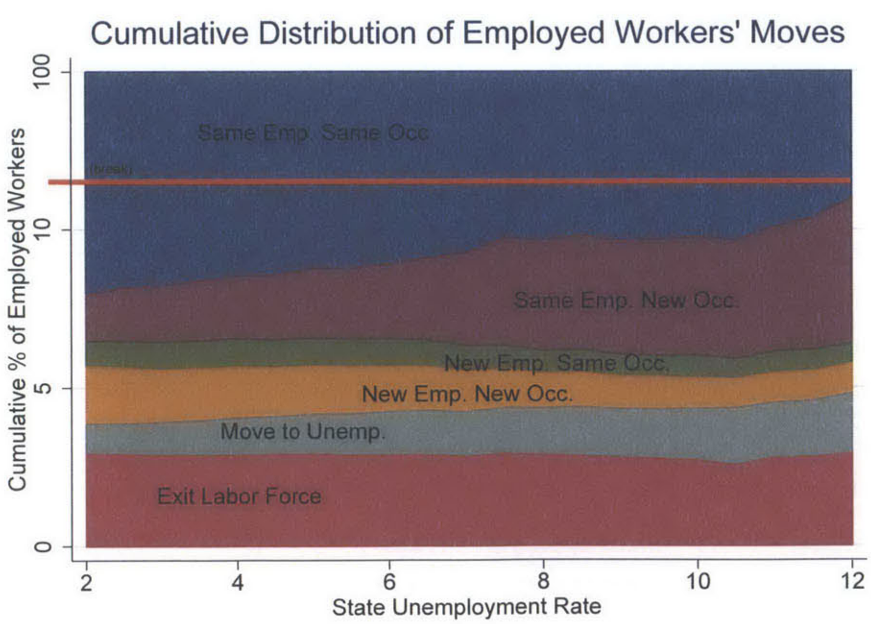


Figure 2.1

we see that the vast majority of individuals stay in their current occupation at the same firm each month (91.14%). The coefficients are reported in relative risk-ratios, thus a coefficient above 1 represents an increase in the share compared with the baseline, which is non-movers. Note that the share of individuals making no change is decreasing slightly with the state unemployment rate.

There are three main points to note in Table 2.7. First, the share of individuals staying within the firm and changing occupations is increasing with the state unemployment rate, although the magnitude is smaller in column (2) after controlling for state and date effects. Second, we see that the share of individuals changing firms falls, but the share changing occupations while changing firms falls by more. At the bottom of the table, I report the result from a Wald test, testing if the effect of the unemployment rate is equal for individuals changing firms with no occupation change and for those changing firms with an occupation change. We can reject this in both specifications, although only at the five percent level in the second specification. Finally, we see that exits to unemployment are increasing and exits from the labor force are a relatively precisely estimated zero.

Thus we see that while occupational mobility increases significantly during recessions, this is due to increased movements within firms. All hiring falls, but conditional on being hired, workers are much less likely to be changing occupations during recessions.

2.3.3 Composition of Movers over the Business Cycle

Now that we have seen how the incidence of occupational mobility varies with the business cycle, we can ask which workers are affected. This is similar to the analysis performed Tables 2.6 and 2.7, where we regress worker characteristics on the types of movements, however now we include the interaction with the state unemployment rate.

In Table 2.8, the dependent variables are proxies for worker skill-level: years of potential experience and years of education. First we notice that the main effects for workers' second-period labor force status: employed, employer change, occupational change between firms, occupational change within firm, as well as the constant, are consistent with the results in Table 2.6. In particular, we see that on average, occupation-changers within firms are the oldest and most educated among mobility categories, and occupation-changers between firms are the youngest and least educated.

The first five rows show the interaction with these main effects and the state unemployment rate. The first row shows that for each additional percentage point of the state unemployment rate, the set of employed workers have on average 0.08 years more of potential experience. This increase is mostly washed out for workers that stay em-

Table 2.7: Change in Distribution of Employed Workers' Moves with the Unemployment Rate

Independent Variable:	Unemployment Rate (1)	Residual Unemployment Rate (2)
0: Baseline: Stay at Same Employer, Same Occ. (91.14%)		
1: Same Firm, New Occupation (2.43%)		
(1) Unemp. Rate, (2) Residual U. Rate	1.1205***	1.033***
	(0.0010)	(0.0020)
Constant	0.0135***	0.0266***
	(0.0001)	(0.0001)
2: New Firm, Same Occupation (0.85%)		
(1) Unemp. Rate, (2) Residual U. Rate	0.9704***	0.9842***
	(0.0016)	(0.0032)
Constant	0.0110***	0.0093***
	(0.0001)	(0.0000)
3: New Firm, New Occupation (1.44%)		
(1) Unemp. Rate, (2) Residual U. Rate	0.9308***	0.9744***
	(0.0012)	(0.0024)
Constant	0.0236***	0.0158***
	(0.0002)	(0.0000)
4: Exit to Unemployment (1.28%)		
(1) Unemp. Rate, (2) Residual U. Rate	1.0703***	1.0616***
	(0.0013)	(0.0028)
Constant	0.0094***	0.0140***
	(0.0001)	(0.0000)
5: Exit Labor Force (2.87%)		
(1) Unemp. Rate, (2) Residual U. Rate	0.9991	0.9982
	(0.0009)	(0.0018)
Constant	0.0317***	0.0315***
	(0.0002)	(0.0000)
N	10500150	10500150
Pseudo R-sq	0.003	0.000
Wald Test: 2: unemp.=3: unemp	382.14***	6.02*

Regression results from multinomial logistic specification. Coefficients reported in relative-risk ratios with standard errors in parentheses. Residual unemployment rate is the state unemployment rate after partialing out state and month-year fixed effects. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Sample includes all employed workers, excluding observations from January 2003.

Table 2.8: Cyclical Demographic Characteristics of Labor Force Participants by Mobility Status

Dependent Variable	Years Potential Experience			Years of Education		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment Rate	0.0827*	0.0867*	0.0835*	0.0184*	0.0186*	0.0177*
	(0.0343)	(0.0343)	(0.0342)	(0.00785)	(0.00787)	(0.00793)
U. Rate × Employed	-0.0543	-0.0646*	-0.0638*	-0.00720	-0.00816	-0.00669
	(0.0271)	(0.0271)	(0.0267)	(0.00694)	(0.00702)	(0.00727)
U. Rate × Employer Change		0.240***	0.0863**		0.0279***	0.0109
		(0.0319)	(0.0299)		(0.00494)	(0.00946)
U. Rate × Occ. Δ Btwn. Firm			0.177***			0.0192*
			(0.0367)			(0.00923)
U. Rate × Occ. Δ W/in Firm			0.111*			-0.00749
			(0.0415)			(0.00512)
Employed	2.494***	2.650***	2.680***	1.148***	1.161***	1.163***
	(0.206)	(0.206)	(0.206)	(0.0321)	(0.0324)	(0.0331)
Employer Change		-5.309***	-1.698***		-0.445***	-0.125**
		(0.197)	(0.178)		(0.0257)	(0.0455)
Occ. Change Between Firms			-5.403***			-0.479***
			(0.254)			(0.0459)
Occ. Change Within Firm			3.357***			0.140*
			(0.299)			(0.0585)
Constant	24.42***	24.44***	24.44***	12.14***	12.15***	12.15***
	(0.268)	(0.268)	(0.268)	(0.0525)	(0.0525)	(0.0525)
N	10500150	10500150	10500150	10500150	10500150	10500150
R-sq	0.010	0.012	0.013	0.024	0.024	0.025

Standard errors in parentheses, clustered at the state level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
All specifications include state and month-year fixed effects.

ployed within the firm in the same occupation, but employer-changers and within-firm occupation-changers all show increases. This shows that even conditional on changes in the labor force and changes in which workers are moving between firms, we still see increases in the potential experience of occupation-changers above and beyond these compositional changes.

In Columns (4) through (6) we see that the set of employed workers are increasingly educated during recessions, although at a modest rate of about one-tenth of a year for a five percentage point increase in the state unemployment rate. We see that the only group that has an increase above this is occupation-changers who are moving between firms, who see twice that rate of increase.

In Table 2.9, we repeat the same analysis as in Table 2.8 for occupational quality rather than worker demographics. That is, the table shows how the quality of jobs the labor force is employed in varies with the business cycle. Of particular interest is if the workers that change occupations are employed in significantly better occupations during recessions. We begin by restricting analysis to individuals that are employed in the first month, as reported in the top panel of Table 2.9. In the bottom five rows, we report the main effects of mobility, which corresponds to the acyclical results in Table 2.7. In general the coefficients are consistent between tables, although the constant terms are a bit larger for both the occupational wage index and the occupational quality index when we take into account cyclical variation.

The addition of cyclical variation shows several new results over Table 2.7. First, we do not see any significant change in the quality of occupations of individuals who are employed in the first month. In contrast to the demographic characteristics in Table 2.8 that indicated the labor force is increasingly experienced and educated during recessions. We do see a small but significant increase in the average quality of occupations for individuals remaining employed in the second period, which shows up for both quality indices. This suggests that during recessions, individuals exiting employment are selected from lower quality occupations, however since this does not carry over to all employed, hires or internal mobility prevent the average occupational quality from falling cyclically. We also see evidence that individuals changing firms are selected from increasingly high quality occupations, however the results from the two quality indices are somewhat at odds in terms of the attribution of this increase. The index derived from median wages suggests that this increase is driven mostly by occupation-changers while the index derived from occupation characteristics indicates an increase for non-changers as well. Neither index shows a significant change in the initial occupational quality for individuals changing occupations within the firm.

2.3.4 Quality of Occupational Mobility

The final question is how the quality of these movements varies over the business cycle. Since the frequency and the individuals affected vary, we want to know how these moves vary. In Table 2.10, the dependent variable is a measure of the job quality: either from the wage quality index, the occupation quality index, or actual earned log wages. When we look at earned wages, the sample size falls dramatically, because wage questions are not asked every month.

In the first, third, and fifth columns, I regress the occupational quality measure on worker mobility interacted with the unemployment rate, in exactly they same procedure I used in Tables 2.8 and 2.9. These columns give estimates for the change in occupation quality during recessions without controlling for changes in the characteristics of the workers moving. Here we see an increase in the quality of occupations hired into for individuals changing occupations when moving firms, although only in log wages do we

Table 2.9: Cyclical Occupational Quality of Labor Force Participants by Mobility Status

Dependent Variable	Occupation Wage Index			Occupation Quality Index		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment Rate	-0.00667	-0.00875	-0.00779	0.00383*	0.00356*	0.00353*
	(0.0128)	(0.0129)	(0.0128)	(0.00152)	(0.00153)	(0.00151)
U. Rate × Employed	0.0411*	0.0369*	0.0401*	0.00520***	0.00472***	0.00497***
	(0.0166)	(0.0167)	(0.0172)	(0.00133)	(0.00134)	(0.00136)
U. Rate × Employer Change		0.0812***	0.0230		0.0111***	0.00590*
		(0.0141)	(0.0218)		(0.00169)	(0.00271)
U. Rate × Occ. Change Btwn. Firms			0.0621*			0.00613
			(0.0272)			(0.00316)
U. Rate × Occ. Change W/in Firm			-0.0132			0.00245
			(0.0153)			(0.00200)
Employed	3.423***	3.494***	3.498***	0.342***	0.349***	0.350***
	(0.0946)	(0.0952)	(0.0970)	(0.00935)	(0.00947)	(0.00951)
Employer Change		-2.221***	-0.926***		-0.231***	-0.136***
		(0.0915)	(0.137)		(0.0109)	(0.0166)
Occ. Change Between Firms			-1.888***			-0.141***
			(0.156)			(0.0175)
Occ. Change Within Firm			1.300***			0.0441
			(0.187)			(0.0243)
Constant	15.45***	15.52***	15.52***	-0.135***	-0.128***	-0.126***
	(0.0933)	(0.0929)	(0.0930)	(0.0135)	(0.0135)	(0.0135)
N	9629623	9629623	9629623	9322279	9322279	9322279
R-sq	0.057	0.058	0.058	0.009	0.010	0.010

Standard errors in parentheses, clustered at the state level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include state and month-year fixed effects.

see an increase for all employer changers. Finally, we do not see any significant changes in the quality of occupations for individuals moving within the firm.

In the even columns, I add worker demographic characteristics and occupation fixed effects. This provides a measure of the change in occupational quality, since the occupational fixed effects subsume the occupational quality metrics, and allows us to partial out as much of the selection effect as possible. The first observation is that the occupational wage index appears to diverge quite substantial from the occupational quality index and log wages. The wage index suggests that occupational quality is rising for those that move between firms during recessions, but not for occupational changers, while this metric indicates no change in the quality of jobs for occupational changers inside firms.

In contrast, the occupational quality index and earned wages both indicate no change for movers between firms. For movers within the firm, instead of no effect these two metrics show occupational quality is declining. Since we know that the skill level for occupation movers is increasing during recessions, these results indicate that for workers moving between firms, the increase in worker skill is washed out by the increased in occupational quality. However, for individuals moving within the firm, the quality of jobs do not change on average, thus controlling for worker characteristics shows us these individuals are working in lower quality occupations than would be expected during good times.

On balance, we do not see any significant changes in the quality of occupations and earned wages of workers hired from unemployment during recessions, despite significant changes in the frequency of such moves, the characteristics of the unemployed, and the characteristics of these individuals' previous occupation.

Overall, we see that occupation-changers within the firm are losing ground during recessions. Although the average quality of jobs does not vary significantly, the individuals do, leading to a negative effect for these workers. For other types of occupation-changers, either between firms or new hires from unemployment, the higher skill-level of these workers is compensated for matching with higher quality occupations and receiving higher wages.

2.4 Cyclical Occupational Mobility for Hires from Unemployment

It is worth exploring how occupational mobility varies for over the business cycle for those hired from unemployment. For these workers, occupational mobility is defined

Table 2.10: Quality of Jobs in Second Month

	(1) Occ. Wage Index	(2) Occ. Wage Index	(3) Occ. Quality Index	(4) Occ. Quality Index	(5) Log Hourly Wages	(6) Log Hourly Wages
Unemployment Rate	-0.00514	0.0101*	0.00398*	0.0000763	-0.00389*	-0.00219
	(0.0130)	(0.00454)	(0.00153)	(0.0000604)	(0.00182)	(0.00138)
U. Rate × Occ. Change W/in Firm	-0.0195	-0.0124	0.000383	-0.00176**	-0.00180	-0.00370*
	(0.0173)	(0.00844)	(0.00198)	(0.000629)	(0.00186)	(0.00158)
U. Rate × Employer Change	0.0172	-0.0259***	0.00554*	0.0000934	0.00587*	0.00173
	(0.0221)	(0.00368)	(0.00271)	(0.000238)	(0.00251)	(0.00183)
U. Rate × Occ. Change Btwn Firms	0.0841**	0.0301*	0.00570*	0.000783	0.000438	-0.00358
	(0.0247)	(0.0125)	(0.00276)	(0.00117)	(0.00279)	(0.00255)
Occ. Change Within Firm	1.075***	0.102	0.0329	0.0170*	0.122***	0.0461**
	(0.186)	(0.0791)	(0.0229)	(0.00751)	(0.0185)	(0.0138)
Employer Change	-1.057***	0.139***	-0.151***	-0.00344*	-0.0688***	-0.0128
	(0.138)	(0.0226)	(0.0170)	(0.00166)	(0.0157)	(0.0106)
Occ. Change Between Firms	-1.798***	-0.0416	-0.130***	-0.00200	-0.171***	-0.0535***
	(0.146)	(0.0714)	(0.0166)	(0.00689)	(0.0167)	(0.0140)
Constant	15.67***	6.530***	-0.111***	0.312	2.178***	0.875*
	(0.0916)	(0.317)	(0.0132)	(0.487)	(0.0129)	(0.435)
N	9186054	9186054	8891549	8891549	1785904	1785904
R-sq	0.058	0.924	0.011	0.953	0.117	0.512
Occupation Fixed Effects	No	Yes	No	Yes	No	Yes

Standard errors in parentheses, clustered at the state level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include state, month-year, and demographic fixed effects.

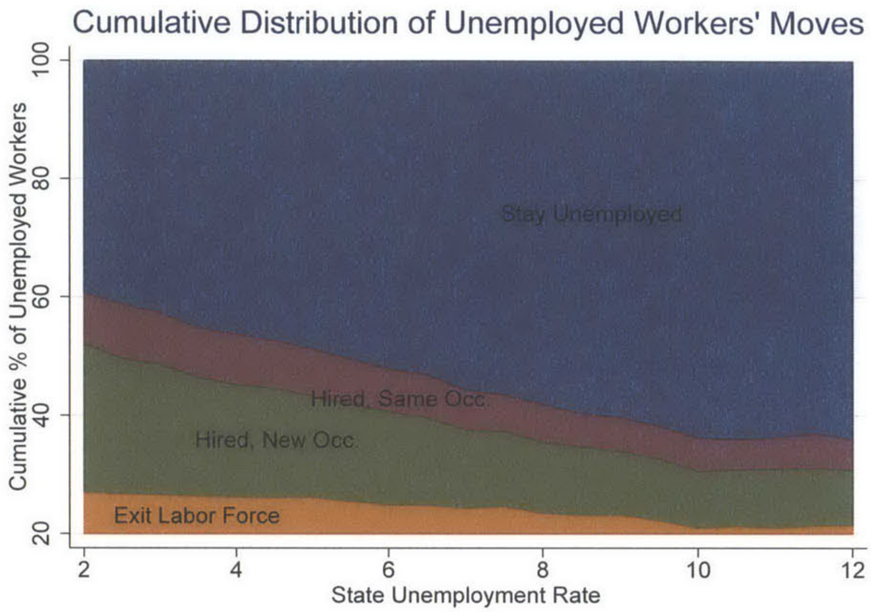


Figure 2.2

as reporting a different occupation from the occupation the worker reported as his last occupation. In Figure 2.2 we see that the share of all workers hired falls dramatically during recessions, but this appears to be driven almost entirely by decreases in the share of workers hired into new occupations.

In Table 2.11, we perform multinomial logit regressions to how this result more rigorously. This is the same analysis as in Table 2.7. The baseline category is individuals who remain unemployed, who comprise about 50% of the sample. Here we see that all three other categories are decreasing in share with the state unemployment rate: hires from unemployment and exits from the labor force are both decreasing in share. However, the coefficient on individuals hired into new occupations is smaller in magnitude than that on those being hired into the same occupation, and, indeed, the Wald test confirms that the share of hires into new occupations decreases by more than that of hires into the same occupation. This is consistent with the result in Table 2.6 that, during recessions, occupational mobility falls for hires from unemployment.

Next we want to understand how the characteristics of unemployed workers changing occupations vary with the business cycle. Table 2.11 reports changes in the potential experience and years of education of hires over the business cycle. The acyclical relationship between being hired and the worker potential experience are similar to those reported in Table 2.8. In particular, workers hired into the same occupation as they previously were employed have more potential experience than other unemployed workers. During recessions, we see that the average hired worker has more experience, however we see con-

Table 2.11: Change in Distribution of Unemployed Workers' Moves with the Unemployment Rate

Independent Variable:	Unemployment Rate (1)	Residual Unemployment Rate (2)
0: Baseline: Stay Unemployed (52.54%)		
1:Hired, Same Occupation (7.22%)		
(1) Unemp. Rate, (2) Residual U. Rate	0.8908***	0.9122***
	(0.0020)	(0.0041)
Constant	0.2915***	0.1400***
	(0.0044)	(0.0007)
2:Hired, New Occupation (15.62%)		
(1) Unemp. Rate, (2) Residual U. Rate	0.8563***	0.8923***
	(0.0014)	(0.0029)
Constant	0.8028***	0.3039***
	(0.0089)	(0.0011)
3: Exit LF (24.62%)		
(1) Unemp. Rate, (2) Residual U. Rate	0.9255***	0.9299***
	(.0012)	(0.0026)
Constant	0.7817***	0.4762***
	(0.0072)	(0.0015)
N	631751	631751
Pseudo R-sq	0.008	0.001
Wald Test: 1: unemp.=2: unemp	225.83***	18.46***

Regression results from multinomial logistic specification. Coefficients reported in relative-risk ratios with standard errors in parentheses. Residual unemployment rate is the state unemployment rate after partialing out state and month-year fixed effects. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Sample includes all employed workers, excluding observations from January 2003.

Table 2.12: Cyclical Demographic Characteristics of Labor Force Participants by Mobility Status

Dependent Variable	Years Potential Experience			Years of Education		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment Rate	0.0998*	0.0762	0.0814	-0.00972	-0.00445	-0.00453
	(0.0480)	(0.0481)	(0.0478)	(0.00656)	(0.00684)	(0.00684)
U. Rate × Hired		0.0443*	-0.145***		-0.0223	-0.0389
		(0.0209)	(0.0356)		(0.0114)	(0.0214)
U. Rate × Hired to New Occ.			0.227***			0.0261
			(0.0379)			(0.0174)
Hired		-1.950***	2.384***		0.200***	0.230**
		(0.178)	(0.291)		(0.0476)	(0.0837)
Hired to New Occ.			-6.019***			-0.0540
			(0.280)			(0.0701)
Constant	21.93***	22.53***	22.51***	12.29***	12.24***	12.24***
	(0.378)	(0.394)	(0.395)	(0.0481)	(0.0479)	(0.0480)
N	575435	575435	575435	575435	575435	575435
R-sq	0.022	0.025	0.031	0.023	0.023	0.024

Standard errors in parentheses, clustered at the state level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
All specifications include state and month-year fixed effects.

vergence in the years of potential experience for occupation-changers and non-changers: although on average hires that do not change occupations have more experience, this value falls with the state unemployment rate. In contrast, hires into new occupations are increasing in potential experience with the state unemployment rate. In terms of education, we do not see a statistically significant cyclical change in the education of hires, but in general we do see that those hired into the same occupation as they previously worked are more educated than those who change occupations, by about 0.2 years.

Now we want to see if individuals hired from unemployment during recessions have different work histories than those hired during good times, in particular, were they employed in better or worse quality jobs? To do this I regress our two measures of occupational quality on the interaction of the state unemployment rate and whether or not a worker was hired into a new occupation, hired into the same occupation or not hired at all. Table 2.13 shows the results. We see that the average previous job quality of those hired into new occupations is increasing during recessions. This is consistent with the changes in the stock of unemployed workers during recessions, growing more representative of the labor force as a whole.

Last, we want to know if the quality of the job in which the unemployed worker is hired into changes over the business cycle. This is shown in Table 2.14. We see that individuals that are hired into new occupations are hired into higher quality jobs in terms of the wage index and the quality index, however we do not observe higher wages

Table 2.13: Cyclical Occupational Quality of Labor Force Participants by Mobility Status

Dependent Variable	Occupation Wage Index			Occupation Quality Index		
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment Rate	0.0257	0.0282	0.0282	-0.00225	-0.00167	-0.00184
	(0.0152)	(0.0173)	(0.0172)	(0.00216)	(0.00237)	(0.00235)
U. Rate × Hired		-0.0149	-0.0646		-0.00466	-0.00845*
		(0.0231)	(0.0390)		(0.00251)	(0.00385)
U. Rate × Hired to New Occ.			0.0746*			0.00749**
			(0.0308)			(0.00274)
Hired		0.0128	0.286		-0.0192	-0.0797***
		(0.128)	(0.191)		(0.0140)	(0.0214)
Hired to New Occ.			-0.408**			0.0767***
			(0.147)			(0.0163)
Constant	12.11***	12.12***	12.12***	-0.573***	-0.564***	-0.563***
	(0.134)	(0.136)	(0.136)	(0.0194)	(0.0193)	(0.0192)
N	546463	546463	546463	529760	529760	529760
R-sq	0.066	0.066	0.066	0.018	0.019	0.020

Standard errors in parentheses, clustered at the state level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
All specifications include state and month-year fixed effects.

and once we account for the quality of the occupation in which they were previously employed, the result disappears. This is consistent with the result in Table 2.13 that the previous occupation of individuals hired during recessions is of increasingly high quality.

2.5 Conclusions

In this paper, I have established that occupational mobility is counter-cyclical. This is due to rising within-firm mobility among employed workers during recessions. Evaluating the characteristics of the within-firm occupation-changing workers who drive this effect, I have found that they are, on average, better educated and more experienced than other workers and are employed in higher quality jobs. However, during recessions, these within-firm occupation changers lose ground, matching with lower quality occupations and receiving lower wages than would be predicted given their demographic characteristics. These results indicate a novel mechanism by which recessions directly impact employed workers.

An open question, then, is to what extent these moves benefit the worker and firm. The deterioration of the outside labor market significantly reduces workers' threat points, opening the possibility that these worse quality moves are taken under duress. On the other hand, it could be the optimal assignment problem changes when the unemployment rate is high, leading to gains for both the worker and firm. I leave to future work an analysis of the longer-term consequences of this heightened cyclical mobility within firms.

Table 2.14: Quality of Jobs in Second Month

	(1) Occ. Wage Index	(2) Occ. Wage Index	(3) Occ. Quality Index	(4) Occ. Quality Index	(5) Log Hourly Wages	(6) Log Hourly Wages
Unemployment Rate	0.0257	0.0218**	-0.00306	0.000435	0.000191	0.000346
	(0.0197)	(0.00677)	(0.00228)	(0.000576)	(0.00462)	(0.00358)
U. Rate × Hired	-0.0431	-0.0147	-0.00692	-0.000247		
	(0.0384)	(0.00741)	(0.00364)	(0.000323)		
U. Rate × Hired to New Occ.	0.0558*	0.0106	0.00763***	0.00135	0.00108	-0.00301
	(0.0227)	(0.0119)	(0.00174)	(0.00119)	(0.00313)	(0.00207)
Hired	-0.736***	0.0318	-0.122***	-0.0147***		
	(0.195)	(0.0451)	(0.0201)	(0.00259)		
Hired to New Occ.	-0.321**	-0.597***	0.0552***	-0.0289**	-0.0907***	-0.0771***
	(0.114)	(0.0690)	(0.0108)	(0.00877)	(0.0204)	(0.0137)
Constant	12.32***	13.15***	-0.541***	0.653***	1.917***	1.387***
	(0.167)	(0.118)	(0.0201)	(0.0221)	(0.0326)	(0.126)
N	448735	440095	435002	426495	37442	35104
R-sq	0.071	0.743	0.023	0.768	0.176	0.461
Occupation Fixed Effects	No	Yes	No	Yes	No	Yes

Standard errors in parentheses, clustered at the state level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All specifications include state, month-year, and demographic fixed effects.

Chapter 3

Why Is There a Market for Experienced Workers? A Model of Careers

3.1 Introduction

Despite the plethora of within-firm employment incentives, many experienced workers change firms and receive higher wages by doing so. By focusing on the market for experienced workers, I mean to distinguish workers with relevant labor market experience from those who are either new to the labor force or new to their occupation. In order for such a market to exist, experienced workers must choose to leave their current firms and firms must be willing to hire such workers.

The careers literature is replete with rationales for workers and firms to favor internal movements over hires from the external experienced labor market. Promotion is valuable for eliciting effort provision by workers further down in the hierarchy (Lazear & Rosen, 1981), as well as providing incentives for worker investments (Prendergast, 1993). Moving costs, hiring costs, and specific capital all make continuing the current relationship more valuable than the outside option for both the firm and worker.

While the turnover literature offers a variety of explanations for movements between firms, few lead to a distinct experienced labor market. Common explanations for movements between firms include imperfect information about match quality and stochastic search (Jovanovic, 1979; Burdett, 1978). In these cases, a worker may match with positions temporarily until he becomes aware there is a superior choice or it is revealed the current position is a poor match. However, when such workers change firms, they are no different from new entrants to the market who happen to make a good initial match.

Suppose instead workers are able to grow from their employment experiences, which allow them to become qualified for new positions. Jovanovic and Nyarko (1997) refer to this as *stepping stone mobility*, evoking the idea that each position is a stepping stone allowing workers to reach higher positions. In this case there can be an experienced labor market, if workers become qualified for positions at other firms. Heterogeneity is key here, otherwise workers have no reason to change firms. Note that even when workers and firms have full information, workers and firms may still separate.

Stepping stone mobility is not the only type of mobility that can lead to an experienced labor market. Negative shocks and congestion can also lead to turnover, and in the context of training, experienced workers may be distinguished from new labor market entrants. For instance, Acemoglu and Pischke (1998) model voluntary turnover as a random disutility shock, realized after firms have invested in training their workers. Workers will then leave the firm if the wage from remaining less disutility is exceeded by an outside offer. Demougin and Siow (1994) consider congestion for top positions, where training is stochastic. If a firm fails to train a worker, they can hire a surplus worker from another firm that trained too many. Hiring costs lead firms to prefer their own workers, but market clearing leads to a single price for skilled labor. While negative utility shocks and congestion are certainly at play in some movements between firms, I will argue that there is better empirical support for stepping stone mobility driving mobility on average in the United States.

While mobility models provide a clean framework for understanding why workers leave their current position in favor of another position, it is not clear how to interpret these movements with respect to firm boundaries. Driven by expositional simplicity as well as data limited to movements between firms, these models tend to model firms as consisting of a single position (an exception is Demougin and Siow). However, it is not uncommon for firms to transfer workers between positions within the firm for many of the reasons given for movements between firms, including poor fit, negative shocks, and human capital accumulation. Within firm movements have added benefit of preserving incentives and accumulated knowledge about the worker. This implies that movements between firms should be even more rare, occurring only when a within firm solution is not preferred.

Gibbons and Waldman (1999) provide a model of within-firm solutions to mobility, using technology similar to stepping stone mobility. Workers are initially assigned to entry-level positions, but through human capital accumulation become qualified for more productive, better-paying positions. While their model captures a number of facts about movements and wages within firms, they simplify the between firm dimension and assume firms are identical and indifferent workers stay at their current firm.

The goal of this paper is to show that despite explicitly modeling the potential for movements within the firm, workers still change firms. I argue that the observed movements between firms are primarily driven by human capital acquisition and firm heterogeneity. The model builds on (Gibbons & Waldman, 1999) by maintaining their within-firm structure and incorporating heterogeneous firms, leading to the possibility of movements between firms. Moreover, I show that such a model is the only of a variety of models that can match the three empirical regularities presented in the next section. Finally, by introducing an extension of specific capital, I show the model is able to match the additional fact of within-firm movements occurring with greater frequency than between firm movements.

3.2 Evidence on the Market for Experienced Workers

Workers change firms an average of 10 times during their career; however, more than two thirds of these transitions occur during a worker's first 10 years in the labor force (Topel & Ward, 1992). In order for the experienced market to be distinct from the entry-level market, it must be that experienced workers are able to transfer human capital improvements between firms. Neal (1995) demonstrates that displaced workers who are able to find work in the same industry as their previous job experience less wage loss than those who change industries. In addition, Neal (1998) shows that once workers change firms within the same occupation, they are much more likely to stay in the same occupation group at future moves between firms. These two papers suggest that workers are able to build careers spanning multiple firms.

On the demand side, several papers demonstrate that firms hire experienced workers and treat them similarly to workers promoted from within the firm. Baker, Gibbs, and Holmstrom (1994), hereafter BGH, look in-depth at the managerial workers at a particular white-collar firm, and find that there are no positions that are exclusively filled by internal workers. Moreover the workers that are hired from the external market have significant previous labor market experience, indicating they are not new labor market entrants. Treble, van Gameren, Bridges, and Barmby (2001) and Dohmen, Kriechel, and Pfann (2004) also find firms hire external workers at all levels of the hierarchy, and Dohmen et al. find that those hired externally have roughly similar labor market experience to those promoted from within. Thus, workers appear to be able to transfer human capital between firms, and firms appear to hire roughly similar workers from outside the firm as those they promote.

However, studies that include detailed information on worker characteristics find that external entrants to positions and promotees differ in important ways. BGH find external candidates have more education on average (by 0.5 to 1 year) and have 2–3 years different experience and age (older, with more experience for lower-level positions, and younger, with less experience for higher-level positions). Dohmen et al. (2004) find that external candidates have more education, are younger at lower-level positions, and are older at higher-level positions. Thus, while there is not enough data to draw clear conclusions, it does appear that firms hire externally somewhat different workers than they would promote — e.g. it is not the case that workers are moving seamlessly between identical firms.

A well-established fact in the careers literature is that wages increase more when workers are promoted than when they stay at their current position (for example, Baker et al., 1994). Topel and Ward (1992) find wage gains at transitions between firms of about 10% over expected wage gains from staying in the previous firm.

Thus, there are three main empirical results a model of movements between firms should be able to address:

1. Experienced workers are hired into advanced positions.
2. Wages increase more at moves between positions (within and between firms) than they do at stays in the same position.
3. Workers promoted into a position and workers hired from outside the firm differ on observable characteristics.

3.3 The Model

3.3.1 Production

There are two types of firms, A and B, which can be thought of as different industries. Each industry has two types of positions, called L and H. Both industries utilize labor with the same dimension of ability. Crucially, position L in industry A is different from L in industry B, and the same for H positions. I will call the 4 types of positions AL, BL, AH, and BH, and refer to them as *jobs*. Output is additively separable by employee, and there is no congestion or other distortions, so each worker can be considered independently. Assume there is free entry into production, so absent any frictions or specific capital all firms will be held to the zero profit constraint and workers will be paid their marginal product.

Crucially, the marginal product depends on the position. In particular, the job-specific production function takes the form $Y_{jk}(\eta_i) = d_{jk} + c_{jk}\eta_i$, where j represents the industry, k the position, and i the worker. d_{jk} is a job fixed effect in production, and c_{jk} represents the return to worker ability; all d_{jk} and c_{jk} are unique positive real numbers. Worker ability η_i is distributed over $\mathbb{R}^+$. For each job to be meaningful, I will assume constraints such that each job is the efficient assignment for some portion of $\mathbb{R}^+$.

Define a job's *risk set* to be the set of workers whose ability is such that they match efficiently with a particular job in a particular period. Denote job x's risk set as $\mathcal{S}(x)$. Since there is no congestion, all workers in the risk set will be employed by the target firm. Note that given the linear production technology, risk sets will be contiguous intervals and will only overlap at intersection points. Assume that a worker who is indifferent always matches with the position with the higher-ability risk set.

To ensure that the L-type positions are the efficient assignment for the lower portion of the ability distribution, assume $\mathcal{S}(AL) \cup \mathcal{S}(BL) \leq \mathcal{S}(AH) \cup \mathcal{S}(BH)$. This rules out the case where one industry's H position matches with lower-ability workers than the other industry's L position. Without loss of generality, let AL match with the lowest part of the distribution, e.g. $\mathcal{S}(AL) \leq \mathcal{S}(BL)$.

Assumption 3 *Let N^L be the ability cutoff such that workers with ability $\eta < N^L$ are assigned to L-type positions, workers with ability $N^L \leq \eta < N^*$ match with BL, and workers with $\eta \geq N^*$ are optimally assigned to H-type positions. Let N^H be the ability cutoff between the two H-type jobs.*

Assumptions to ensure N^* and N^L are well-defined are listed in the Appendix, Section 3.8.1.

There are two possible cases for the ordering of the high jobs. First, if AH matches with the highest portion of the distribution, the ranking of risk sets will be $\mathcal{S}(AL) \leq \mathcal{S}(BL) \leq \mathcal{S}(BH) \leq \mathcal{S}(AH)$. I will refer to this case as the *heterogeneous variance of ability* case, because A-type firms hire workers with a much larger variance of ability than B-type firms. This is illustrated in Figure 3.1. B-type firms are much more likely to have internal promotions than A-type firms in this case, due to industry structure. Formally, $d_{BH} > d_{AH}$, $c_{BH} < c_{AH}$, and

$$\frac{d_{BL} - d_{BH}}{c_{BH} - c_{BL}} < \frac{d_{BH} - d_{AH}}{c_{BH} - c_{AH}}.$$

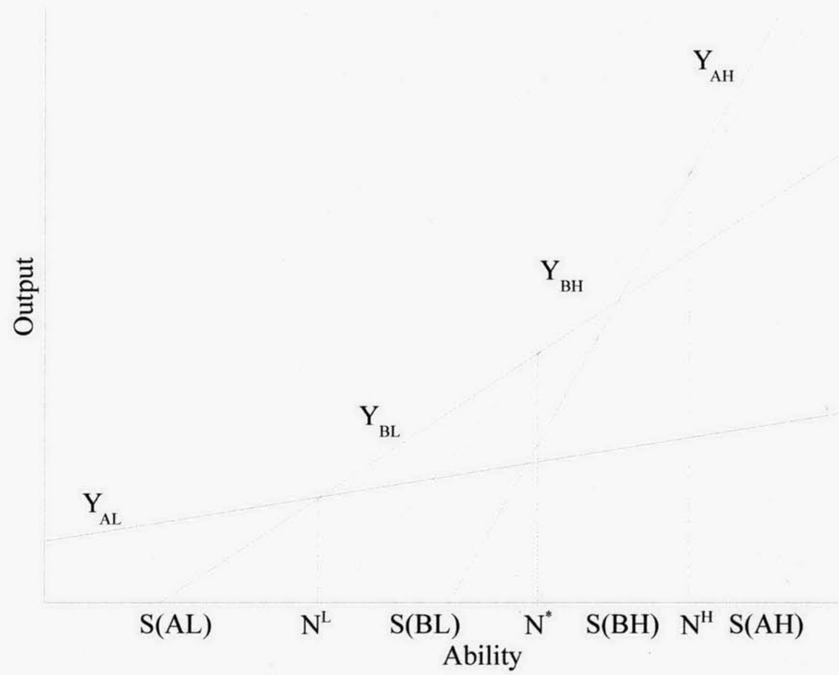


Figure 3.1: Heterogeneous Variance of Ability

The second case occurs when AH and BH are reversed. I will call this case *homogeneous variance of ability*, because A-type firms match with lower ability workers for each position than B-type firms. Formally, this case occurs when $d_{BH} < d_{AH}$, $c_{BH} > c_{AH}$, and

$$\frac{d_{BL} - d_{AH}}{c_{AH} - c_{BL}} < \frac{d_{AH} - d_{BH}}{c_{AH} - c_{BH}}.$$

In the heterogeneous case, one industry has firms that hire both the best and worst workers, and the other industry has fairly homogeneous firms. An example is large fast food chains versus small chains of sit down restaurants: automated fast food technology can be operated by very low ability workers, but fast food executives run giant multinational corporations and must be highly skilled. Alternatively, a small restaurant chain may need to hire better workers because operations are less automated, while hiring less talented executives to run the smaller and less complicated organization.

In the homogeneous case, one industry hires better workers for each position. This is consistent with evidence of heterogeneous wages between industries after controlling for individual characteristics. For instance, Kruger and Summers (1988) find manufacturing, construction, and mining firms pay a wage premium compared with services and wholesale/retail trade firms, even though executives in service firms earn higher wages than miners. Note that the heterogeneous case may also lead to an industry effect on average if there are many more workers in the low positions.

3.3.2 Ability

Each worker enters the labor market with a fixed innate ability denoted θ_i. This is ability that is acquired before entering the labor force, so could be thought of as education or work ethic. In order to have movements between positions, one of three things must happen. First, workers could gain ability through the process of employment. Alternatively, firms could have imprecise information about workers' ability and reassign workers to more appropriate positions as information becomes available. As this most likely does not occur in isolation from human capital accumulation, I will abstract from learning and assume all ability is common knowledge to all participants at all times. Finally, it could be that firm needs evolve over time, leading to changes in efficient assignment. However, this is unlikely to be the primary driver of mobility, so I will not focus on this possibility.

To reduce the number of cases, assume that $\theta_i \in [0, N^*]$. This implies that no workers are assigned to high positions in the first period.

After the first period of production, the worker's ability is $\eta_{i2} = \theta_i + h$, where h represents human capital accumulation and is positive and fixed. Each period, workers' assignment is determined by their effective ability η_{it}.

Proposition 3 *Under the heterogeneous variance of ability case, workers with ability $\eta_i < N^L$ are assigned to job AL, workers with ability $N^L \leq \eta_i < N^*$ with job BL, workers with ability $N^* \leq \eta_i < N^H$ with job BH, and workers with $\eta_i \geq N^H$ with job AH. Under the homogeneous variance of ability case, workers with ability $\eta_i < N^L$ are assigned to job AL, workers with ability $N^L \leq \eta_i < N^*$ with job BL, workers with ability $N^* \leq \eta_i < N^H$ with job AH, and workers with $\eta_i \geq N^H$ with job BH.*

3.3.3 Movements

As discussed above, worker movements occur when workers pass boundaries between jobs. This depends on the workers' innate ability θ_i, the magnitude of human capital acquisition h, and the cutoff points between jobs N^L, N^*, and N^H.

To be able to compare movements, the widths of each position's risk set need to be precisely ranked. This allows us to predict for a given h and θ_i whether a worker will cross the boundary between risk sets and move into a new job. Assume that the risk sets are weakly decreasing in width. Note however that the risk set that matches with the top of the ability distribution (either AH or BH depending on the case) is arbitrarily big, and for very large h will end up being a dumping ground for all workers. Finally, assume that $\mathcal{S}(AL)$ is smaller than the union of the middle two risk sets.

Assumption 4 *Under the heterogeneous variance ability case, let* $\mathcal{S}(BH) \leq \mathcal{S}(BL) \leq \mathcal{S}(AL) \leq \mathcal{S}(BH) \cup \mathcal{S}(BL)$. *Under the homogeneous variance of ability case, let* $\mathcal{S}(AH) \leq \mathcal{S}(BL) \leq \mathcal{S}(AL) \leq \mathcal{S}(AH) \cup \mathcal{S}(BL)$.

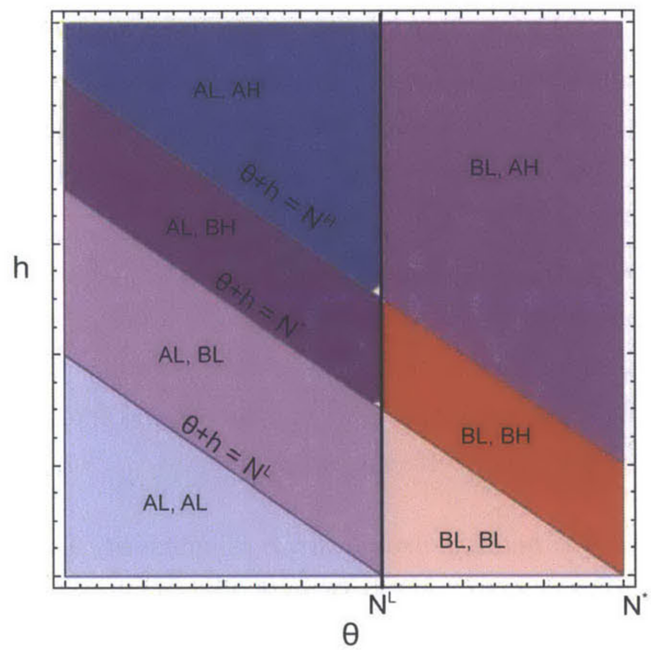


Figure 3.2: Heterogeneous Variance of Ability. Each region represents a different two period assignment.

Now we can determine movements based on the magnitude of h. First consider the heterogeneous variance of ability case, displayed in Figure 3.2 (see Table 3.1 in the Appendix for a full derivation). Each region represents the two period assignments. Note that h is fixed for all workers, so each θ has a unique optimal two period assignment. For $\theta < N^L$, workers are assigned to AL in the first period, otherwise they are assigned to BL. When $\theta + h < N^L$, workers are assigned to AL in the second period, if between N^L and N^* workers are assigned to BL, if between N^* and N^H workers are assigned to BH and above N^H workers are assigned to AH. Purple regions represent movements between firms. Note that for all h, there is a purple region. The dark blue and red regions represent promotions within the firm. Note that workers assigned to firm A are only promoted of h is sufficiently large, and in this case all workers from firms of type B also end up in AH. For all h below the boundary to be promoted to AH, there will be some workers promoted in firm B.

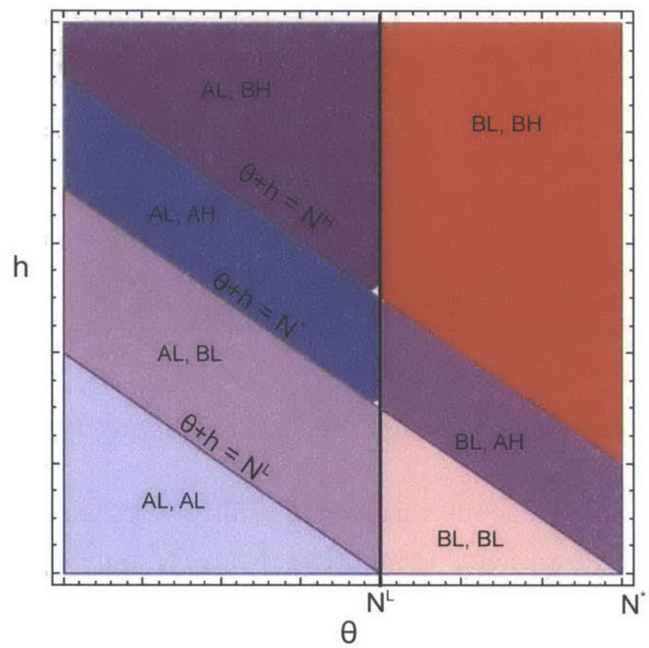


Figure 3.3: Homogeneous Variance of Ability. Each region represents a different two period assignment.

Next consider the homogeneous variance of ability case, shown in Figure 3.3 and Table 3.2 in the Appendix. In the first period, workers are assigned according to θ. In the second period, for an h some workers from firm A will enter the experienced market and switch to a firm of type B. Similarly for h not too large, there will be some workers from firms of type B who enter the experienced market. Workers will only be promoted if h is large enough, but not too large in the case of firms of type A.

Proposition 4 *In both heterogeneous and homogeneous variance of ability cases for any h there is an experienced labor market in which workers move from their firm to a firm in the other industry. In addition, there is always at least one industry that has internal promotions.*

3.3.4 Differences Between Stayers, Movers, and Promotees

Among different workers occupying the same position, how is their past assignment associated with differences in current ability? Note that the assignment is not causal, it is determined by their innate ability.

First focus on the heterogeneous variance of ability case, where the most-productive workers are efficiently assigned to job AH. AH will only be staffed when h is sufficiently large for BL workers to move, and promotions from AL only occur for very large values of h. When AH is staffed by both types of workers, promotees will be less productive and paid less than external hires.

For position BH, promotions will occur for all positive h. For $h \geq N^* - N^L$, BH will get external hires from AL. These will be less productive and paid less than promotees.

Proposition 5 *Under the heterogeneous variance of ability case, at firms of type A, workers will only be promoted for very large h, and promotees will always have lower ability than external hires. At firms of type B, there will always be promotions for positive h. Promotees will always be more productive and paid more than external hires.*

Next consider the homogeneous variance of ability case, where position BH matches with the most productive workers. Promotions from BL only occur if $h \geq N^H - N^*$. If $h \geq N^H - N^L$, workers will be promoted from AL. These workers will be less productive and paid less than promoted workers.

Workers move to AH from either BL or AL. The workers that move from firm B will always be more productive than the promotees. For $h > 0$ there will be workers that move from BL. Workers will only be promoted internally if $h \geq N^H - N^L$.

Proposition 6 *Under the homogeneous variance of ability case, for small h there are no promotions; workers either stay in the same position or move between firms. When h is large enough to allow promotions, promotees will be less productive and paid less than movers.*

3.3.5 Discussion

Recall the three empirical findings: experienced workers are hired into advanced positions, wages rise more at movements between positions within and between firms than at stays in the current firm, and external hires and promotees differ on observables.

The first finding is true for any amount of human capital accumulation h, however, it will not necessarily occur in both industries. The second finding is true because workers are paid their marginal product and workers only move to positions at which they are more productive. Finally, I demonstrated that whenever workers move between firms, these individuals come from a different part of the ability distribution from those who are promoted internally into the position.

However, as of yet, I have ignored a major fact of experienced labor markets. Although few firms have positions in which only internal candidates are hired, firms are much more likely to promote than to hire from the experienced market. In the next section, I demonstrate that there is strong empirical support for promotion being the predominant method of staffing, and then derive a modeling extension that delivers this result.

3.4 Specific Capital

While frictions could take a variety of forms, such as moving or hiring costs, I will focus on specific capital. Specific capital is compelling because it is non-wasteful; workers with experience at the firm are simply additionally productive. The main result is that stays within the firm are now much more likely, however moves between firms will still be optimal for some workers. In addition, promotions are weakly more prevalent.

The challenge to modeling specific capital is that we labor market decisions in each period can no longer be separated because firm choice in the first period now impacts second-period productivity. For workers who know that their optimal assignment in the first period and second period are at the same type of firm, this distortion will not come into play. However, workers who know that their ability will lead to efficient assignment to different types of firms in each period may be better off matching with the same firm each period.

3.4.1 Evidence of Promotion Preference

Define *promotion intensity* to be the fraction of all entrants to a position who come from within the firm. Doeringer and Piore (1971) studied blue-collar manufacturing plants, and found that workers tended to be hired at *entry points*, e.g. positions at which workers enter the firm. In the purest firm, all non-entry positions would have promotion intensities of 100%, because all movements occur internally. When Baker et al. (1994) sought to test the entry points prediction, they found significant entry at all levels of the hierarchy. However, Doeringer and Piore (1971) have been affirmed in a weaker sense: all of the firm case studies find promotion intensities of well above 50%. For instance, Baker et al. (1994) find that for lower-level management positions promotion intensity is 70–75%, and for upper management promotion intensity is about 90%. Treble et al. (2001) find promotion intensities of between 65% and 90%, and, finally, Seltzer and Merrett (1988) find *no* external hires.

Fernandez and Abraham (2010a, 2010b) have rare data on the applicants to positions for a particular firm. In this case, they find that while many workers are hired from outside the firm, the internal hires always comprise a larger proportion of the hires than they do of the applicant pool. Ultimately, I would like to see how the qualifications of external and internal applicants differ, and how that relates to the hiring decision. However, to the best of my knowledge, no firm has made this information available.

Thus, while few positions exclusively promote, most positions appear to be more likely to be filled via promotion than external hire, or, at least, internal candidates have a higher probability of being selected for a given position.

3.4.2 Modeling Specific Capital

The production technology is very similar to the baseline model, however now for each position there are two production functions: when a worker has never worked for the firm previously and when the worker is incumbent. Note that this is a firm-level effect, so specific capital will improve productivity in any position at the firm. In particular, in the first period of a worker and firm match output is $d_{jk} + c_{jk}\eta_{it}$, and in the second period of a match, output is $d_{jk} + c_{jk}(\eta_{it} + h)$, where, as before, j represents industry, k represents position, i represents the worker, and t represents the period.

Consider again the same two cases: heterogeneous variance of ability and homogeneous variance of ability. Recall heterogeneous variance of ability occurs when one industry matches with the lowest and highest segments of the ability distribution and the other matches with the middle segment, and homogeneous variance of ability occurs when one industry matches with the higher portion of each of the bottom parts of the distribution and the top parts of the distribution (as before, assume that all L tasks match with a lower segment of the distribution than the H tasks).

Heterogeneous Variance of Ability with Specific Capital

First consider assignment in the second period. Recall the cutoffs in the non-specific capital world: N^L is the boundary between assignment to position AL and BL, N^* is the boundary between BL and BH, and N^H is the boundary between BH and AH. These cutoffs now change, depending on if the worker was at a firm of type A or B in the first period. Call these $N^x(A)$ and $N^x(B)$.

Note that it is always strictly more productive for workers to stay with their current firm rather than to change firms within the same industry. This is driven by the fact that specific capital is a firm-level effect, so the worker is now strictly more productive at their current firm.

Consider a worker who started in a firm of type A in the first period. Movements are governed by the three cutoffs: $N^L(A)$, $N^*(A)$, and $N^H(A)$, illustrated in Figure 3.4. In particular,

$$N^L(A) = N^L + \frac{c_{AL}}{c_{BL} - c_{AL}} s,$$
$$N^*(A) = N^*,$$

and

$$N^H(A) = N^H - \frac{c_{AH}}{c_{AH} - c_{BH}} s.$$

Observe that the regions for which the worker will stay in the firm grow with s. Finally, to ensure that there is always some region of the ability distribution for which workers are assigned to each position, assume $N^L(A) < N^* < N^H(A)$.

Assumption 5 *Let*

$$s < \min\left\{\frac{c_{BL} - c_{AL}}{c_{AL}}(N^* - N^L), \frac{c_{BL} - c_{AL}}{c_{AL}}(N^H - N^*)\right\}.$$

Then $N^L(A) < N^* < N^H(A)$.

Proposition 7 *The efficient assignment in the second period for a firm-A incumbent in the heterogeneous variance of ability case is as follows: if* $\theta_i + h < N^L(A)$, *assign to* AL *in the same firm; if* $N^L(A) \leq \theta_i + h < N^*$, *assign to* BL *in any firm in industry* B*; if* $N^* \leq \theta_i + h < N^H(A)$, *assign to* BH *in any firm in industry* B*; and if* $N^H(A) \leq \theta_i + h$, *assign to* AH *in the same firm.*

Now consider a worker who started in a firm of type B in the first period, illustrated in Figure 3.5. The cutoffs are as follows:

$$N^L(B) = N^L - \frac{c_{BL}}{c_{BL} - c_{AL}} s,$$
$$N^*(B) = N^* - s,$$

and

$$N^H(B) = N^H + \frac{c_{BH}}{c_{AH} - c_{BH}} s.$$

As s grows, the boundary for assignment in position BL moves left and the boundary for assignment in position BH moves right. Thus, the region for which workers would stay in the firm grows. Also the boundary between BL and BH moves left, so workers are more likely to be promoted.

Proposition 8 *The efficient assignment in the second period for a worker who is incumbent in a firm in industry B is: assign to position AL in any firm in industry A if* $\theta_i + h < N^L(B)$*; assign to position BL in the current firm if* $N^L(B) \leq \theta_i + h < N^*(B)$*; assign to position BH in the current firm if* $N^*(B) \leq \theta_i + h < N^H(B)$*; and assign to position AH in any firm in industry A if* $N^H(B) \leq \theta_i + h$*.*

In addition, $N^L(B) < N^L < N^L(A) < N^*(B) < N^* < N^H(A) < N^H < N^H(B)$.

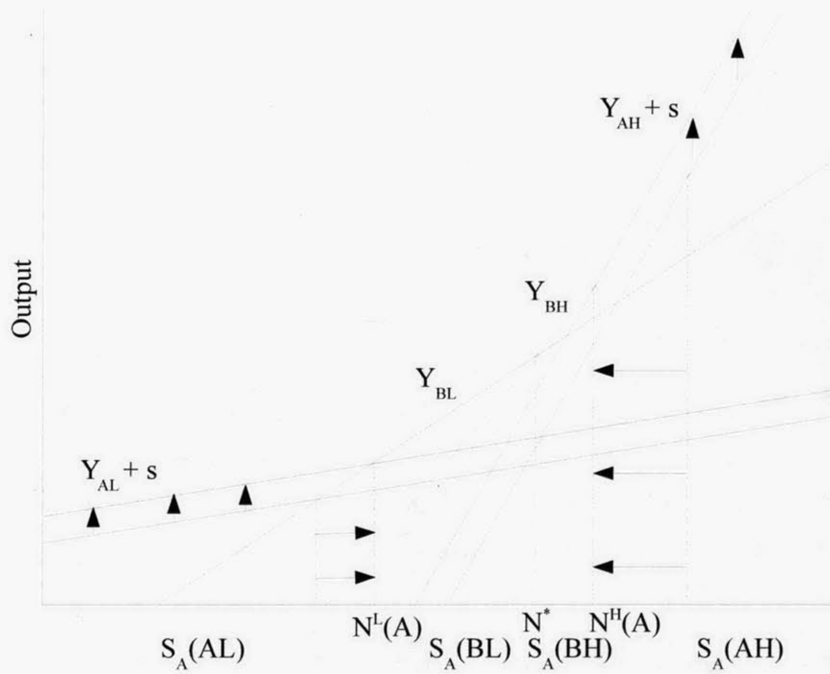


Figure 3.4: Heterogeneous Variance of Ability with Specific Capital, Type-A Firm Incumbent

Now consider the efficient assignment in the first period. As discussed above, this may not be the myopically optimal assignment, since specific capital gives an extra benefit to remaining at the same firm in both periods. Thus, to determine the efficient assignment, we must compare the myopic assignment with alternatives. Let N^A be the indifference point between Y_{AL} and Y_{AH}. Thus, if θ is below N^A, the alternative assignment would place the worker in Y_{AL} in the first period, and then in the second period optimal position as described above. Similarly, let N^B represent the cutoff between the two B positions.

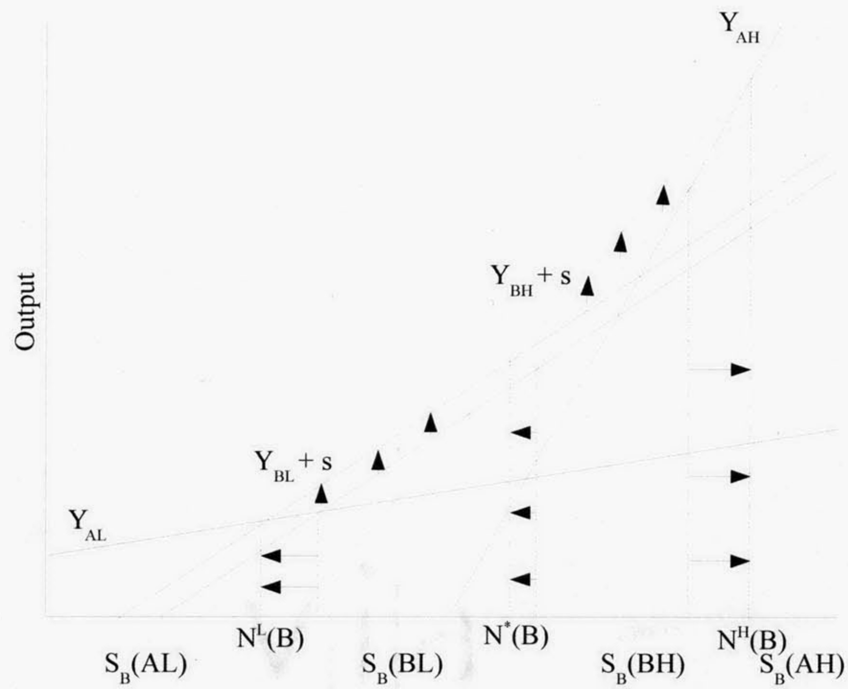


Figure 3.5: Heterogeneous Variance of Ability with Specific Capital, Type-B Firm Incumbent

Consider Figure 3.6 which illustrates the key dynamics (see Table 3.3 for specific details). In the first pane, $s = 0$ and the myopic assignment is identical to the two period optimal assignment. All workers with $\theta < N^L$ are assigned to AL in the first period, and move according to the magnitude of h. Observe there are regions of all types of movements: stay in the same position, promote within firm, and move between firms.

In the second pane, s is small but positive. In this case, we start to see some myopically suboptimal assignment in the first period for θ around the N^L, marked by the hatched shading. Observe the regions where movements between firms were optimal when $s = 0$ are already shrinking in favor of staying within the same firm.

In the third pane, s is of a medium value. We see an expansion of the trends in the second pane, however movements within A are beginning to dominate. This is because s is multiplied by c_{ij} in the production function, so each increase in s leads to a larger increase in output at AL than at other positions.

Finally, in the fourth pane, s is large and workers are no longer assigned to firms of type B.

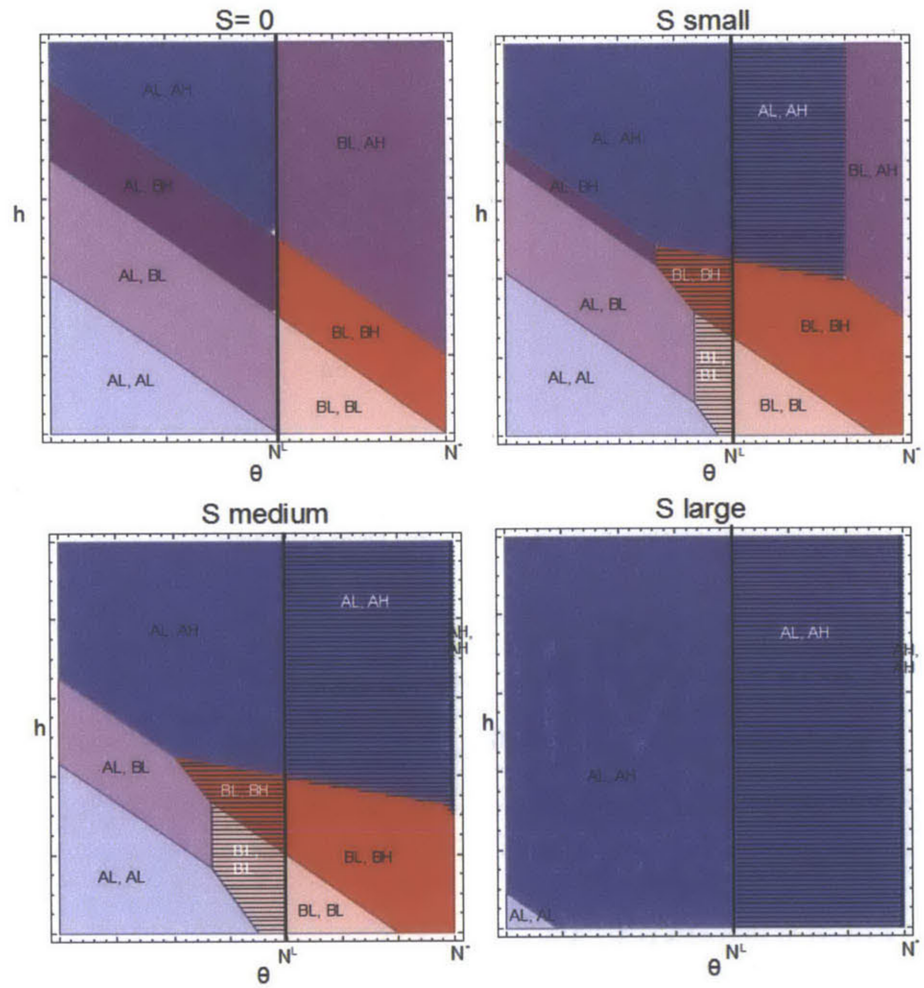


Figure 3.6: Heterogeneous Variance of Ability with Specific Capital. Hatched regions represent values of θ and h such that the first period myopic assignment is suboptimal. Each region represents a different two period optimal assignment.

Homogeneous Variance of Ability Case with Specific Capital

Now consider the homogeneous variance of ability case. Recall that this occurs when industry A-type firms efficiently match with lower-ability workers than industry B-type firms in each both positions L and H. First define the cutoffs between AL and BL, BL and AH, and AH and BH:

$$N^L(A) = N^L + \frac{c_{AL}}{c_{BL} - c_{AL}} s,$$
$$N^*(A) = N^* - \frac{c_{AH}}{c_{AH} - c_{BL}} s,$$

and

$$N^H(A) = N^H + \frac{c_{AH}}{c_{BH} - c_{AH}} s.$$

Finally, to ensure that $N^L(A) < N^* < N^H(A)$, so there is always some region of the ability distribution for which workers are assigned to each position, assume the following:

Assumption 6 *Let*

$$s < \frac{(c_{AH} - c_{BL})(c_{BL} - c_{AH})}{c_{BL}(c_{AH} - c_{AL})}(N^* - N^L).$$

Then $N^L(A) < N^*(A) < N^H(A)$.

Proposition 9 *The efficient assignment in the second period for a firm-A incumbent is as follows: if* $\theta_i + h < N^L(A)$, *assign to AL in the same firm; if* $N^L(A) \le \theta_i + h < N^*(A)$, *assign to BL in any firm in industry B; if* $N^*(A) \le \theta_i + h < N^H(A)$, *assign to BH in any firm in industry B; and if* $N^H(A) \le \theta_i + h$, *assign to AH in the same firm.*

Now consider a firm-B incumbent. The cutoffs are now

$$N^L(B) = N^L - \frac{c_{BL}}{c_{BL} - c_{AL}} s,$$
$$N^*(B) = N^* + \frac{c_{BL}}{c_{AH} - c_{BL}} s,$$

and

$$N^H(B) = N^H - \frac{c_{BH}}{c_{BH} - c_{AH}} s.$$

Finally, assume $N^L(B) < N^*(B) < N^H(B)$, so there is always some region of the ability distribution for which workers are assigned to each position.

Assumption 7 *Let*

$$s < \frac{(c_{AH} - c_{BL})(c_{BH} - c_{AH})}{c_{AH}(c_{BH} - c_{BL})}(N^H - N^*).$$

Then $N^L(B) < N^*(B) < N^H(B)$.

Proposition 10 *The efficient assignment in the second period for a firm-B incumbent is as follows: if* $\theta_i + h < N^L(B)$, *assign to AL in the same firm; if* $N^L(B) \le \theta_i + h < N^*(B)$, *assign to BL in any firm in industry B; if* $N^*(B) \le \theta_i + h < N^H(B)$, *assign to BH in any firm in industry B; and if* $N^H(B) \le \theta_i + h$, *assign to AH in the same firm.*

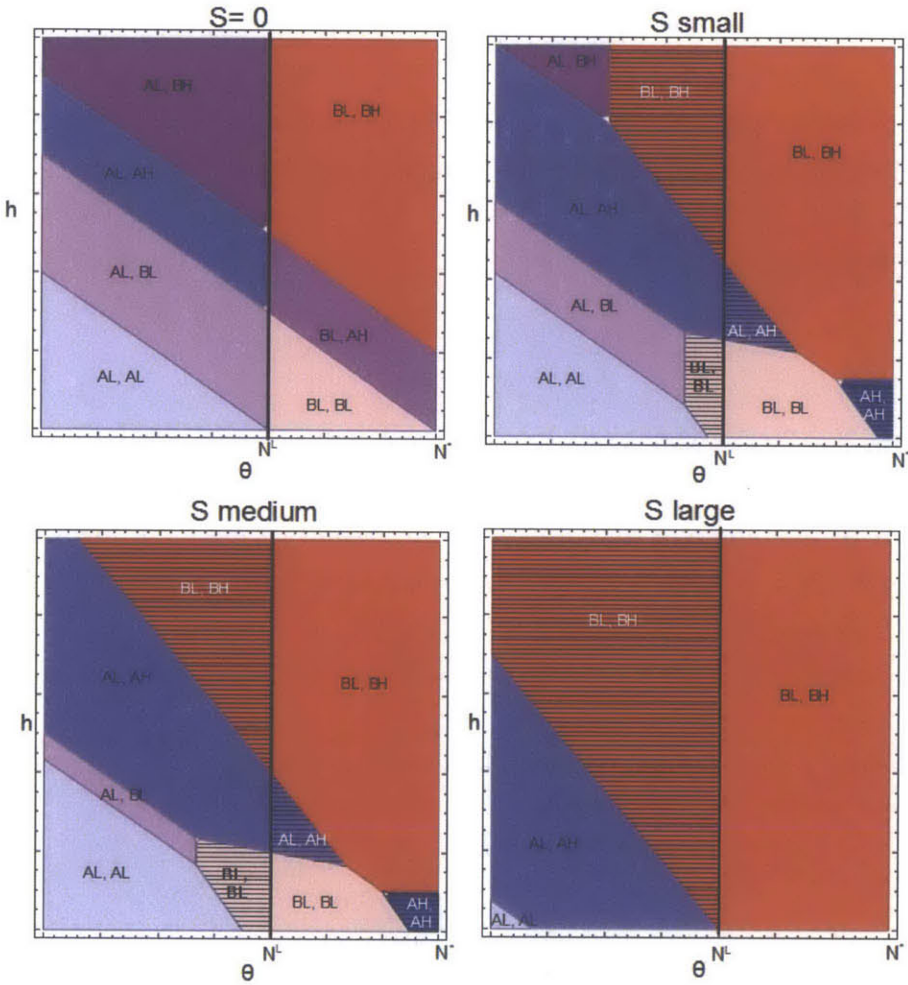


Figure 3.7: Homogeneous Variance of Ability with Specific Capital. Hatched regions represent values of θ and h such that the first period myopic assignment is suboptimal. Each region represents a different two period assignment.

Observe Figure 3.7 (see Table 3.4 in the Appendix for more details). When $s = 0$, assignment is very similar to the heterogeneous case, however workers are assigned to AH for lower values of h than for BH. As before, myopic assignment is always optimal. When s is small, we start to see two period assignments that are myopically suboptimal in the first period. This primarily occurs around the boundary N^L, but there is also a region of very large θ and very small h in which workers are optimally assigned to AH in both periods. This is because s incentivizes bumping workers up to AH in the first period, rather than changing firms as they do in this region when $s = 0$. Note that the regions in which workers change firms are shrinking, in fact, no workers assigned to BL in the first period change firms — they either stay in BL when they would have moved, or move within the firm to BH.

In the third pane, where s is medium, the regions in which workers change firms have shrunk considerably, but plenty of workers are promoted within their firms. By the fourth pane, where s is large, workers no longer move firms, but almost all workers are promoted. This is because s makes the high positions additionally valuable, so when s is large enough, almost all workers are candidates for promotion.

Discussion

With specific capital, careers within firms are much more likely for two reasons. First, the cutoffs of ability for changing firms grow more restrictive, leading workers to be more likely to stay at their firm. Moreover, when workers optimize over their career, even more workers may choose to match suboptimally in the first period for higher returns over their career.

Provided h and s are not too large, this model delivers movements between firms and within firms in equilibrium. While it still matches the baseline empirical facts (that workers move to positions that build upon previous positions, wages increase more at moves between jobs than at stays, and promotees and external hires into the same position are different), it also captures the fact that promotion is more common than external hiring.

3.5 Comparison With Alternative Models

Recall the three empirical findings: experienced workers are hired into advanced positions, wages rise more at movements between positions within and between firms than at stays in the current firm, and external hires and promotees differ on observables. Not only does this model match the fact pattern, but no other models do.

Consider the second finding regarding wage increases at moves. This is intuitive via revealed preference, nonetheless few models are able to provide it. Models of careers within firms assume firms are identical, so workers are at best indifferent (and wages constant) at moves between firms (e.g. Gibbons & Waldman, 1999). Next consider match-specific capital (Jovanovic, 1979). In this case, the quality of each match is an independent draw from a distribution. For a worker to change firms, it must be revealed that their current match is likely to be low quality. However, the independence of match-specific quality means that the worker is like a new worker upon moving, which is not consistent with wage growth leading up to moves and continuing after moves (Topel & Ward, 1992).

Two theories are consistent with wages increasing at movements: congestion (Demougin & Siow, 1994) and search (Burdett, 1978). Under congestion, workers may prefer promotion at their current firm but are forced to move due to a lack of positions. In this case, wages will increase because the worker is moving to a higher productivity position at the new firm. Thus congestion is consistent with the first empirical result as well: experienced workers are hired into advanced positions. However, since all firms are identical and all workers are identical, there is no reason for promoted and externally hired workers to be any different. Even if Demougin and Siow's model was extended to allow workers to be heterogeneous in their training, identical firms and competitive pricing imply that firms should be indifferent between the quality of workers, and thus there is no clean prediction regarding heterogeneous hires and promotees.

Finally, it could be that searching is costly or imperfect and workers and firms do not necessarily find the best possible match. If a better-quality match comes along, the worker may leave to take the position. In this case, one might expect to have wages increase at moves. Unlike the match-specific capital case where workers learn about the quality of the current match, there is no reason for wages to deteriorate under search. Suppose the model was extended to include multiple positions in firms. If workers have better information about positions within the firm than positions outside the firm, it could be that workers promoted within the firm have different characteristics (e.g. labor market experience, tenure) than those who find the position from outside the firm. However, the model fails to capture the first fact, that experienced workers are hired into more advanced positions than new labor market entrants.

3.6 Evidence of Heterogeneous Production Technologies

One of the central features of this model is that different jobs utilize different production technologies. If all firms were identical, workers would be indifferent between staying at their current firm and switching. There is a large literature documenting heterogeneous productivity between firms: for instance, firms in the same industry have been shown to utilize widely varying human resource and management practices, which in turn are associated with different TFP, wages, and profitability (see Bloom & van Reenen, 2010). Within industries and occupation groups, firms pay divergent wages, which is not fully explained by sorting. For instance, Arai (2003) finds that in Sweden, wages are positively correlated with profits and the capital-labor ratio, after controlling for worker ability.

Within firms, it is well know that wages rise dramatically as workers rise in the hierarchy. The fact that wages increase more at movements between positions than at movements within position (e.g. Baker et al., 1994), indicates that there is content to the job titles. An alternative hypothesis is that promotion hierarchies are set up as tournaments, and the wage increases are prizes to induce effort. However, such a structure would require firms to distort hiring practices at the top of the hierarchy in order to provide optimal incentives throughout the hierarchy. The weight placed on executive talent makes such a policy seem unlikely to be the primary driver.

3.7 Conclusions

In this paper I present a simple model of stepping stone mobility to explain why there is a market for experienced workers. Using firm heterogeneity and worker human capital accumulation, I show that this model is able to capture a variety of empirical results regarding movements within and between firms that other models are unable to match. By extending the model to include specific capital, I show that it is possible to still have movements between firms, but at a lower frequency then the basic model.

For the sake of precision of argument, I have pushed aside many other factors that are likely to play a role in career development and movements between positions and firms. Congestion certainly constrains careers, employees are fired for poor performance, and many quits are driven by personality or culture conflicts. The extent to which these other factors interact with stepping stone mobility is an open question that I leave to future research. In addition, while I have shown that within firm mobility can coexist with between firm mobility, it remains unknown the extent to which incentives and assignment interact to influence employee and firm effort and staffing decisions.

3.8 Mathematical Appendix

3.8.1 Assumptions

To ensure N^* and N^L are well defined, assume the following technicalities:

$$
\begin{aligned}
d_{AL} > d_{BL} > \max\{d_{AH}, d_{BH}\}, \\
c_{AL} < c_{BL} < \min\{c_{AH}, c_{BH}\}, \\
\frac{d_{AL} - d_{BL}}{c_{BL} - c_{AL}} < \min\{\frac{d_{AL} - d_{AH}}{c_{AH} - c_{AL}}, \frac{d_{AL} - d_{BH}}{c_{BH} - c_{AL}}\}, \\
\min\{\frac{d_{BL} - d_{AH}}{c_{AH} - c_{BH}}, \frac{d_{BL} - d_{BH}}{c_{BH} - c_{BH}}\} < \frac{d_{AH} - d_{BH}}{c_{BH} - c_{AH}}, \\
\frac{d_{AL} - d_{BL}}{c_{BL} - cAL} < \min\{\frac{d_{BL} - d_{AH}}{c_{AH} - c_{BL}}, \frac{d_{BL} - d_{BH}}{c_{BH} - c_{BL}}\}.
\end{aligned}
$$

Table 3.1: Movements under Heterogeneous Variance of Ability Case

Assignment	Condition for Assignment	Valid bounds on h
1st Period AL: $\theta_i < N^L$		
2nd Period:		
Stay	$0 \leq \theta < N^L - h$	$h < N^L$
Move to BL	$N^L - h \leq \theta < N^* - h$	$h < N^L$
Move to BH	$N^* - h \leq \theta < N^H - h$	$N^* - N^L \leq h < N^H$
Promote	$N^H - h \leq \theta$	$N^H - N^L \leq h$
1st Period BL: $N^L \leq \theta_i < N^*$		
2nd Period:		
Stay	$N^L \leq \theta < N^* - h$	$h < N^* - N^L$
Promote to BH	$N^* - h \leq \theta < N^H - h$	$h < N^H - N^L$
Move to AH	$N^H - h \leq \theta$	$N^H - N^* \leq h$

Table 3.2: Movements under Heterogeneous Variance of Ability Case

Assignment	Condition for Assignment	Valid bounds on h
1st Period AL: $N^L < \theta_i$		
2nd Period:		
Stay	$0 \leq \theta < N^L - h$	$h < N^L$
Move to BL	$N^L - h \leq \theta < N^* - h$	$h < N^L$
Promote to AH	$N^* - h \leq N^H - h$	$N^* - N^L \leq h < N^H$
Move to BH	$N^H - h \leq \theta$	$N^H - N^L \leq h$
1st Period BL: $N^L < \theta_i \leq N^*$		
2nd Period:		
Stay	$N^L \leq \theta < N^* - h$	$h < N^* - N^L$
Move to AH	$N^* - h \leq \theta < N^H - h$	$h < N^H - N^L$
Promote to BH	$N^H - h \leq \theta$	$N^H - N^* \leq h$

Table 3.3: Movements In Heterogeneous Variance of Ability Case with Specific Capital

Bounds $\theta_i + h$	Bound s	Movement
First Period AL		
Case A: $\theta_i < N^L$	(Myopic optimal)	
$\theta_i + h < N^L(B)$	all s	stay in AL
$N^L(B) \leq \theta_i + h < N^L(A)$	$s < 2(N^L - \theta_i) - h$	stay in AL
$N^L(A) \leq \theta_i + h < N^*(B)$	$s < \frac{c_{BL}-c_{AL}}{c_{BL}}(N^L - \theta_i)$	move to BL
$N^*(B) \leq \theta_i + h < N^*$	$s < \frac{c_{BH}-c_{AL}}{c_{BH}}(N^* - \theta_i - h) + \frac{c_{BL}-c_{AL}}{c_{BH}}(N^L - \theta_i)$	move to BL
$N^* \leq \theta_i + h < N^H(A)$	$s < \frac{c_{BL}-c_{AL}}{c_{BH}}(N^L - \theta_i)$	move to BH
$N^H(A) \leq \theta_i + h < N^H(B)$	$s < \frac{c_{BL}-c_{AL}}{c_{AH}-c_{BH}}(N^L - \theta_i) - N^* + \theta_i + h$	promote to AH
$N^H(B) \leq \theta_i + h$	all s	promote to AH
Case B: $N^L \leq \theta_i < N^*$	(Myopic suboptimal)	
$N^H(A) \leq \theta_i + h < N^H(B)$, $\theta_i < N^A$	$s > N^H - \theta_i - h + \frac{c_{BL}-c_{AL}}{c_{AH}-c_{BH}}(\theta_i - N^L)$	promote to AH
First Period BL		
Case A: $\theta_i < N^L$	(Myopic suboptimal)	
$N^L(B) \leq \theta_i + h < N^L(A)$	$s > 2(N^L - \theta_i) - h$	stay in BL
$N^L(A) \leq \theta_i + h < N^*(B)$	$s > \frac{c_{BL}-c_{AL}}{c_{BL}}(N^L - \theta_i)$	stay in BL
$N^*(B) \leq \theta_i + h < N^*$	$s > \frac{c_{BH}-c_{AL}}{c_{BH}}(N^* - \theta_i - h) + \frac{c_{BL}-c_{AL}}{c_{BH}}(N^L - \theta_i)$	promote to BH
$N^* \leq \theta_i + h < N^H(A)$	$s > \frac{c_{BL}-c_{AL}}{c_{BH}}(N^L - \theta_i)$	promote to BH
$N^H(A) \leq \theta_i + h < N^H(B)$	$s > \frac{c_{BL}-c_{AL}}{c_{AH}-c_{BH}}(N^L - \theta_i) - N^* + \theta_i + h$	promote to BH
Case B: $N^L \leq \theta_i < N^*$	(Myopic optimal)	
$\theta_i + h < N^H(A)$	all s	stay in BL
$N^H(A) \leq \theta_i + h < N^H(B)$, $\theta_i < N^A$	$s < N^H - \theta_i - h + \frac{c_{BL}-c_{AL}}{c_{AH}-c_{BH}}(\theta_i - N^L)$	promote to BH
$N^H(A) \leq \theta_i + h < N^H(B)$, $N^A \leq \theta_i$	$s < 2(N^H - \theta_i) - h - \frac{c_{BH}-c_{BL}}{c_{AH}-c_{BH}}(N^* - \theta_i)$	promote to BH
$N^H(B) \leq \theta_i + h$, $\theta_i < N^A$	all s	move to AH
$N^H(B) \leq \theta_i + h$, $N^A \leq \theta_i$	$s < \frac{c_{BH}-c_{BL}}{c_{AH}}(N^* - \theta_i) + \frac{c_{AH}-c_{BH}}{c_{AH}}(N^H - \theta_i)$	move to AH
First Period AH		
Case B: $N^L \leq \theta_i < N^*$	(Myopic suboptimal)	
$N^H(A) \leq \theta_i + h < N^H(B)$, $N^A \leq \theta_i$	$s > 2(N^H - \theta_i) - h - \frac{c_{BH}-c_{BL}}{c_{AH}-c_{BH}}(N^* - \theta_i)$	stay in AH
$N^H(B) \leq \theta_i + h$, $N^A \leq \theta_i$	$s > \frac{c_{BH}-c_{BL}}{c_{AH}}(N^* - \theta_i) + \frac{c_{AH}-c_{BH}}{c_{AH}}(N^H - \theta_i)$	stay in AH

Table 3.4: Movements in Homogeneous Variance of Ability Case with Specific Capital

Bounds $\theta_i + h$	Bound s	Movement
First Period AL		
Case A: $\theta_i < N^L$	(Myopic optimal)	
$\theta_i + h < N^L(B)$	all s	stay in AL
$N^L(B) \leq \theta_i + h < N^L(A)$	$s < 2(N^L - \theta_i) - h$	stay in AL
$N^L(A) \leq \theta_i + h < N^*(A)$	$s < \frac{c_{BL}-c_{AL}}{c_{BL}}(N^L - \theta_i)$	move to BL
$N^*(A) \leq \theta_i + h < N^*(B)$	$s > N^* - \theta_i - h - \frac{c_{BL}-c_{AL}}{c_{AH}-c_{BL}}(N^L - \theta_i)$	promote to AH
$N^*(B) \leq \theta_i + h < N^H(B)$	all s	promote to AH
$N^H(B) \leq \theta_i + h < N^H(A)$	$s < N^H - \theta_i - h + \frac{c_{BL}-c_{AL}}{c_{BH}-c_{AH}}(N^L - \theta_i)$	promote to AH
$N^H(A) \leq \theta_i + h$	$s < \frac{c_{BL}-c_{AL}}{c_{BH}}(N^L - \theta_i)$	move to BH
Case B: $N^L \leq \theta_i < N^*$	(Myopic suboptimal)	
$N^*(A) \leq \theta_i + h < N^*(B)$, $\theta_i < N^A$	$s > N^* - \theta_i - h + \frac{c_{BL}-c_{AL}}{c_{AH}-c_{BL}}(\theta_i - N^L)$	promote to AH
$N^*(B) \leq \theta_i + h < N^H(B)$, $\theta_i < N^A$	$s > \frac{c_{BL}-c_{AL}}{c_{BL}}(\theta_i - N^L)$	promote to AH
$N^H(B) \leq \theta_i + h < N^H(A)$, $\theta_i < N^A$	$s < N^H - \theta_i - h - \frac{c_{BL}-c_{AL}}{c_{BH}-c_{AH}}(\theta_i - N^L)$	promote to AH
First Period BL		
Case A: $\theta_i < N^L$	(Myopic suboptimal)	
$N^L(B) \leq \theta_i + h < N^L(A)$	$s > 2(N^L - \theta_i) - h$	stay in BL
$N^L(A) \leq \theta_i + h < N^*(A)$	$s > \frac{c_{BL}-c_{AL}}{c_{BL}}(N^L - \theta_i)$	stay in BL
$N^*(A) \leq \theta_i + h < N^*(B)$	$s > N^* - \theta_i - h - \frac{c_{BL}-c_{AL}}{c_{AH}-c_{BL}}(N^L - \theta_i)$	promote to AH
$N^H(B) \leq \theta_i + h < N^H(A)$	$s > N^H - \theta_i - h + \frac{c_{BL}-c_{AL}}{c_{BH}-c_{AH}}(N^L - \theta_i)$	promote to BH
$N^H(A) \leq \theta_i + h$	$s > \frac{c_{BL}-c_{AL}}{c_{BH}}(N^L - \theta_i)$	promote to BH
Case B: $N^L \leq \theta_i < N^*$	(Myopic optimal)	
$\theta_i + h < N^*(A)$	all s	stay in BL
$N^*(A) \leq \theta_i + h < N^*(B)$, $\theta_i < N^A$	$s < N^* - \theta_i - h + \frac{c_{BL}-c_{AL}}{c_{AH}-c_{BL}}(\theta_i - N^L)$	stay in BL
$N^*(A) \leq \theta_i + h < N^*(B)$, $N^A \leq \theta_i$	$s < 2(N^* - \theta_i) - h$	stay in BL
$N^*(B) \leq \theta_i + h < N^H(B)$, $\theta_i < N^A$	$s < \frac{c_{BL}-c_{AL}}{c_{BL}}(\theta_i - N^L)$	move to AH
$N^*(B) \leq \theta_i + h < N^H(B)$, $N^A \leq \theta_i$	$s < \frac{c_{AH}-c_{BL}}{c_{AH}}(N^* - \theta_i)$	move to AH
$N^H(B) \leq \theta_i + h < N^H(A)$, $\theta_i < N^A$	$s > N^H - \theta_i - h - \frac{c_{BL}-c_{AL}}{c_{BH}-c_{AH}}(\theta_i - N^L)$	promote to BH
$N^H(B) \leq \theta_i + h < N^H(A)$, $N^A \leq \theta_i$	$s > N^H - \theta_i - h - \frac{c_{AH}-c_{BL}}{c_{BH}-c_{AH}}(N^* - \theta_i)$	promote to BH
$N^H(A) \leq \theta_i + h$	all s	promote to BH
First Period AH		
Case B: $N^L \leq \theta_i < N^*$	(Myopic Suboptimal)	
$N^*(A) \leq \theta_i + h < N^*(B)$, $N^A \leq \theta_i$	$s > 2(N^* - \theta_i) - h$	stay in AH
$N^*(B) \leq \theta_i + h < N^H(B)$, $N^A \leq \theta_i$	$s > \frac{c_{AH}-c_{BL}}{c_{AH}}(N^* - \theta_i)$	stay in AH
$N^H(B) \leq \theta_i + h < N^H(A)$, $N^A \leq \theta_i$	$s < N^H - \theta_i - h - \frac{c_{AH}-c_{BL}}{c_{BH}-c_{AH}}(N^* - \theta_i)$	stay in AH

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