Why Don't Firms Hire Young Workers During Recessions?

Eliza C. Forsythe*

January 11, 2014

Abstract

Using data from the CPS, I find that during recessions the probability of being hired falls for young workers, while for experienced workers it rises. I argue this can be explained by firms choosing to hire workers with greater work experience when labor markets are slack. I extend Michaillat's 2012 search and matching model to allow for heterogeneous workers and firms. I find sufficient conditions such that firms optimally choose not to hire young workers during downturns: (1) worker productivity increases with experience, and firm production functions exhibit (2) diminishing marginal productivity of labor and (3) fixed operating costs per position. 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.

JEL Classification Numbers: E32, J11, J23, J62, M51

*MIT Department of Economics, 77 Massachusetts Avenue, E19-750 Cambridge, MA 02139, Email: forsythe@mit.edu. See http://economics.mit.edu/grad/forsythe/research for the most recent version of this paper. I am grateful to my advisors Bob Gibbons, Daron Acemoglu and David Autor for their guidance and support. I also thank Adam Sarcany, Jennifer Peck, Conrad Miller, Benjamin Feigenberg, Miikka Rokkanen, Annalisa Scognamiglio, Henry Swift, Stephanie Hurder, and participants at the MIT labor, organizational, and summer applied microeconomics field lunches for useful comments and suggestions, and Natty Forsythe for editorial assistance.

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 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

[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

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 recessions. 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

[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.

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),

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

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 (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 pro-cyclical, 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 and 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

[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.

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 2, I describe the data and the empirical strategy. Section 3 presents the main empirical results. Section 4 develops the model and derives testable predictions. Section 5 describes the construction of the occupational quality indices and wage data, and presents further results. I offer conclusions in Section 6.

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), 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 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 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:

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

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

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

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

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 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 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.

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 2 shows substantial reductions in hiring during each recession, with levels as of late 2013 still well below the peak in 2000. In the second panel of Figure 2, I plot the share of workers hired each month in the CPS (see Section 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 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 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-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 2 contains the main empirical results, as described in Equation 1 and illustrated in Figure 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 potential 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 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 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 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.

3.1 Sensitivity Analysis

Next I explore the robustness of the finding that experienced workers' probability of hiring rises during recessions. Figure 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 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 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.

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 5a–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 5d–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 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 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.

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 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.

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 5, where I introduce evidence on occupation 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 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.

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.

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

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

per worker employed. Thus, the firm solves following problem:

$$\max_{N_L, N_H} g(A, \gamma N_L + N_H) - N_L(k + w_L) - N_H(k + w_H) - C(q(A), N_L, N_H) \tag{2}$$

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 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 $V_L = \dfrac{H_L}{q(A)\delta}$ vacancies, and to hire H_H high-skill workers, the firm must post $V_H = \dfrac{H_H}{q(A)(1-\delta)}$ 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:

$$w_L = \gamma\beta \frac{\partial g}{\partial N}(A, N) - \beta k \tag{3}$$

$$w_H = \beta \frac{\partial g}{\partial N}(A, N) - \beta k \tag{4}$$

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,

$$\max_{V_A, V_H} g(A, \gamma N_L + N_H) - N_L(w_L + k) - N_H(w_H + k) - c \times (V_A + V_H)$$

$$\text{such that} \quad N_L = q(A)\delta V_A, \quad N^H = \frac{1-\delta}{\delta}(\delta q(A) V_A) + (1-\delta) q(A) V_H,$$

$$w_L = \gamma\beta \frac{\partial g}{\partial N}(A, N) - \beta k \text{ and } w_H = \beta \frac{\partial g}{\partial N}(A, N) - \beta k \tag{5}$$

The first-order conditions are as follows:

$$V_A\colon (1-\beta)\frac{\partial g}{\partial N}(N^*) - \beta N^* \frac{\partial^2 g}{\partial N^2}(N^*) \leq \frac{(1-\beta)k}{1-\delta+\gamma\delta} + \frac{c}{q(A)(1-\delta+\gamma\delta)} \tag{6}$$

$$V_H\colon (1-\beta)\frac{\partial g}{\partial N}(N^*) - \beta N^* \frac{\partial^2 g}{\partial N^2}(N^*) \leq (1-\beta)k + \frac{c}{q(A)(1-\delta)} \tag{7}$$

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 $\dfrac{\partial g}{\partial N}(N) < 0$ by construction, a sufficient condition is $\beta < \dfrac{1}{2}$ and $\dfrac{\partial^3 g}{\partial N^3}(N) \geq 0$. 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

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

decreasing with A by assumption, we have the firm will hire all workers if

$$A \geq \hat{A} \text{ such that } \frac{1}{q(\hat{A})} = \frac{1-\gamma}{\gamma} \frac{k(1-\delta)(1-\beta)}{c} \tag{8}$$

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).

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.

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.

4.2.1 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:

$$x(N^V, N^S) = \frac{N^V N^S}{N^V + N^S} \tag{9}$$

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

$$p_{ij} = \frac{N_{Vj} I_{ij}}{N_S + N_V} \tag{10}$$

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

$$q_{iB} = \frac{N_{Ui}}{N_S + N_V} \tag{11}$$

$$q_{iG} = \frac{N_{Si}}{N_S + N_V} \tag{12}$$

where Equation 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:

$$N_S = N_{SL} + N_{SH} \tag{13}$$

$$N_{Si} = N_{Ui} + N_{Bi}, \text{ for } i = \{L, H\} \tag{14}$$

$$N_V = N_{VB} + \sum_{j=1}^{M} N_{VGjt} \tag{15}$$

4.2.2 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,

$$N'_{UL} = (1 - p'_{GL} - p'_{BL})N_{UL} + s(N'_{BL} + N'_{GL}) \tag{16}$$

$$N'_{UH} = (1 - p'_{GH} - p'_{BH})N_{UH} + s(N'_{BH} + N'_{GH}) \tag{17}$$

$$N'_{BL} = (1 - s - p'_{GL})N_{BL} + p'_{BL}N_{UL} \tag{18}$$

$$N'_{BH} = (1 - s - p'_{GH})N_{BH} + p'_{BH}N_{UH} \tag{19}$$

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

[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.

workers in bad jobs,

$$N_{GL} = \delta - N_{UL} - N_{BL} \tag{20}$$

$$N_{GH} = 1 - \delta - N_{UH} - N_{BH} \tag{21}$$

Using the expressions for the probability of a worker matching with a vacancy (p_{ij}) from Equation 10, we can rewrite Equations 16-19 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.

4.2.3 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:

$$V_B = -c_b + q_L(J_{BL} - V_B') + (1-r)q_H(J_{BH} - V_B') \tag{22}$$

$$J_{BL} = A\gamma F^B - w_{BL} + (1-r)(1-s)(1-p_{GL}')J_{BL}' + (1-r)(s + (1-s)p_{GL}')V_B' \tag{23}$$

$$J_{BH} = AF^B - w_{BH} + (1-r)(1-s)(1-p_{GH}')J_{BH}' + (1-r)(s + (1-s)p_{GH}')V_B' \tag{24}$$

By free entry, each period V_b is driven to zero, thus we can re-write Equation 22 as

$$c_b = q_L J_{BL} + q_H J_{BH} \tag{25}$$

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

$$(1-\beta)(E_{Bi} - U_i) = \beta J_{Bi} \tag{26}$$

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:

$$U_i = (1-r)(1-p'_{Bi}-p'_{Gi})U'_i + (1-r)p'_{Bi}E'_{Bi} + (1-r)p'_{Gi}E'_{Gi} \tag{27}$$

$$E_{Bi} = w_{Bi} + (1-r)(1-s)(1-p'_{Gi})E'_{Bi} + (1-r)(1-s)p'_{Gi}E'_{Gi} + (1-r)sU'_i \tag{28}$$

$$E_{Gi} = w_{Gi} + (1-r)(1-s)E'_{Gi} + (1-r)sU'_i \tag{29}$$

Combining and rearranging Equations 27 and 28 yields

$$E_{Bi} = U_i + w_{Bi} + (1-r)((1-s)(1-p'_{Gi}) - p'_{Bi})(E'_{Bi} - U'_i) - (1-r)p'_{Gi}s(E'_{Gi} - U'_i) \tag{30}$$

which combined with the bargaining equation yields expressions for wages

$$w_{BL} = \beta A\gamma F^B + \beta(1-r)p'_{BL}J'_{BL} + (1-\beta)(1-r)p'_{GL}s(E'_{GL} - U'_L) \tag{31}$$

$$w_{BH} = \beta AF^B + \beta(1-r)p'_{BH}J'_{Bh} + (1-\beta)(1-r)p'_{GH}s(E'_{GH} - U'_H) \tag{32}$$

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.

$$J_{BL} = \frac{(1-\beta)A\gamma F^B - (1-\beta)(1-r)p_{GL}s(E_{GL} - U_L)}{1-(1-r)(\beta p_{BL} + (1-s)(1-p_{GL}))} \tag{33}$$

$$J_{BH} = \frac{(1-\beta)AF^B - (1-\beta)(1-r)p_{GH}s(E_{GH} - U_H)}{1-(1-r)(\beta p_{BH} + (1-s)(1-p_{GH}))} \tag{34}$$

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.

4.2.4 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 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

$$\max_{\{V_A, V_H\, F_L, F_H\}_{t=0}^{t=\infty}} \sum_{t=0}^{\infty} (1-r)^t \Big[g(N_t) - (w_{Lt}+k)(N_{Lt}) - (w_{Ht}+k)(N_{Ht}) - c(V_{At}+V_{Ht}) \Big] \quad (35)$$

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:

$$J_{GL} = \gamma \frac{\partial g(N^t)}{\partial N} - k - w^{GL} + (1-r)(1-s) J'_{GL} \quad (36)$$

$$J_{GH} = \frac{\partial g(N^t)}{\partial N} - k - w^{GH} + (1-r)(1-s) J'_{GH} \quad (37)$$

and thus the bargaining condition is

$$(1-\beta)(E_{Gj} - U_j) = \beta J_{Gj} \quad (38)$$

Using Equations 36, 37, and 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

$$w_{GL} = \gamma \frac{\partial g(N^t)}{\partial N} - k - \Omega_L \tag{39}$$
$$w_{GH} = \frac{\partial g(N^t)}{\partial N} - k - \Omega_H \tag{40}$$

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 35, yielding the following optimality conditions:

$$\frac{\partial}{\partial V_{At}} : -\frac{\partial^2 g(N_t)}{\partial N_t^2}(\gamma N_{Lt} + N_{Ht}) - (1-r)(1-s)\frac{\partial^2 g(N_{t+1})}{\partial N_{t+1}^2}(\gamma N_{Lt+1} + N_{Ht+1}) = \frac{c - q_{LGt}(\Omega_{Lt} + (1-r)(1-s)\Omega_{Lt+1}) - q_{HGt}(\Omega_{Ht} + (1-r)(1-s)\Omega_{Ht+1})}{\gamma q_{LGt} + q_{HGt}} \tag{41}$$

$$\frac{\partial}{\partial V_{Ht}} : -\frac{\partial^2 g(N_t)}{\partial N_t^2}(\gamma N_{Lt} + N_{Ht}) - (1-r)(1-s)\frac{\partial^2 g(N_{t+1})}{\partial N_{t+1}^2}(\gamma N_{Lt+1} + N_{Ht+1}) = \frac{c - q_{HGt}(\Omega_{Ht} + (1-r)(1-s)\Omega_{Ht+1})}{q_{HGt}} \tag{42}$$

As in the example in Section 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

$$\frac{1}{q_{GHt}} \geq \frac{\gamma \Omega_{Ht} - \Omega_{Lt} + (1-r)(1-s)(\gamma \Omega_{Ht+1} - \Omega_{Lt+1})}{\gamma c} \tag{43}$$

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 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 the 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 25), the good firms' optimization problem (Equation 35), and the laws of motion for worker flows (Equations 16-19).*

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 43) becomes:

$$\frac{1}{q_H} \geq \frac{1-\beta}{\beta} \frac{(1+(1-r)(1-s))^2(\gamma J_{GH} - J_{GL})}{\gamma c} \tag{44}$$

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:

$$c_b = q_L J_{BL} + q_H J_{BH} \tag{45}$$

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

$$\hat{J_{GL}} = (1-\beta)\gamma g(N^*) - (1-\beta)k \tag{46}$$

$$\hat{J_{GH}} = (1-\beta)g(N^*) - (1-\beta)k \tag{47}$$

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.

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 $\overline{A}$ 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 economies in the $\overline{A}$ equilibrium and $\underline{A}$ equilibrium respectively?

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

$$\text{Pr(EE mobility} \mid \text{employed worker type } i) = \frac{p_{Gi} N_{Bi}}{N_{Bi} + N_{Gi}} \tag{48}$$

$$\text{Pr(hired} \mid \text{nonemployed worker type } i) = p_{Gi} + p_{Bi} \tag{49}$$

For low-skill workers, since p_{GL} is zero in the $\underline{A}$ economy, all mobility is reduced compared with the $\overline{A}$ 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 $\overline{A}$ 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 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 $\overline{A}$ 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.*

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 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 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 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 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

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

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 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, 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 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.

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 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.

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 inconsistent 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.

References

Abraham, K., & Spletzer, J. (2009). New Evidence on the Returns to Job Skills. *The American Economic Review*, 52–57.

Acemoglu, D. (1999). Changes in Unemployment and Wage Inequality: an Alternative Theory and Some Evidence. *The American Economic Review*.

Acemoglu, D. (2001). Good Jobs versus Bad Jobs. *Journal of Labor Economics*, *19*(1), 1–21.

Akerlof, G., Rose, A., & Yellen, J. (1988). Job Switching and Job Satisfaction in the US Labor Market. *Brookings Papers on Economic Activity*, *1988*(2), 495-594.

Barlevy, G. (2002). The Sullying Effect of Recessions. *Review of Economic Studies*, *69*(1), 65-96.

Bewley, T. (1999). *Why Don't Wages Fall During Recessions?* Mass: Cambridge.

Davis, S., & Haltiwanger, J. (1999). Gross Job Flows. *Handbook of Labor Economics*, *3*.

Devereux, P. J. (2002). Occupational Upgrading and the Business Cycle. *Labour*, *16*(3), 423-452.

Diamond, P. (1982). Wage Determination and Efficiency in Search Equilibrium. *Review of Economics Studies*, *49*(2), 217-227.

Elsby, M., & Michaels, R. (2013, January). Marginal Jobs, Heterogeneous Firms, and Unemployment Flows. *American Economic Journal: Macroeconomics*, *5*(1), 1–48.

Elsby, M., Michaels, R., & Solon, G. (2009a). The Ins and Outs of Cyclical Unemployment. *American Economic Journal*(November 2006), 84–110.

Elsby, M., Michaels, R., & Solon, G. (2009b). The Ins and Outs of Cyclical Unemployment. *American Economic Journal*(November 2006), 84–110.

Fallick, B., & Fleischman, C. (2004). *Employer-to-Employer Flows in the US Labor Market: The Complete Picture of Gross Worker Flows.*

Hall, R. (2005). Employment Fluctuations with Equilibrium Wage Stickiness. *American Economic Review*, *95*(1), 50–65.

Hoynes, H., Miller, D. L., & Schaller, J. (2012). Who Suffers During Recessions? *Journal of Economic Perspectives*, *26*(3), 27–48.

Hyatt, H., & McEntarfer, E. (2012). Job-to-Job Flows in the Great Recession. *American Economic Review*, *102*(3), 580–583.

Hyatt, H., & Spletzer, J. (2013). *The Recent Decline in Employment Dynamics* (No. 7231).

Kahn, L. B. (2008). Job Durations , Match Quality and the Business Cycle : What We Can Learn from Firm Fixed Effects.

Kahn, L. B. (2010). The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy. *Labour Economics*, *17*(2), 303-316.

Kahn, L. B., & Mcentarfer, E. (2013). *Worker Flows Over the Business Cycle : the Role of Firm Quality.*

Lazear, E. P., & Spletzer, J. (2011). *Hiring, Churn and the Business Cycle.*

Madrian, B. C., & Lefgren, L. J. (1999). A Note on Longitudinally Matching Current Population Survey (CPS) Respondents. *NBER Working Paper No. t0247.*.

McLaughlin, K. J., & Bils, M. (2001). Interindustry Mobility and the Cyclical Upgrading of Labor. *Journal of Labor Economics*, *19*(1), 94–135.

Michaillat, P. (2012). Do Matching Frictions Explain Unemployment? Not in Bad Times. *American Economic Review*, *102*(4), 1721–1750.

Molloy, R., Smith, C., & Wozniak, A. (2013). *Declining Migration within the US: the Role of the Labor Market.*

Mortensen, D. (1982, December). Property Rights and Efficiency in Mating, Racing and Related Games. *American Economic Review*, *72*, 968-979.

Nagypál, E. (2008). *Worker Reallocation over the Business Cycle: The Importance of Employer-to-Employer Transitions.*

Okun, A. (1973). Upward Mobility in a High-Pressure Economy. *Brookings Papers on Economic Activity*.

Oreopoulos, P., Von Wachter, T., & Heisz, A. (2012). The Short- and Long-Term Career Effects of Graduating in a Recession. *American Economic Journal: Applied Economics*, *4*(1).

Pissarides, C. (1990). *Equilibrium Unemployment Theory.* Cambridge, MA.: Basil Blackwell.

Pissarides, C. (1994). Search Unemployment with On-the-Job Search. *The Review of Economic Studies*, *61*(3), 457–475.

Poletaev, M., & Robinson, C. (2008). Human Capital Specificity: Evidence from the

Dictionary of Occupational Titles and Displaced Worker Surveys, 19842000. *Journal of Labor Economics*, *26*(3), 387–420.

Reder, M. (1955). The Theory of Occupational Wage Differentials. *The American Economic Review*, *45*(5), 833–852.

Shimer, R. (2012). Reassessing the Ins and Outs of Unemployment. *Review of Economic Dynamics*, *15*(2), 127–148.

Stole, L., & Zwiebel, J. (1996). Intra-firm bargaining under non-binding contracts. *The Review of Economic Studies*, *63*(3), 375–410.

Topel, R. H., & Ward, M. P. (1992). Job Mobility and the Careers of Young Men. *The Quarterly Journal of Economics*, *107*(2), 439-479.

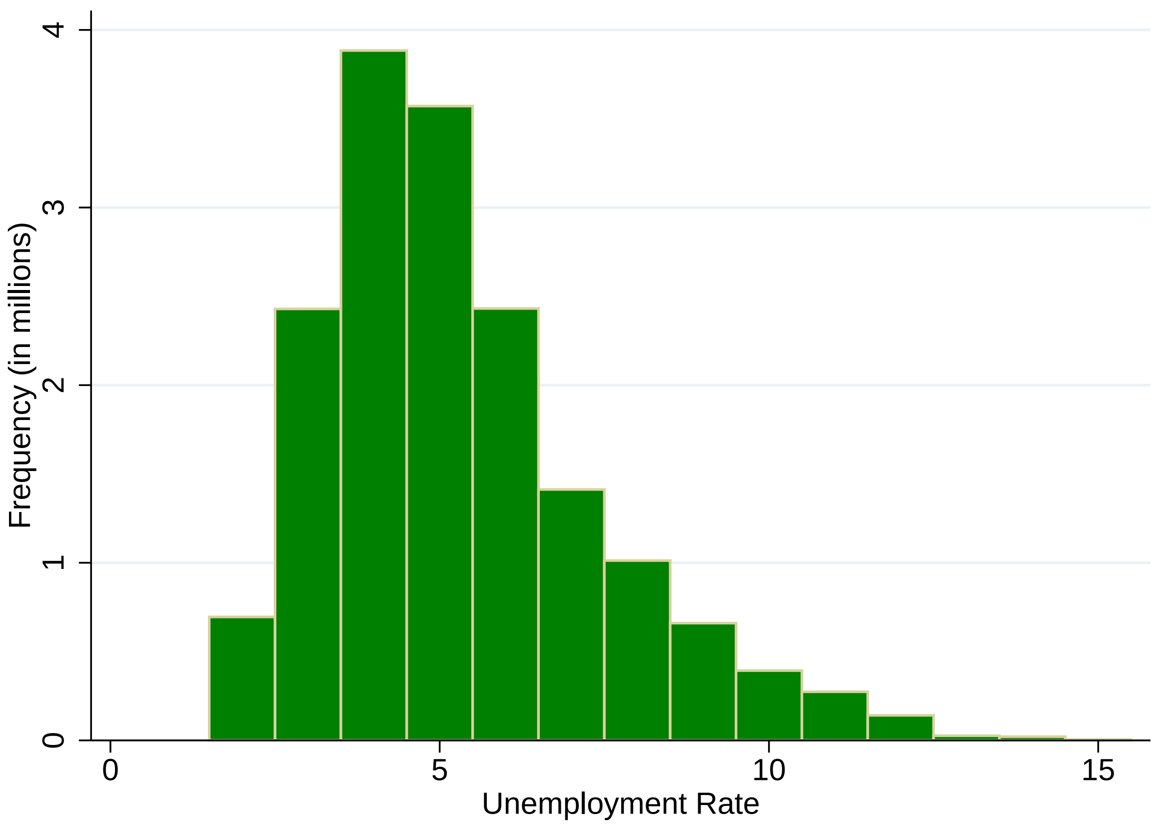
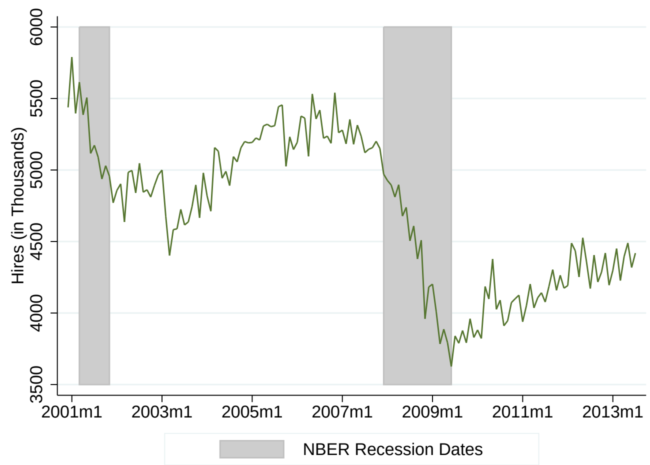
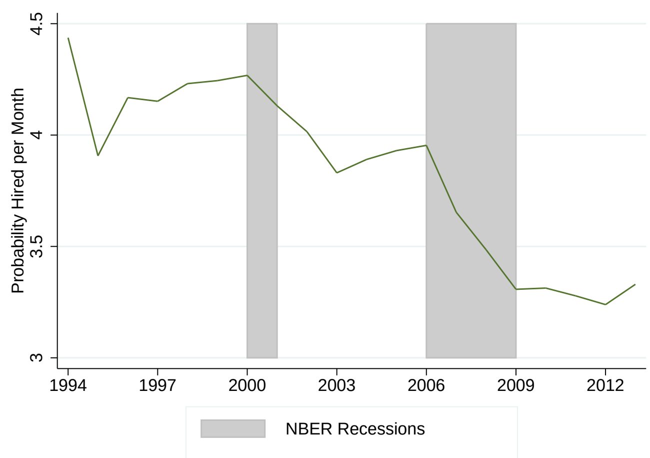


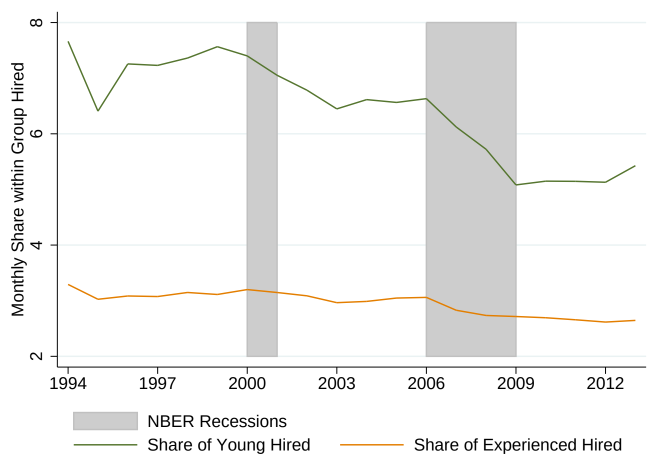
Figure 1: Distribution of Observations by State Unemployment Rate



(a) Seasonally Adjusted Monthly Hiring Flows, JOLTS

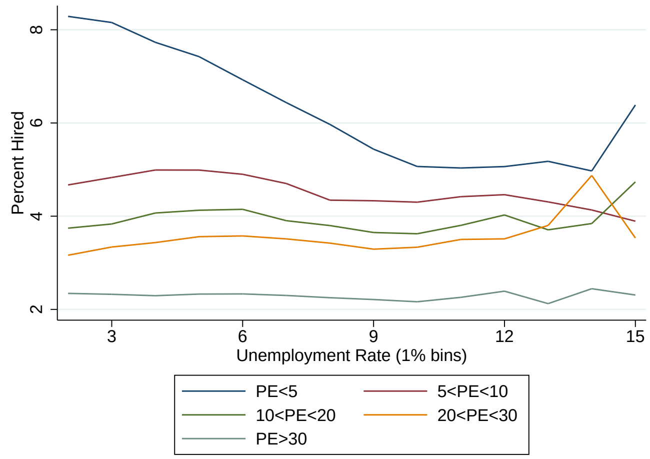


(b) Fraction Hired per Month, CPS

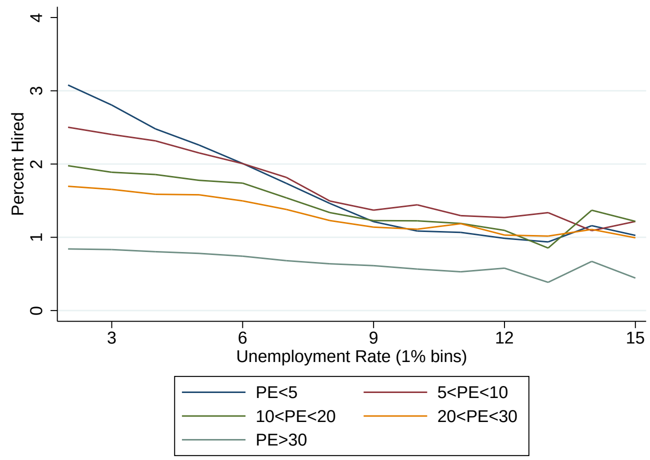


(c) Fraction Hired per Month, CPS

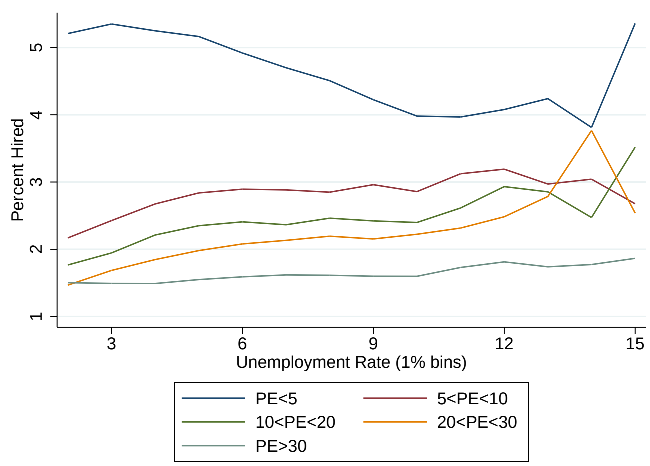
Figure 2: Hiring Over the Business Cycle



(a) Hire Rate, All Hires

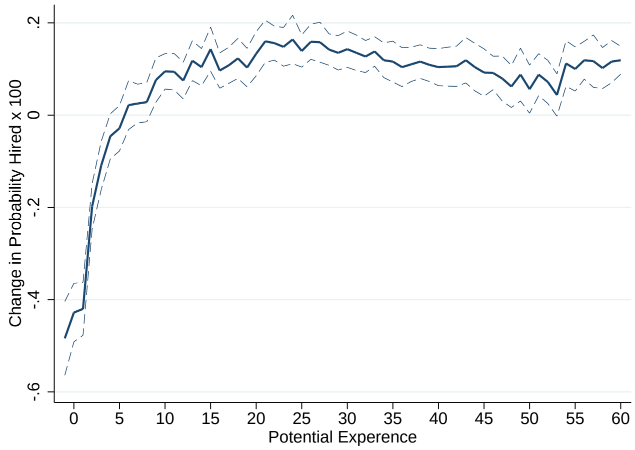


(b) Hire Rate from Employment

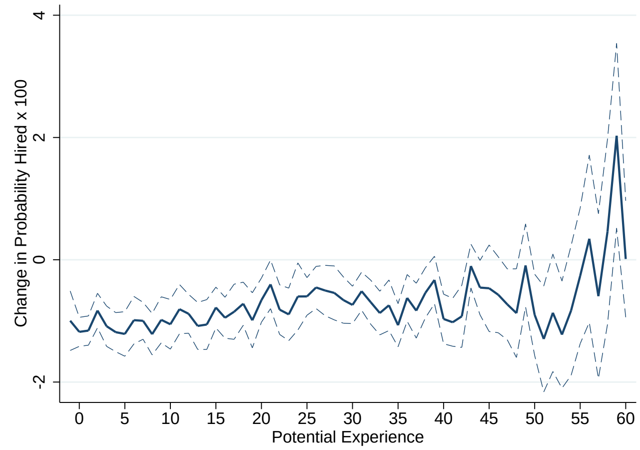


(c) Hire Rate from Non-Employment

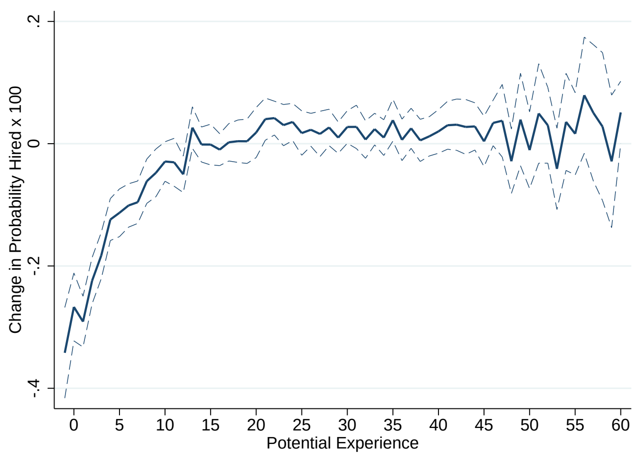
Figure 3: Hiring Rates by State Unemployment Rate



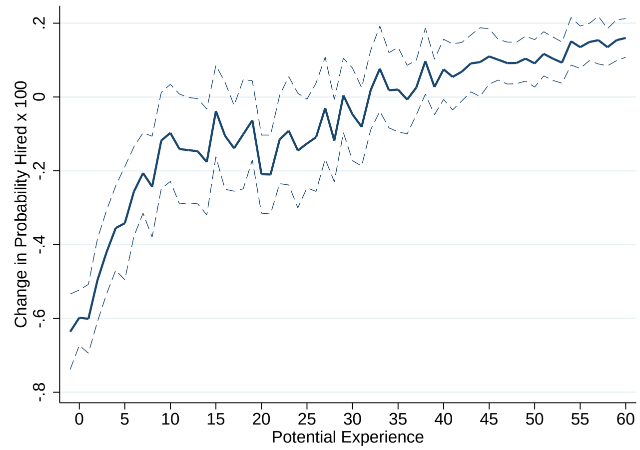
(a) All Hires



(b) UE Hires

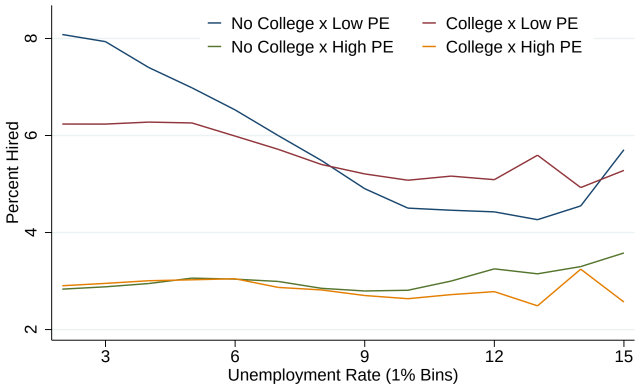


(c) EE Hires

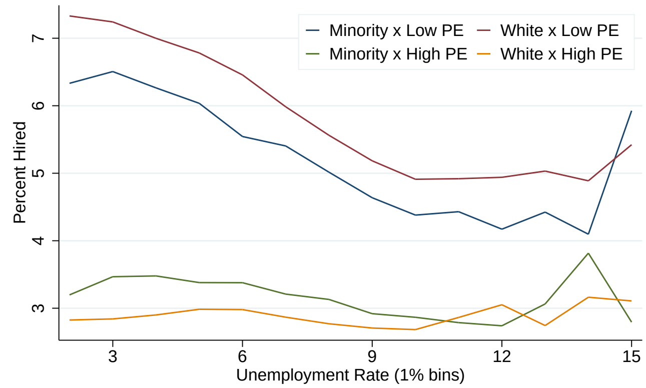


(d) NILFE Hires

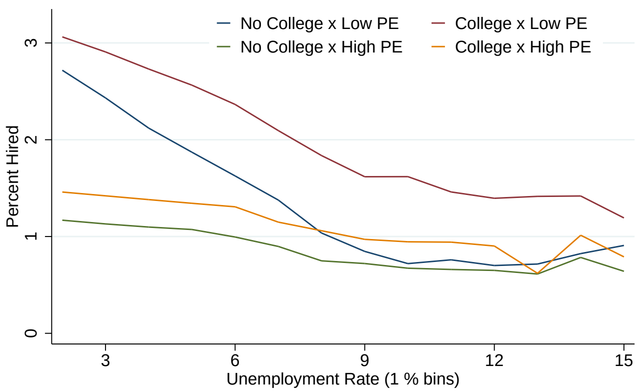
Figure 4: Coefficients from regressing probability of hire on the state unemployment rate for one year potential experience bins, partialling out main effects and state and month-year fixed effects. Figures include 95% confidence intervals.



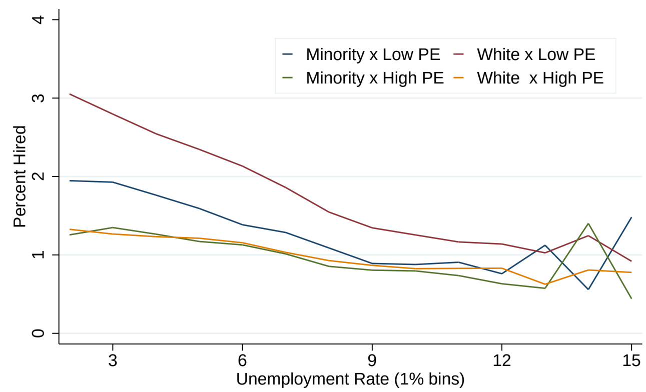
(a) All hires: Potential Experience × Education



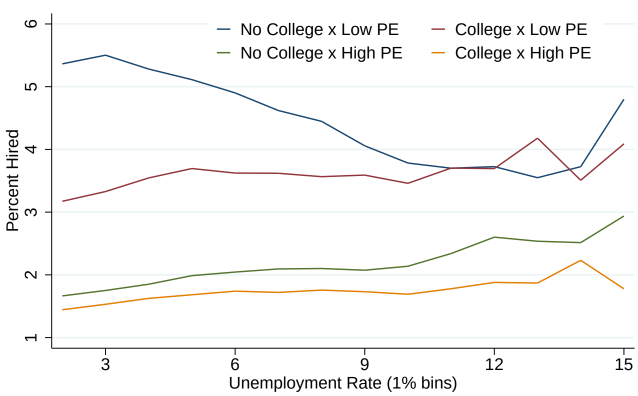
(d) All Hires: Potential Experience × Race



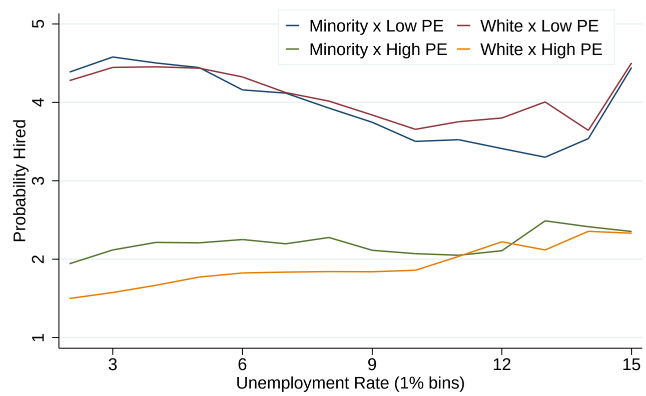
(b) EE Hires: Potential Experience × Education



(e) EE Hires: Potential Experience × Race



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



(f) NEE Hires: Potential Experience × Race

Figure 5: Hiring by Education and Race

Table 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

Table 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 $\times$ U. Rate	-0.484***	-0.997***	-0.342***	-0.637***
	(0.0409)	(0.248)	(0.0378)	(0.0522)
0 $\leq$PE$<$ 1 $\times$ U. Rate	-0.429***	-1.179***	-0.268***	-0.598***
	(0.0324)	(0.121)	(0.0284)	(0.0383)
1 $\leq$PE$<$ 2 $\times$ U. Rate	-0.420***	-1.158***	-0.291***	-0.601***
	(0.0293)	(0.122)	(0.0212)	(0.0477)
2 $\leq$PE$<$ 3 $\times$ U. Rate	-0.199***	-0.831***	-0.224***	-0.496***
	(0.0252)	(0.144)	(0.0193)	(0.0574)
3 $\leq$PE$<$ 4 $\times$ U. Rate	-0.109***	-1.088***	-0.183***	-0.421***
	(0.0267)	(0.168)	(0.0193)	(0.0575)
4 $\leq$PE$<$ 5 $\times$ U. Rate	-0.0461	-1.184***	-0.124***	-0.356***
	(0.0248)	(0.163)	(0.0175)	(0.0582)
5 $\leq$PE$<$ 6 $\times$ U. Rate	-0.0289	-1.213***	-0.114***	-0.342***
	(0.0251)	(0.186)	(0.0199)	(0.0784)
6 $\leq$PE$<$ 7 $\times$ U. Rate	0.0214	-0.989***	-0.101***	-0.257***
	(0.0270)	(0.198)	(0.0181)	(0.0617)
7 $\leq$PE$<$ 8 $\times$ U. Rate	0.0248	-0.999***	-0.0958***	-0.207***
	(0.0214)	(0.154)	(0.0177)	(0.0555)
8 $\leq$PE$<$ 9 $\times$ U. Rate	0.0279	-1.218***	-0.0614**	-0.244**
	(0.0217)	(0.173)	(0.0185)	(0.0698)
9 $\leq$PE$<$ 10 $\times$ U. Rate	0.0757**	-0.982***	-0.0477*	-0.119
	(0.0244)	(0.192)	(0.0199)	(0.0667)
10 $\leq$PE$<$ 15 $\times$ U. Rate	0.0975***	-0.977***	-0.0166	-0.141*
	(0.0153)	(0.134)	(0.0112)	(0.0560)
15 $\leq$PE$<$ 20 $\times$ U. Rate	0.115***	-0.854***	-0.0000752	-0.0900*
	(0.0152)	(0.145)	(0.0109)	(0.0436)
20 $\leq$PE$<$ 25 $\times$ U. Rate	0.152***	-0.675***	0.0332**	-0.155***
	(0.0169)	(0.152)	(0.0112)	(0.0435)
25 $\leq$PE$<$ 30 $\times$ U. Rate	0.146***	-0.550***	0.0184	-0.0755
	(0.0144)	(0.112)	(0.0114)	(0.0450)
30 $\leq$PE$<$ 35 $\times$ U. Rate	0.132***	-0.716***	0.0191	-0.001000
	(0.0134)	(0.113)	(0.0107)	(0.0350)
35 $\leq$PE$<$ 40 $\times$ U. Rate	0.110***	-0.699***	0.0180	0.0336
	(0.0141)	(0.126)	(0.0118)	(0.0304)
40 $\leq$PE$<$ 45 $\times$ U. Rate	0.107***	-0.743***	0.0270*	0.0788*
	(0.0179)	(0.128)	(0.0133)	(0.0362)
45 $\leq$PE$<$ 50 $\times$ U. Rate	0.0832***	-0.548**	0.0166	0.100***
	(0.0195)	(0.195)	(0.0147)	(0.0259)
PE$\geq$ 50 $\times$ 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 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.

Table 4: Hiring Without Time Fixed Effects

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

Table 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 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.

Table 7: Youth Share of Hires

Outcome: $Pr(young \mid hired)$	(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.

Table 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 of 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 of 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 of Ed.	-0.0592
	Acute Care Nurses	Dealing with aggressive people	Age	-0.0436

Table 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.

Table 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.