Why Don't Firms Hire Young Workers During Recessions?

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Abstract

Recessions are known to be particularly damaging to young workers' employment outcomes. I find that during recessions the hiring rate falls faster for young workers than for more-experienced workers. I show this cannot be explained by the composition of jobs or workers' labor supply decisions, and I conclude that firms preferentially hire experienced workers during periods of high unemployment. I develop a new model of cyclical upgrading that relaxes the classic assumptions of exogenous firm size and rigid wages. I show this model predicts larger log wage decreases during recessions for young workers than for experienced workers, a prediction that is supported by the data. I conclude that policy makers should consider extending unemployment insurance coverage during recessions to new labor market entrants.

The costs of recessions fall particularly heavily on young workers. The unemployment rate for new labor market entrants rises more quickly during recessions than the rate for more-experienced workers. When young workers do find jobs during recessions, the jobs are more likely to be lower quality and lower paying than the jobs they could expect to find during economic expansions.[1]

The cause of these poor labor market outcomes for young workers remains an open question. Is it because the types of jobs that hire young workers are especially affected by

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[1]See, for instance, Hoynes, Miller, and Schaller (2012), Kahn (2010), Oreopoulos, Von Wachter, and Heisz (2012), and B. J. Hershbein (2012).

recessions? Is it due to labor-supply decisions, with young workers choosing not to accept the jobs that are available during recessions? Or is it due to *cyclically selective hiring*, that is, changes in firm hiring behavior during recessions? Such firm behavior may affect labor market outcomes for both non-employed and employed young workers. Disentangling this mechanism has direct policy implications. There are a variety of active labor market policies and social insurance programs governments may deploy to assist workers during recessions, and the efficacy of these programs will vary greatly depending on the source of the market failure.

I find that cyclically selective hiring is the most persuasive explanation for young workers' high unemployment rate and lack of job mobility during recessions. I accomplish this in three stages. First, I use state-level variation in the unemployment rate to show that the hiring rate falls much faster with the unemployment rate for young workers than for more-experienced workers. Second, I show this cannot be explained by the industry or occupational composition of job openings, nor can it be explained by heterogeneous labor supply behavior. Third, I develop a cyclical upgrading model with flexibly bargained wages and endogenous firm size. I then show cyclical wage changes are consistent with my model, and inconsistent with other leading models.

In the first part of the paper, I use matched monthly data from the Current Population Survey (CPS) to show that when the state unemployment rate is higher, young workers are significantly less likely to be hired. In contrast, hiring of more-experienced workers shows little variation with the unemployment rate. For instance, a five percentage point increase in the state unemployment rate is associated with a 1.7 percentage point decrease in the hiring rate for workers with less than or equal to ten years of potential experience (off of a mean hiring rate of 7.7 percent), while for workers with more than ten years of potential experience, the same increase is associated with at most a 0.18 percentage point decrease in the hiring rate (off a mean of 2.6 percent).

I first investigate whether cyclical changes in the industry or occupation of new jobs can account for the cyclical behavior of youth hiring. If younger and older workers choose to work in different types of jobs, cyclical changes in the composition of jobs could affect the age profile of new hires. However, I show that the average potential experience of new hires increases with the state unemployment rate within narrowly-defined industry and occupation cells, indicating the composition of jobs is not the primary driver of the fall in youth hiring during periods of high unemployment. I then consider the possibility that young workers may have more elastic labor supplies, substituting non-market activities such as education or family formation for market activity during periods of high unemployment. However, I show that worker availability and search behavior cannot account for the change in the age composition of hires. I thus turn to the labor demand side of the market to explain the cyclical changes in hiring.

If age is correlated with productivity through human capital accumulation or other transmission mechanisms, employers may prefer to hire more-experienced workers when there are many applicants per vacancy. Consistent with this, I show that education protect young workers from cyclical upgrading, with young workers with college degrees experiencing a substantially more modest decrease in hiring with the state unemployment rate. Nonetheless, for both college graduates and non-college graduates the changes in hiring rates exhibit a gradient with age, with individuals in the first five to ten years post-graduation experiencing a reduction in hiring with the state unemployment rate and individuals with more labor market experience exhibiting no such reduction in hiring.

I develop a stylized model of a single firm's hiring decision that includes random search, endogenous firm size, and wage bargaining with two types of workers. Young workers are less productive and a per head fixed cost results in higher costs to employ young workers per unit of output. However, it is also costly to only hire experienced workers, since the firm must post additional costly vacancies if they plan to only hire a portion of the applicant pool. Further, the number of vacancies needed to achieve a particular hiring target depends on how many job seekers there are per vacancy. Thus, I show that the firm's hiring strategy will vary depending on the state of the labor market: during economic expansions when there are fewer applicants per vacancy, the firm will hire all applicants. During downturns, as applicants per vacancy rises, the firm will switch to only hiring experienced applicants.

The model predicts young workers' log wages should be more cyclically responsive than experienced workers. In contrast, a frictionless competitive model predicts young and more-experienced workers' log wages should rise and fall identically over the business cycle, while a classic cyclical upgrading model predicts that wages should be rigid and thus acyclical. I show empirically that log wages fall faster with the state unemployment rate for young workers compared with more-experienced workers. This evidence offers clear support for the bargained cyclical upgrading model.

These results have important policy implications. Since young workers are particularly disadvantaged during recessions due to behavior by firms, I argue that policy makers should consider extending unemployment insurance systems to cover new labor market entrants. This would help insure young workers against the risk of entering the labor market during poor labor market conditions, which may have lasting effects on their careers (Kahn (2010), Oreopoulos et al. (2012)).

While the analysis in this article is based on data ending in 2016, these findings have a particular salience to the Covid-19 pandemic. During the early pandemic, young workers' hiring and employment fell substantially more than other age groups (Cortes and Forsythe (2020)), while at the same time, young non-employed workers were much less likely to report receiving unemployment insurance benefits (Forsythe (2021)). Thus, despite the massive expansion in unemployment insurance coverage in the United States, young workers were both disproportionately exposed to labor market risks and disproportionately underinsured.

However, by the summer of 2021 youth employment had recovered faster than some other age groups, in stark contrast to the recovery from the Great Recession (Cortes and Forsythe (2020)). A key difference from past recessions is that labor markets have been surprisingly tight, due to a lack of search by non-employed workers (Forsythe, Kahn, Lange, and Wiczer (2020)). Consistent with the model I develop in this paper, labor market tightness may have made it prohibitively expensive for employers to screen out young and inexperienced workers, preventing the typical slow recovery for young workers.

Although I find that firms hire more-experienced workers during recessions, the CPS evidence is not rich enough to document the mechanism by which firms accomplish this. B. Hershbein and Kahn (2018) and Modestino, Shoag, and Ballance (2015) find that firms change their job ads to request that workers have more years of relevant work experience when local labor markets are slack, indicating that some firms explicitly seek out more-experienced workers during recessions. Other firms may simply find their pool of applicants becomes more skilled, allowing the firm to hire more-experienced job seekers. This is supported by Bewley (1999) who found that managers reported an increase in both applicant volume and quality during the recession of the early 1990s, despite no changes in firm recruitment strategies.

This paper contributes to a growing literature on the effect of recessions on labor market flows. Fallick and Fleischman (2004) find that mobility between employers is pro-cyclical (also using data from the CPS) and I find similar patterns continuing through 2016. Hyatt and McEntarfer (2012) document a reduction in labor market reallocations during the Great Recession. Kahn and McEntarfer (2013) and Moscarini and Postel-Vinay (2016) find this fall in reallocations can be attributed to a reduction in separation rates from either low-wage firms or small firms, respectively. Since young workers have higher rates of mobility between firms overall and are more likely to be employed at low-wage firms, the fall in hiring rates I document for young workers is likely related to this fall in separation rates.

In addition, this paper contributes to a recent literature on how recessions can lead to inefficiencies in the labor market. Barlevy (2002) shows that recessions can reduce match quality when workers search on-the-job. In Barlevy's model, no workers are uniquely disadvantaged by the downturn, because worker-firm match quality is idiosyncratic. In contrast, under cyclically selective hiring the burden of reduced hiring falls on the least-productive workers. Michaillat (2012) shows that during recessions labor markets may suffer from what he calls *rationing unemployment*, that is, unemployment that persists even in the absence of matching frictions. Under cyclically selective hiring a firm's choice to not hire young workers during recessions has similar properties to rationing unemployment, which suggests that if firms find it optimal to ration employment they will first choose to ration the least-productive job seekers.

The structure of the paper is as follows. In Section 1, I describe the data and the empirical strategy. Section 2 presents the main empirical hiring results and investigates whether education can help insulate young workers from the effect of recessions on hiring. Section 3 shows that the composition of jobs and worker labor supply behavior cannot explain the fall in hiring. Section 4 develops the cyclically selective hiring model and presents wage evidence to distinguish between this model and other leading models. I offer conclusions and policy suggestions in Section 5.

1 Data Description and Empirical Strategy

I use variation in state unemployment rates to identify the effect of recessions on worker hiring rates. In order to measure hiring, I construct a panel from CPS monthly interviews conducted January 1994 through September 2016. The CPS has the advantages of a large sample size (approximately 72,000 households per month), monthly frequency, and detailed individual-level data. To capture labor market flows I use a procedure developed by Madrian and Lefgren (1999), matching individuals using administrative IDs and confirming matches using sex, race, and age.[2]

Before 1994, employment questions were structured in such a way as to prevent observation of mobility between firms. Such mobility comprises a significant fraction of hires (approximately one-third in this sample); thus I begin my sample in 1994. I further restrict it to individuals with non-missing age and education data for whom the CPS collected employment data (civilians over the age of 16). This leaves a sample of 16.9 million observations.[3] Table B.1 shows summary statistics of the data.

I use the state monthly unemployment rate as a proxy for local business cycle conditions. An advantage to using the unemployment rate over other business cycle metrics is that it

[2] The CPS sampling frame is constructed using physical addresses and does not follow individuals after a move; thus, estimates of job mobility using CPS data will underestimate true mobility. Saks and Wozniak (2011) find that interstate migration does vary cyclically, with young workers more responsive to labor market conditions. However, in Section 3.2 I show evidence that the sample does not appear to suffer from such cyclical attrition.

[3] Data from May through August 1995 are missing their longitudinal link ID, which prevents matching months, so these dates have been excluded. I also exclude pairs of months spanning the eight month sampling break between the fourth and fifth months of the survey.

serves as a measure of the stock of job-seekers, which is an important determinant of hiring behavior in the model. Ideally I would use information on job seekers regardless of current employment status; however, the CPS only surveys non-employed individuals about their job search behavior. Using variation at the state level permits controlling for national and time-series events via month-year dummy variables, while still providing sufficient power to include state fixed effects to dispose of any state heterogeneity in labor flows. There are 51 state unemployment rates per month, including the District of Columbia.

Since the CPS does not directly collect an individual's labor force 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 typical worker could have been in the labor market.

The basic empirical specification is as follows:

$$D^{\text{hired}}_{ikst} = \alpha_s + \delta_t + \sum_{k=1}^{K} (\beta_k D^{\text{PE}}_k + \gamma_k \times D^{\text{PE}}_k \times \text{State Unemp. Rate}_{st}) + \epsilon_{ikst}, \qquad (1)$$

where D^{hired} is an indicator that is equal to 100 if individual worker i is hired in month t, given worker i is in potential experience group k, resides in state s, and is observed in month-years $t-1$ and t. D^{PE}_k is an indicator equal to 1 if the worker is in potential experience group k. Since the object of interest is the different evolution of hiring for workers across experience categories, I exclude the main effect of the state unemployment rate in exchange for including all potential experience interactions with the state unemployment rate.

A worker is hired if one of two things happens: (1) he is non-employed in period $t-1$ and employed in period t, or (2) he is employed in period $t-1$ and in period t indicates he has changed firms since last month. Workers whose new job is classified as self-employed are not counted as hires, to ensure that every employment change is the result of a hiring decision. In some specifications I restrict the sample based on the worker's labor market status in period $t-1$.

The error term ϵ_{ikst} includes any other sources of variation in the worker's probability of being hired. As mobility rates are likely correlated within states, I cluster standard errors at the state level. I weight all specifications using the average of the CPS sampling weights between the pairs of months. The coefficient of interest, γ_k, measures the responsiveness of hiring rates to the state unemployment rate for a worker in potential experience group k. The null hypothesis is that the γ's are equal across potential experience groups.

In the main regressions I interact the state unemployment rate with one-year potential experience bins, allowing the data to reveal the exact number of years of potential experience at which the hiring rates become positive. For clarity of exposition, I will also divide the sample into young workers (those with less than or equal to ten years of potential experience) and experienced workers (those with more than ten years of potential experience). This is consistent with the definition of young workers used by Topel and Ward (1992) as a break point in job mobility rates, and also reflects the approximate inflection point in cyclical hiring rates in my data. In Columns (2) and (3) of Table B.1 I show how average worker characteristics vary between young and experienced workers. Young workers have slightly fewer years of education and are slightly more likely to be female, non-white, and Hispanic. In most specifications, I include non-parametric demographic fixed effects[4] to ensure demographic differences in labor market behavior are not driving differences between potential experience groups. In practice these characteristics appear to have little impact on the estimates and all results are robust to excluding these controls.

My preferred specification does not restrict hires based on their labor market status in period $t-1$. Although historically many analyses of hiring only included hires from unemployment, there are two drawbacks to this approach. First, individuals' membership in the labor force varies over the business cycle, so the sample varies 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 in-the-labor-force during the previous month, while about a third are hired from employment. Thus, from a firm's perspective, the appropriate set of potential hires includes all working-age individuals, which is the measure I use.

2 Hiring over the Business Cycle

In this section, I present the key empirical fact: that hiring rates change differentially with potential experience during periods of high unemployment rates. I then present several additional related facts, investigating how other labor market flows vary cyclically.

2.1 Hiring

The share of young workers hired fell dramatically during the two recessions of the 2000s, while the share of experienced workers hired exhibited much more modest variation. Figure 1 shows that during the 2001 recession the share of young workers hired each month dropped by about half of a percentage point, while during the Great Recession it fell another percentage

[4]Specifically, indicators for the interaction between four sets of demographic characteristics: gender, race (white and non-white), Hispanic descent, and education (less than high school degree, high school degree, some college, four year college degree, masters degree, professional degree, and PhD)

point. In contrast, for workers with more than ten years of potential experience the monthly share of hires exhibited minimal cyclical response.

Since the hiring rates of young workers also exhibit a strong secular decline over the time period, in the bottom graph of Figure 1 I apply an HP-filter to the annualized hiring rates in order to isolate the cyclical response. Here we see that the youth hiring rate is strongly cyclical, while the hiring rate for more-experienced workers is largely acyclical.

Panel A of Table 1 shows how the hiring rate for all working-age individuals in the sample varies with the state unemployment rate. Column (1) shows the raw data with no fixed effects: one additional percentage point of the state unemployment rate is associated with a 0.1 percentage point reduction in the hiring rate off of a base of 3.2% of individuals hired per month, which is significant at the .01% level. Including state and demographic fixed effects does not change the basic relationship, although including month-year fixed effects does reduce the magnitude of the effect by more than two-thirds. The primary result is that hiring rates decrease with the state unemployment rate in a small but statistically significant way.

Panel B of Table 1 expands the analysis to compare cyclical changes in hiring for young and experienced workers. This represents the results from a regression run using the specification from Equation 1 with two potential-experience groups (one with less than or equal to ten years of potential experience and the other with more than ten years of potential experience). Column (1) shows that, without any controls, an additional percentage point of unemployment decreases young workers' hiring rate by 0.34 percentage points off of a base rate of 7.7% of young workers hired per month. This amounts to a 4% decrease in hiring for each one percentage point increase in the state unemployment rate. In comparison, experienced workers show an 0.04 percentage point reduction in hiring, off a base rate of 2.5% of experienced workers hired per month. This amounts to a 1.5% decrease in hiring for each 1 percentage point increase in the state unemployment rate. Thus, without any fixed effects, young workers experience a substantially larger drop in their hiring rate compared with experienced workers, in both absolute and percentage terms.

Since I am interested in isolating the effect of the state unemployment rate on hiring, in Columns (2) through (4) of Table 1 I add state, then demographic, and then month-year fixed effects, ending with the preferred specification in Column (4). Adjusting for time-invariant differences between states slightly increases the magnitude of the cyclical decrease in hiring for both types of individuals, suggesting that states with higher hiring rates also have slightly higher unemployment rates. Adding non-parametric demographic fixed effects has a minimal impact on the point estimates, indicating that worker demographic heterogeneity plays a minor role in explaining cyclical variation in hiring rates.

The most substantial change in the estimated relationship between hiring rates and the state unemployment rate occurs when I include month-year fixed effects. In particular, the magnitude of the fall in hiring decreases for young workers by about one-fourth, while for experienced workers the relationship between hiring and the state unemployment rate becomes positive and significant. This indicates that, within a particular month, states with elevated unemployment rates (compared to their typical rate) hire experienced workers at a slightly higher rate compared with other states, despite the fact that, overall, hiring rates for experienced workers fall slightly during recessions. Thus, the main relationship remains robust with and without removing national variation: young workers experience substantially larger reductions in hiring compared with experienced workers.

Figure 2 presents the main empirical results, based on the regression in Equation 1.[5] Figure (1) shows that, for the unrestricted sample, workers with less than 1 year of potential experience are approximately half a percentage point less likely to be hired for each additional percentage point of the state unemployment rate. This effect falls steadily up until 9 years of potential experience, at which point it is statistically indistinguishable from zero. Individuals with above 15 years of potential experience are about 0.05 percentage points more likely to be hired for each additional percentage point of the state unemployment rate, which is significant in each five year bin at the 0.01% level.

Figure (2) shows that the pattern from Figure (1) is mirrored in the effect for currently employed workers. The magnitude is slightly smaller for workers with less than 1 year of potential experience. Again the change in the hiring rate with the state unemployment rate decreases with each year of potential experience until between 10 and 15 years of potential experience, at which point it is statistically indistinguishable from zero; it becomes positive for older workers. Workers hired from outside of the labor force, shown in Figure (3), demonstrate a similar pattern, although estimates are much noisier.

Hires from unemployment are shown in Figure (3). For all potential experience bins the hiring rate declines significantly with the state unemployment rate. Nonetheless, we see that the magnitudes decline with potential experience, falling from a high of between 1.7 and 2.2 percentage points for individuals with ten or less years of potential experience to a rate of about 1.2 to 1.5 percentage points for individuals with more than ten years of potential experience.

Finally, in Table 2 I collapse the results from Figure 2 into young and experienced groups and show that, for each origin group (employed, unemployed, or not in the labor force (NILF)), cyclical hiring rates for young workers are more negative than those of experienced workers and the coefficients are statistically distinct. Thus, across a variety of specifications,

[5] The Table version of Figure 2 is available in the Online Appendix.

I have shown that the fall in hiring during recessions is substantially more acute for young workers.

2.2 Quits and Other Flows

In this section I briefly investigate how other labor market flows vary with labor market conditions and then return to the motivating fact of elevated youth unemployment rates during recessions. In Column (1) of Table 3, I show that young workers are no more likely to leave an employer when the state unemployment rate increases, even though experienced workers see a substantial increase in their exit rate. Columns (2), (3), and (4) explain this result: while young workers and experienced workers see similar increases in their rates of exit to unemployment, flows between employers fall dramatically only for young workers. Thus, the fact that young workers are less likely to be hired to new employers fully offsets the increase in exits from employment.

In addition, in Columns (5) and (6) of Table 3 I document flows between unemployment and NILF, which reflects changes in whether the non-employed individual reports actively searching for employment. Here we see that young and experienced workers experience similar increases in reporting active search. Both groups report decreased outflows from unemployment to NILF, but the magnitude of this decrease is larger for more-experienced workers.

In order to better understand exits from employment, in Table 4 I separate the flows from employment to unemployment into voluntary and involuntary separations. Voluntary separations are individuals who report that they quit, while involuntary separations include layoffs and temporary jobs that ended. In Column (1), we see that involuntary exits increase similarly for young and experienced workers. Thus, although firms may be slightly more likely to lay off younger workers, these differences cannot explain the cyclical increase in youth unemployment rates. On the other hand, in Column (2) of Table 4 we see that young workers are less likely to quit employment as the unemployment rate increases, while experienced workers are more likely to quit. Hence, elevated youth unemployment rates are not due to young workers choosing to quit.

Overall, the results from Tables 3 and 4 show that the fact that young workers see larger increases in unemployment rates than experienced workers during recessions is primarily due to larger decreases in hiring from unemployment for young workers. This is consistent with Forsythe and Wu (2021) who find a similar result for young workers using formal flow decompositions.

2.3 Experience and Human Capital

Why might firms prefer to hire more experienced workers? Under standard models of human capital accumulation, individuals gain knowledge and skills through work experience. This means that, all else equal, younger workers are likely to be less productive than more experienced workers. Consistent with this, many job listings require some number of years of relevant work experience. During the Great Recession, hiring employers increased both their experience and educational requirements (B. Hershbein and Kahn (2018) and Modestino et al. (2015)). This suggests that education may help insulate younger individuals from the fall in hiring during recessions. In this section I examine the relationship between hiring, education, and age.

I begin by investigating the direct relationship between education and hiring. In Table 9 I replicate Table 1, but compare individuals with and without a four year college degree. We see a greater reduction in hiring with the state unemployment rate for individuals without a college degree compared to those with a college degree. In Column (4), which includes state, demographic, and month-year fixed effects, individuals with a college degree see a 0.04 percentage point increase in the hiring rate, while those without a college degree see a 0.06 percentage point decrease. Thus, while those without a college degree are less likely to be hired during periods of high unemployment, the point estimate is much smaller in magnitude than the 0.25 percentage point decrease for young workers in Table 1. Nonetheless, this is consistent with the hypothesis that employers are selectively hiring individuals with more human capital.

In order to see how the hiring gradient across potential experience differs by education, in Figure 3 I plot the hiring rate by potential experience bins for individuals with and without a college degree. For individuals without a college degree, the gradient is very similar to Figure 2, while for individuals with a college degree the gradient is much flatter. Although there is a statistically significant reduction in hiring for college-educated individuals in their first two years, the point estimates are substantially smaller than those for non-college-educated individuals. For individuals without a college degree the reduction in hiring is significant up to 9 years after exiting school.

For older workers, we see the relationship reversed. Hiring rates increase with the state unemployment rate for individuals without a college degree and over 21 years of potential experience, while for college graduates the point estimates are close to zero for all workers with more than 10 years of potential experience. Thus, the small relative increase in hiring rates during periods of high unemployment rates we saw for older workers appears to be driven by individuals without a college degree.

So while education moderates the negative relationship between the unemployment rate and hiring for younger workers, it does not completely eliminate the negative effect of recessions on youth hiring. Young individuals without a college degree are doubly disadvantaged and bear the brunt of the reduction in hiring.

3 Composition of Jobs and Labor Supply

In the previous section, I documented that young workers are disproportionately less likely to be hired during periods of high unemployment rates. In this section, I consider and rule out two possible explanations for this result: the composition of jobs and young workers' labor supply behavior.

3.1 Composition of Jobs

One explanation for the reduction in youth hiring is that the composition of jobs changes over the business cycle. For instance, Krause and Lubik (2006) and Kahn and McEntarfer (2013) have found that lower-quality jobs are more prevalent during recessions. If young and more-experienced workers sort to different jobs, variations in exposure to the business cycle between industries or occupations could lead to a reduction in hiring for young workers without reflecting changes in hiring behavior within individual jobs.

To test for this, I regress the average potential experience of new hires on the state unemployment rate both with and without detailed occupation and industry fixed effects.[6] If composition was the primary driver of hiring changes, the state unemployment rate would lose its explanatory power with the inclusion of these controls. In particular, I estimate the following specification:

$$PE_{istond} = \beta \text{ State Unemp. Rate}_{st} + \alpha_s + \delta_t + \gamma_o + \omega_n + \kappa_d + \epsilon_{istond}, \tag{2}$$

where PE is the potential experience of individual i hired into occupation o in industry n in state s and month-year t. κ_d represent non-parametric demographic fixed effects as described in Section 1. Standard errors are clustered at the state level and estimates are weighted using CPS sampling weights.

Column (1) of Table 5 shows that each additional percentage point of unemployment raises the average potential experience of hires by about a month and a half. The addition of occupation and industry fixed effects, shown in Column (2), makes little difference to the

[6]Specifically, I crosswalk occupation and industry to consistent 2002 census codes (508 occupations and 261 industries) using crosswalks produced by the U.S. Census Bureau (retrieved from https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html).

point estimates. Thus, although a small portion of the change in hiring behavior may be explained by variation in the types of jobs hiring during recessions, the bulk of the increase in the average potential experience of hires remains unexplained.

As an additional check, Tables B.4 and B.5 in the Online Appendix show separate specifications by major occupation and industry groups, respectively. Although most cells are under-powered, across a variety of job classifications I show that the average potential experience of new hires has a positive point estimate. Thus, it does not appear to be the case that the increase in the average potential experience of hires is due to cyclical composition changes in hiring jobs.

3.2 Labor Supply

Another explanation for the fall in youth hiring during periods of high unemployment is that young workers choose to exit the labor market. In Table 4, I have already shown that young workers are decreasingly likely to quit jobs to unemployment as the state unemployment rate increases. In this section, I conduct additional tests to show that young workers' labor supply decisions cannot explain this reduction in hiring. I focus on three related measures: worker hires compared with the set of potential hires, worker search intensity, and hires based on worker availability.

I begin by examining whether there is a divergence between the set of workers hired and the set of potential hires in each employment category. In Panel A of Table 6 I regress the average potential experience within the state-month-year cell on the state unemployment rate. In Column (1) we see that the average potential experience of all working-age individuals within the state does not change with the state unemployment rate.

Continuing with Table 6, in Column (1) of Panel B I replicate the first column of Table 5, which shows that the average potential experience of new hires rises by a bit more than one month for each percentage point of state unemployment. Thus, despite the fact that the set of working-age individuals in the state does not vary with the state unemployment rate, the average potential experience of hires rises robustly.

In Column (1) of Panel C, I further test whether this relative increase in the potential experience of hires occurs within state-month-year cells. In particular, I construct the ratio of the average potential experience of new hires to the working-age population in the state by month by year cell. I find that the average potential experience of hires increases faster than the average potential experience of the working age population within the cell. That is, the relationship we saw in Panels A and B holds within state-year cells.

In Columns (2) through (4), I repeat this exercise for the three component labor force categories: employed, unemployed, and NILF. In Panel C we see that for each subgroup the point estimate is positive, indicating that the potential experience of hires increases weakly more than the potential experience of individuals in the labor market category; however, only the estimate for NILF is statistically significant.

Nonetheless, in Panel A we do see that the average potential experience within cells varies cyclically: during periods of high unemployment the stock of employed individuals becomes slightly more experienced, while the stock of unemployed becomes substantially more experienced, and the stock of NILF becomes substantially less experienced. Panels (B) and (C) show that for each subset of the population the potential experience of hires increases above and beyond what would be expected by the change in the stock of potential applicants.

Another way in which worker behavior could drive cyclical hiring rates is if young workers put forth less effort to search for jobs compared with more-experienced workers during periods of high unemployment rates. In order to measure this, I use a metric developed in Shimer (2004) to capture how much effort unemployed individuals are investing in the search process. In particular, I count the different methods of search the individual reports using to find a job and test to see if the number of methods used changes over the business cycle. Since only unemployed individuals are asked about search methods, this test is limited to the unemployed.

Table 7 shows that young job seekers use slightly fewer (0.3) methods than older job seekers on average. However, for each additional percentage point of unemployment, younger workers' search intensity rises either faster (Column (1), with no demographic controls) or at the same rate (Column (2), with demographic controls added). This shows job seekers react to higher unemployment rates by increasing their search intensity in similar ways. Hence it is unlikely that other unobserved changes in search behavior are driving the differences in hiring by potential experience during recessions.

Finally, it could be that young workers are differentially unavailable for work during recessions, either because they are in school or engaged in other non-market activities, such as child-rearing. For instance, B. J. Hershbein (2012) found an increase in college enrollment for young men who graduate high school during recessions, which would depress the hiring rate for young workers. In order to test the extent to which worker availability may drive the hiring result, I repeat the analysis from Table 2, but restrict the sample to individuals who affirm they are available to begin work. Depending on the individuals' labor force status they are asked slightly different questions, so I run the analysis separately for unemployed and NILF individuals.

First, workers who are currently unemployed are asked if they would be available to start a job in the next week. In Column (1) of Table 8 I reproduce the estimates for all unemployed workers from Column (3) of Table 2 and compare them with estimates from the same regression restricted to unemployed individuals who report they are available to start a job in Column (2). This restriction reduces the sample by approximately 14%; however, the point estimates remain similar, indicating the fall in hiring for young unemployed workers is not driven by job seekers who are unavailable to begin work.

Second, individuals who are classified as NILF are asked if they are currently in school, a common reason for being out of the labor force. I reproduce Column (4) from Table 2 in Column (3) of Table 8 and compare it to estimates in Column (4) restricted to individuals who are not in school. With this restriction, the sample is reduced by about 20%; however, again the point estimates remain similar to the estimates from the full sample. Thus, even if individuals may be returning to school or taking up other activities that prevent them from starting jobs, this is not driving the drop in hiring for young workers during recessions.

Thus, across a variety of measures, I have shown that young workers' labor supply behavior cannot explain the fall in youth hiring during recessions.

4 A Stylized Model of Firm Hiring Behavior

In Section 2.1 I established that during periods of high unemployment, the hiring rate for young workers falls faster than does the rate for more-experienced workers. In Section 3 I showed that the composition of jobs and worker labor supply behavior cannot explain these results. In this section, I focus on a third explanation: firm hiring behavior.

There is a long literature focusing on how the skill level of hires fluctuates cyclically. Beginning with Reder (1955), the cyclical upgrading hypothesis emphasizes how labor demand can drive cyclical variation in hiring.[7] If labor markets are subject to frictions and wages are inflexible, firms may prefer to hire higher-skilled workers. If applicant volume per vacancy increases during recessions, firms will be able to be choosier during recessions, leading to cyclical upskilling. The key intuition of these models is that if firms are not indifferent between workers of different skill levels, firms may change hiring behavior in response to labor market tightness.

In the classic models, firm hiring preferences are driven by wage rigidities and exogenous firm-size constraints. In this section, I develop a stylized model of a single firm's hiring choice that relaxes these assumptions, allowing for wage bargaining and endogenous firm-size decisions. I introduce a wedge in the production process that causes low-skilled workers to be more expensive to employ per unit of output compared with high-skilled workers. This

[7] Other work includes Okun (1973) and Akerlof, Rose, and Yellen (1988).

requirement is quite flexible and can be operationalized in a variety of ways. I choose to model the friction as a per-worker capital cost; however, other possibilities include outside options that do not scale precisely with individual productivity and rigid wages.[8] The idea of a fixed cost per worker is not unreasonable: mechanisms that would satisfy this description include physical capital or tasks that can only be performed by one person at a time, as well as benefit and amenity costs that accrue per employee rather than per efficiency unit. This fixed capital cost is similar to the assumption used by Acemoglu (1999) to explain endogenous job creation in the face of heterogeneously skilled labor.[9]

In the absence of hiring frictions, firms would choose to only employ high-skilled workers. However, vacancy posting is costly for firms, so exclusively employing high-skilled workers would require the firm to post additional vacancies and screen out low-skilled workers. When the labor market is tight, I show that firms optimally pursue a hiring strategy by which they hire all applicants, regardless of skill. However, during times with sufficient slack in the labor market, firms will find it optimal to switch strategies and only hire high-skilled workers.

Matching is modelled as random search, under which each vacancy attracts both young and experienced applicants. A key contribution of the model is that it allows the firm to endogenously choose how many workers of each type to hire *after* matching has occurred. This allows the model to more closely reflect real-world hiring procedures in which firms choose among a set of applicants, without imposing exogenous restrictions on the number of applicants that can be hired.

4.1 Model Preliminaries

In order to capture the empirical results from Section 2.1, any model requires the following features. First, young and more-experienced workers are substitutes and thus can both be productively hired for a particular job. This is consistent with the evidence from Section 3.1 that the cyclical variation in hiring is due to changes occurring within job types, rather than changes in the composition of jobs. Second, young workers are (weakly) less productive than more-experienced workers. Third, recessions lead to a reduction in aggregate demand for labor.

Since I do not model life cycle dimensions, I refer to young workers as “low-skilled” (L-type) and experienced workers as “high-skilled” (H-type). γ is the relative productivity of low-skilled workers and lies between zero and one. If γ equals one, firms will be indifferent between low- and high-skilled workers. For γ less than one, a single low-skilled employee

[8] However, depending on how rigid wages are modelled, this may be inconsistent with the wage results I derive in Section 4.6.

[9] However in Acemoglu (1999) the capital choice is endogenous.

will produce share γ of what a high-skilled employee produces. There is mass 1 of searching workers, with share δ low-skilled and the rest high-skilled.

The firm's decision-making proceeds in two phases. In the matching phase, the firm chooses how many vacancies to post (V). In the hiring phase, after observing how many applicants of each type of worker have applied ($\hat{N}_{\mathrm{L}}$ and $\hat{N}_{\mathrm{H}}$), it chooses how many to hire (N_{L} and N_{H}). After the firm has chosen which applicants to hire, it bargains with each worker over wages. Since the hiring decision and wage bargaining occur after the vacancy posting cost has been sunk, the firm must take into account its future behavior when choosing how many vacancies to post.

Matching Applicants to Jobs

The matching process governs how applicants are connected to vacancies. Similar to other discrete-time multi-worker hiring models[10] I impose two tractability assumptions that allow the discrete-time model to approximate the continuous-time matching process. First, I assume the matching process is deterministic: the firm knows with certainty the measure of workers of each type that will match with a measure of vacancy postings V, conditional on the state of the labor market. Second, each vacancy can match with at most a single applicant.

Under these conditions, if the firm posts V vacancies each vacancy has a probability $q_i(A)$ of matching with each type of worker and $q_{\mathrm{L}}(A)+q_{\mathrm{H}}(A) < 1$. A is the aggregate productivity parameter, so I impose that $q_i(A)$ is strictly decreasing in A for each worker type i. Thus, the q_i's in this single-firm model exogenize the market-level relationship between aggregate productivity and hiring probabilities.

Production Process

In order to clearly illustrate the trade-offs the firm faces, I focus on a particular functional form for the firm's profit function that permits an explicit solution to the hiring problem:

$$\Pi(N_L, N_H) = A(\gamma N_{\mathrm{L}} + N_{\mathrm{H}})^{\alpha} - N_{\mathrm{L}}(k + w_{\mathrm{L}}) - N_{\mathrm{H}}(k + w_{\mathrm{H}}) - cV, \tag{3}$$

where α is positive and less than one. This condition ensures diminishing marginal productivity of labor, which pins down the firm's optimal size decision. w_{L} and w_{H} represent the wages each type of worker earns, k is the per-worker production cost, and c is the cost of posting a single vacancy.

[10] Such as Michaillat (2012) and Elsby and Michaels (2013).

Wage Determination

Wages are determined by the firm bargaining with each worker as if he is the marginal worker, which is an application of the Stole and Zwiebel (1996) bargaining solution. However, because the firm is bargaining with two different types of workers, this bargaining procedure will produce a system of differential equations that determines the two wages w_{L} and w_{H}.[11]

Let $J(N_{\mathrm{L}}, N_{\mathrm{H}})$ be the value to the firm of employing N_{L} L-type and N_{H} H-type workers. The value of employing the marginal worker of each type is given by the partial derivative of J with respect to labor of that type. For each worker the value of the job is the bargained wage less the flow value of unemployment which, for tractability, is set equal to zero. Then the bargaining expressions can be written as follows:

$$(1-\beta)w_{\mathrm{i}} = \beta \frac{\partial J(N_{\mathrm{L}}, N_{\mathrm{H}})}{\partial N_{\mathrm{i}}}, \tag{4}$$

for $i \in \{L, H\}$, where β is between zero and one and represents the worker's bargaining power.

Since bargaining occurs after the cost of vacancy posting has been sunk and the firm has already selected the set of workers to employ, the firm's value function is given by:

$$J(N_{\mathrm{L}}, N_{\mathrm{H}}) = A(\gamma N_{\mathrm{L}} + N_{\mathrm{H}})^{\alpha} - N_{\mathrm{L}}(k + w_{\mathrm{L}}(N_{\mathrm{L}}, N_{\mathrm{H}})) - N_{\mathrm{H}}(k + w_{\mathrm{H}}(N_{\mathrm{L}}, N_{\mathrm{H}})), \tag{5}$$

where wages are now written to explicitly depend on employment of each type of worker.

Since the firm's value function depends on employment of both types of workers, wages for each type of worker will also depend on wages for the other type. However, due to the choice of production function, a closed-form solution to the wage system exists. Using Equations 4 and 5 yields:

$$w_{\mathrm{L}}(N_{\mathrm{L}}, N_{\mathrm{H}}) = \frac{\gamma\alpha\beta A(\gamma N_{\mathrm{L}} + N_{\mathrm{H}})^{\alpha-1}}{1+\beta(\alpha-1)} - \beta k \text{ and} \tag{6}$$

$$w_{\mathrm{H}}(N_{\mathrm{L}}, N_{\mathrm{H}}) = \frac{\alpha\beta A(\gamma N_{\mathrm{L}} + N_{\mathrm{H}})^{\alpha-1}}{1+\beta(\alpha-1)} - \beta k. \tag{7}$$

These bargained wages show the relationship between wages and the relative productivity parameter γ. If there was no fixed-cost parameter k, low-skilled workers' wages would be share γ of high-skilled workers' wages. In addition, wages are decreasing with the total number of workers employed, which follows directly from the diminishing marginal productivity

[11]See Cahuc, Marque, and Wasmer (2008) for a more generalized solution to the problem of multi-worker firms bargaining with heterogeneous labor inputs.

of labor of the production function.

4.2 Hiring Phase

Now that the wage expressions have been pinned down, I can consider the optimal employment decision. In particular, if the firm has matched with $\hat{N}_{\mathrm{L}}$ L-type workers and $\hat{N}_{\mathrm{H}}$ H-type workers in the matching phase, the firm solves the following:

$$\begin{aligned} \max_{N_{\mathrm{H}},N_{\mathrm{L}}} A(\gamma N_{\mathrm{L}} + N_{\mathrm{H}})^{\alpha} - N_{\mathrm{L}}(k + w_{\mathrm{L}}) - N_{\mathrm{H}}(k + w_{\mathrm{H}}) \\ \text{such that } 0 \leq N_{\mathrm{L}} \leq \hat{N}_{\mathrm{L}} \\ 0 \leq N_{\mathrm{H}} \leq \hat{N}_{\mathrm{H}} \\ \text{and wages are given by Equations 6 and 7.} \end{aligned} \tag{8}$$

which is similar to Equation 3 but without the cost of vacancy posting.

First, suppose the firm posted so many vacancies in the matching phase that the hiring constraints ($\hat{N}_{\mathrm{L}}$ and $\hat{N}_{\mathrm{H}}$) do not bind. Then, by choosing N_{L} and N_{H} to maximize Equation 8, the following conditions are obtained:

$$\begin{aligned} \frac{\alpha(1-\beta)A(\gamma N_{\mathrm{L}}^{*} + N_{\mathrm{H}}^{*})^{\alpha-1}}{1+\beta(\alpha-1)} \leq \frac{1}{\gamma}(1-\beta)k \text{ and} \\ \frac{\alpha(1-\beta)A(\gamma N_{\mathrm{L}}^{*} + N_{\mathrm{H}}^{*})^{\alpha-1}}{1+\beta(\alpha-1)} \leq (1-\beta)k, \end{aligned}$$

where N_i^* are the optimal hiring choices. For $\gamma < 1$, both constraints cannot simultaneously hold with equality. These two constraints represent the marginal benefit (net wage costs) of hiring an additional efficiency unit of labor, which is bounded by the marginal fixed cost for each type of labor. Since the fixed cost does not scale with γ, this shows how hiring an additional efficiency unit of L-type workers is more costly than hiring an additional H-type worker.

The firm's choice of vacancy posting in the matching phase will lead to distinct hiring regions in the hiring phase. If $\hat{N}_{\mathrm{H}}$ is large enough, the firm will only hire H-type workers. For smaller values of $\hat{N}_{\mathrm{H}}$, the firm will be forced to hire some of the L-type matches, but it will not hit the $\hat{N}_{\mathrm{L}}$ hiring constraint. Finally, when both $\hat{N}_{\mathrm{L}}$ and $\hat{N}_{\mathrm{H}}$ are small enough, the firm will hire all workers with which it has matched. Optimal hiring is derived in detail in the Online Appendix in Lemma 4.

4.3 Matching Phase

Although the solution to Equation 8 describes hiring for any combination of H- and L-type matches, in practice the firm only has one degree of freedom to choose how many workers match: the number of vacancies posted (V). Each vacancy matches with $q_{\mathrm{H}}(A)$ H-type workers and $q_{\mathrm{L}}(A)$ L-type workers. Thus, for a given choice of V and for $i \in \{L, H\}$:

$$\hat{N}_{\mathrm{i}} = q_{\mathrm{i}}(A)V. \tag{9}$$

The firm's optimal choice of V is given by

$$\max_{V} A(\gamma N_{\mathrm{L}} + N_{\mathrm{H}})^{\alpha} - N_{\mathrm{L}}(k + w_{\mathrm{L}}) - N_{\mathrm{H}}(k + w_{\mathrm{H}}) - cV,$$

subject to w_{L} and w_{H} given by Equations 6 and 7, N_{L} and N_{H} given by the solution to Equation 8, and hiring-constraints given by Equation 9.

In the Online Appendix I show the firm will optimally choose between two strategies: either the firm hires all matches regardless of type or the firm only hires the H-type matches and discards all the L-type matches. The optimal choice between these two regions is given by Proposition 1.

Proposition 1 *If A is small enough such that*

$$\frac{c}{q_{\mathrm{H}}(A)} \leq (1-\beta)k\frac{1-\gamma}{\gamma},$$

the firm will optimally post enough vacancies such that it will choose to only hire H-type workers. Otherwise, the firm will hire all workers with whom it matches.

See the Online Appendix for proof and full characterization of the vacancy-posting rule.

Define $\hat{A}$ as the cutoff such that the inequality in Proposition 1 holds. The firm's optimal vacancy-posting decision depends on the state of the aggregate economy via the probability that the vacancy matches with an H-type worker, $q_{\mathrm{H}}(A)$. L-type workers are more costly to employ in terms of cost per unit of output, but are cheaper to hire. When $A \geq \hat{A}$, vacancy posting is too costly for the firm to pursue a strategy under which it posts many vacancies and only hires the H-types who match. As A falls, the cost of posting additional vacancies falls relative to the fixed cost k, until the firm switches to only hiring H-type workers. In the extreme, the following lemma holds, which follows directly from Proposition 1.

Lemma 1 *If there is no fixed cost per position ($k = 0$), the firm's optimal decision is to hire all workers, regardless of the state of economy A. If there is no hiring cost ($c = 0$), the firm's optimal decision is to only hire H-type workers, regardless of the state of economy A.*

4.4 Comparative Statics and Testable Predictions

Now we can consider the properties of the cutoff level of aggregate productivity, $\hat{A}$. Lemma 2 follows from Lemma 4 and the fact that $q_{\mathrm{H}}(A)$ is strictly decreasing in A.

Lemma 2 *$\hat{A}$ decreases the closer the productivity of low- and high-skilled labor (e.g. larger γ), the smaller the fixed cost of hiring (k), and the more costly it is to post a vacancy (c).*

The smaller $\hat{A}$, the worse the economy must become before a particular firm will switch its hiring practices. Thus, for firms with a production process under which low- and high-skilled workers are close substitutes, the economy will have to fall into a much more severe recession for the firm to stop hiring low-skilled workers.

In addition, we can derive comparative static predictions for wages.

Proposition 2 *As long as A is large enough such that the firm hires both types of workers, $\frac{\partial ln(w_{\mathrm{L}})}{A} > \frac{\partial ln(w_{\mathrm{H}})}{A}$.*

If there is no fixed cost k, log wages will move identically for both types of workers. Since the fixed cost takes a larger percent of wages for L-type than H-type workers, an increase in A will result in a larger increase in log wages for L-type than H-type workers. I will directly test this prediction in Section 10.

4.5 Comparing Alternative Theories of Cyclical Hiring

In this section, I briefly consider two alternative theories of cyclical hiring and show that they present distinct predictions about the cyclical behavior of wages. First consider a standard competitive benchmark, in which labor markets are perfectly competitive and frictionless and young and experienced workers are perfect substitutes.[12] In this case, if young workers produce fraction γ of what experienced workers produce their wages will be fraction γ of experienced workers' wages. This means that employers are indifferent between hiring young and more-experienced workers, so any cyclical decline in youth hiring must be driven by a higher labor supply elasticity of young workers. I have already shown in Section 3 that young workers are no more likely to exit the labor market or reduce search effort during recessions, thus there is no evidence that they have more elastic labor supply behavior over the cycle. In addition, such a model predicts the effect of recessions on log wages should be identical for young and more-experienced workers.

Second, consider a classic cyclical upgrading model, such as in (Reder, 1955). In these models, wages are exogenously set at the position-level. In this case, labor markets do

[12] See for instance Card and DiNardo (2002) for a related model, of which this is a simplification.

not necessarily clear and this excess labor supply may lead to queuing for jobs. During a recession, as aggregate labor demand falls, rigid wages prevent workers from accepting lower wages in exchange for maintaining employment and firms are able to be more choosy about which applicants they hire, reducing the hiring rate of young workers. In this case, we would expect to see log wages that are acyclical for both young and experienced workers.

Both models provide unique predictions about how log wages move with the unemployment rate: they either decrease symmetrically for both types of workers (competitive benchmark), remain unchanged for both types of workers (classic cyclical upgrading), or decrease more for young than for experienced workers (bargained cyclical upgrading). I test these predictions directly in the next section.

4.6 Testing Wage Predictions

I again use CPS data to measure wages of new hires. Wage information is only collected in the fourth and eighth months of the CPS sample, which cuts the sample by 2/3. In order to capture the change in wages within jobs, I include detailed industry and occupation fixed effects to control for compositional changes in hiring firms. In addition, I include demographic fixed effects to control for cyclical variation in the demographic characteristics of job seekers. I restrict the sample to new hires and use non-allocated log weekly wages, deflated to 1994 prices. All specifications include state and month-year fixed effects and standard errors are clustered at the state level. It is important to emphasize that these estimates will capture the cyclicality of wages holding composition fixed, which is different from the macro-level estimates of real wage cyclicality that are often calculated.

In Panel A of Table 10, I combine all hires together, while in Panel B I separate hires into young (ten or less years of potential experience) and experienced. In Column (1) I include all hires, while in Columns (2) through (4) I restrict the sample to hires from employment, unemployment, and out of the labor force, respectively. In Panel A we see starting wages decrease by 1.7% on average. In Columns (2) through (4) we find the largest decreases are for hires from out of the labor force (2.4%), while hires from unemployment see close to the average (1.7%) and hires from employment the smallest (0.8%).

In Panel B, we now see that while both young and experienced workers face wage losses, the losses are substantially larger for young workers. For the aggregated category in Column (1), young workers have losses of 2.6%, while experienced workers have losses of 1.2%.[13] When we examine differences by labor market status, we see that experienced hires from employment and out of the labor force have non-significant wage losses of 1% or less, while

[13] In the Online Appendix, I show that reduced hiring rates and larger log wage losses for young workers compared with experienced workers holds within major occupational categories.

young workers in those categories have losses of 1.6% and 3.5%, respectively. On the other hand, for hires from unemployment, young and experienced workers' estimates are not statistically distinguishable, although the point estimates are somewhat larger for young workers (2.1%) than for experienced workers (1.8%). Finally, young workers receive weekly wages that are on average 14% lower than experienced workers, a difference that is somewhat larger for hires from employment and unemployment (18%) and much smaller for hires from out of the labor force (3%).

We can now compare these wage changes with the predictions from the theories discussed in the previous subsection. The fact that young workers receive lower weekly wages than experienced workers is consistent with the assumption in all three models that worker productivity increases with labor market experience. The fact that log wages fall with the unemployment rate by more for young workers than for experienced workers is consistent with the bargained cyclical upgrading model, and inconsistent with both the competitive benchmark and the classic cyclical upgrading models. I conclude that the wage evidence is most consistent with a model in which frictions prevent wages from perfectly equating marginal productivity, but firms are not so rigid as to insulate workers from market fluctuations.

How do these estimates compare with estimates in the literature? In a survey of the literature, Abraham and Haltiwanger (1995) found that estimates of wage cyclicality are highly sensitive to the specification, cyclical indicator, and time period. In particular, estimates from the literature include positive, negative, and no correlation between real wages and the business cycle indicator. Recent examples include Haefke, Sonntag, and van Rens (2013) and Gertler, Huckfeldt, and Trigari (2016), who, respectively, found that wages for new hires during the Great Recession were positively correlated with labor productivity and uncorrelated with the unemployment rate.

Most relatedly, Martins, Solon, and Thomas (2012) examine wages holding the firm-position fixed, finding that each additional percentage point of unemployment is associated with 1.8% lower wages for Portuguese workers. This estimate is similar to my estimate of 1.7% for all workers pooled. Similarly, Solon, Barsky, and Parker (1994) and Martins et al. (2012) show that accounting for composition bias in the cyclical distribution of matches leads to estimates of robust decrease in real wages during recessions.

5 Conclusions and Policy Implications

In this paper I present evidence that cyclically selective hiring is the most persuasive explanation for young workers' high unemployment and lack of job mobility during recessions. I find young workers are substantially less likely to be hired during recessions. This is consistent with the results of Kahn (2010) and Oreopoulos et al. (2012), who find that workers who graduate college during a recession experience long-lasting wage losses. I find these negative effects appear to extend beyond just new labor market entrants, affecting those with up to 15 years of potential experience. Further, the fact that more-educated young workers see a smaller decrease in hiring is consistent with results from Oreopoulos et al. (2012) regarding heterogeneity within college graduates in the effect of graduating during recessions.

I develop a stylized model of cyclically selective hiring, which can explain why firms may optimally choose to stop hiring young workers during recessions. These results indicate that the intuition behind classic models of cyclical upgrading is consistent with endogenous firm size and flexibly bargained wages. As long as labor markets are slack, firms will have more applicants than they can hire and will be able to pick and choose the most desirable candidates.

These results suggest that the problems young workers face during recessions are not due to matching frictions, but rather to insufficient labor demand. For workers consistently at the end of the queue, such as inexperienced workers, less-educated workers, or workers who face labor market discrimination, labor market interventions targeted at the search process are less likely to be successful during recessions, unless the program can help the worker find firms that are less cyclically selective.[14]

In the United States, unemployment insurance programs target previously employed individuals who face involuntary unemployment. New labor market entrants are generally excluded from such programs. While entrants typically can expect to find work quickly during expansions, I find that these workers' hiring rates fall much faster than those of any other group during recessions. As the evidence indicates this is due to firm behavior rather than job seekers' search behavior, there may be a role for expanding unemployment insurance during recessions to include new labor market entrants.

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[14]For instance, firms in which productivity differences between young and more-experienced workers are slight.

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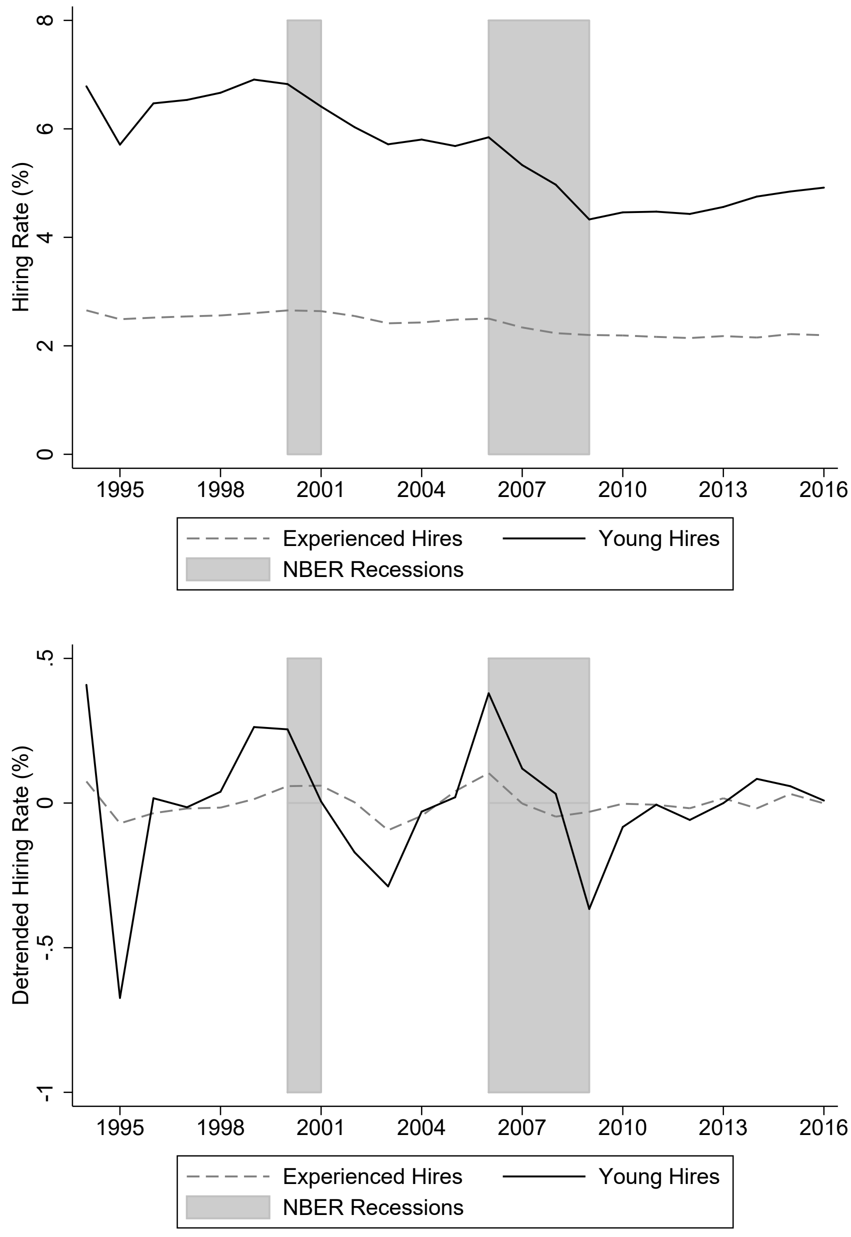
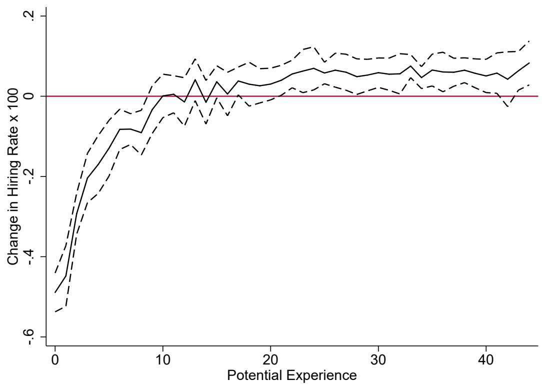
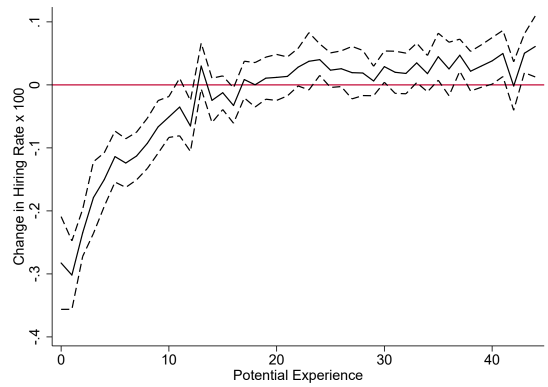


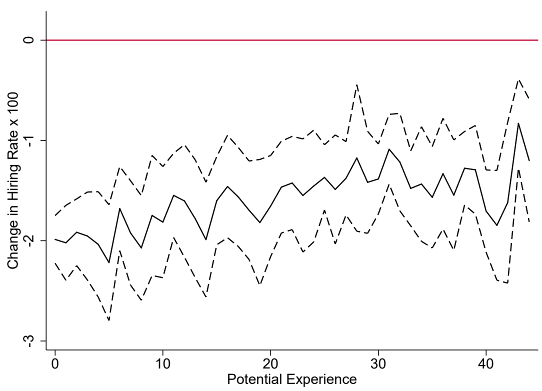
Figure 1: In the top figure, each line reflects the raw share of workers in the potential experience category hired each month in the CPS, weighted using CPS sampling weights and smoothed by averaging across the year. In the bottom figure, an HP-filter with smoothing factor 6.25 has been applied to each series. NBER Recessions are the recession dates as reported by the NBER Business Cycle Dating Committee.



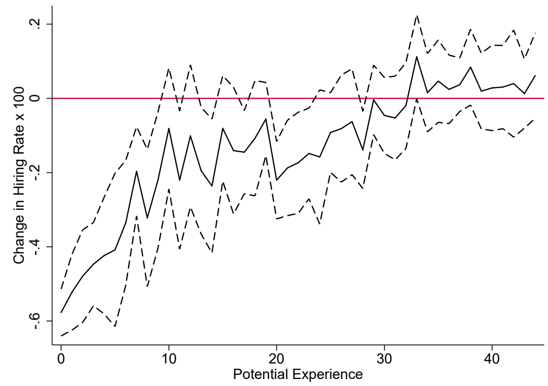
(1) All Hires



(2) EE Hires



(3) UE Hires



(4) NILF Hires

Figure 2: Coefficients from regressing the hiring rate on the state unemployment rate for one-year potential experience bins, partialling out main effects and state, demographic, and month-year fixed effects and weighted using CPS sampling weights. Figures include 95% confidence intervals.

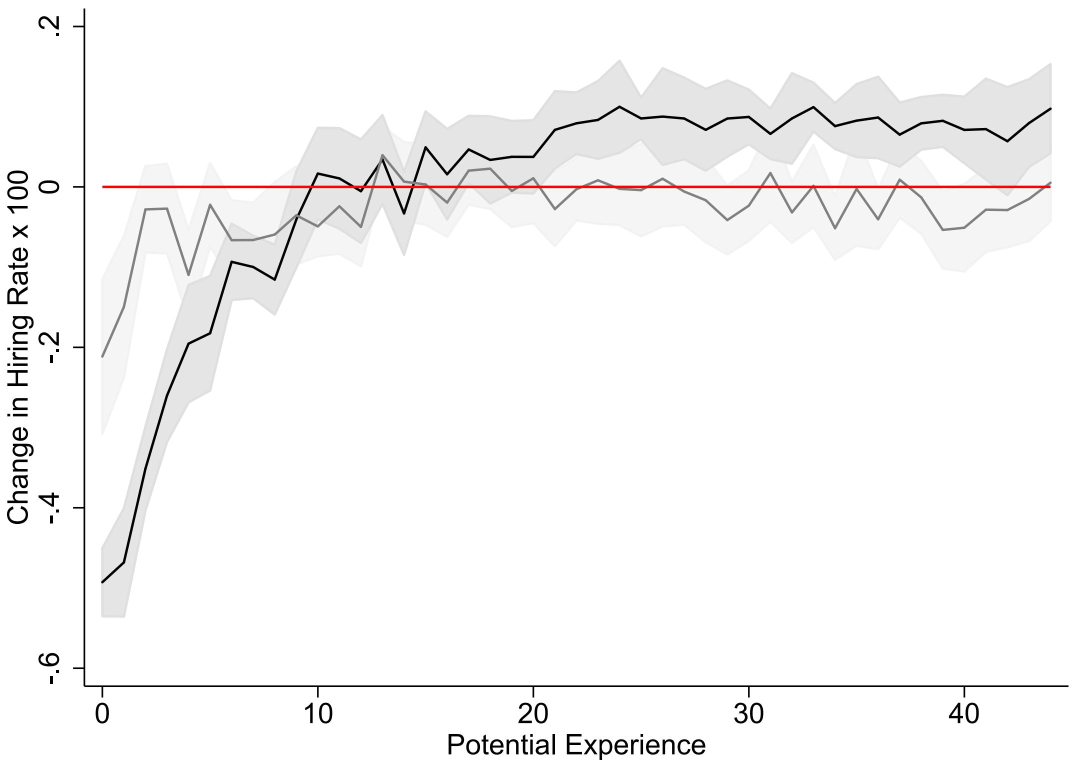


Figure 3: Coefficients from regressing the hiring rate on the state unemployment rate for one-year potential experience bins, partialling out main effects and state, demographic, and month-year fixed effects and weighted using CPS sampling weights. The black line represents individuals without a college degree and the gray line represents individuals with a college degree. Shaded areas represent 90% confidence intervals, based on standard errors clustered at the state level.

Table 1: Hiring Over the Business Cycle: With and Without Controls

Outcome: Pr(Hired) × 100	(1)	(2)	(3)	(4)
	Panel A			
State Unemp. Rate	-0.119***	-0.149***	-0.149***	-0.0326*
	(0.0150)	(0.0100)	(0.00906)	(0.0132)
R-sq	0.000	0.000	0.002	0.003
	Panel B			
PE ≤ 10	5.039***	5.040***	4.987***	4.988***
	(0.120)	(0.122)	(0.117)	(0.117)
PE ≤ 10 × U. Rate	-0.335***	-0.365***	-0.369***	-0.253***
	(0.0203)	(0.0177)	(0.0166)	(0.0185)
PE > 10 × U. Rate	-0.0367**	-0.0656***	-0.0662***	0.0496**
	(0.0131)	(0.00911)	(0.00882)	(0.0142)
R-sq	0.007	0.007	0.008	0.009
State FE:	No	Yes	Yes	Yes
Demographic FE:	No	No	Yes	Yes
Month-Year FE:	No	No	No	Yes
N	16948516	16948516	16948516	16948516

"Hired" refers to beginning a job at a new firm. "PE" refers to potential experience, defined as (age − education − 6). Specifications are weighted using CPS sampling weights. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 2: Hiring Over the Business Cycle: Young and Experienced

Outcome: Pr(Hired) × 100	(1)	(2)	(3)	(4)
PE ≤ 10	4.988***	2.662***	6.137***	8.089***
	(0.117)	(0.0960)	(0.660)	(0.316)
PE ≤ 10 × U. Rate	-0.253***	-0.168***	-1.928***	-0.490***
	(0.0185)	(0.0156)	(0.167)	(0.0332)
PE > 10 × U. Rate	0.0496**	0.0179	-1.505***	0.0148
	(0.0142)	(0.0101)	(0.176)	(0.0364)
N	16948516	10814088	653100	5481328
R-sq	0.009	0.004	0.031	0.018
Wald Test:	569.88***	206.51***	38.15***	237.47***
Sample	All	Employed	Unemployed	NILF

"Hired" refers to beginning a job at a new firm. "PE" refers to potential experience, defined as (age − education − 6). Estimates include main effects and state, demographic, and month-year fixed effects. Specifications are weighted using CPS sampling weights. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. The Wald test is for whether the PE ≤ 10 × U. Rate and PE > 10 × U. Rate coefficients are statistically distinct.

Table 3: Exits and Other Flows

Outcome: Pr(Exit) $\times$ 100	(1)	(2)	(3)	(4)	(5)	(6)
PE $\leq$ 10	5.950***	0.866***	2.604***	2.479***	3.824***	3.947***
	(0.147)	(0.0590)	(0.0951)	(0.127)	(0.191)	(0.498)
PE $\leq$ 10 $\times$ U. Rate	-0.0217	0.156***	-0.161***	-0.0165	0.286***	-0.453***
	(0.0274)	(0.00876)	(0.0156)	(0.0198)	(0.0250)	(0.0888)
PE > 10 $\times$ U. Rate	0.187***	0.148***	0.0232	0.0150	0.310***	-0.890***
	(0.0242)	(0.00593)	(0.0116)	(0.0189)	(0.0187)	(0.103)
N	10814088	10814088	10814088	10814088	5481328	653100
R-sq	0.018	0.006	0.004	0.014	0.015	0.037
Wald	200.57***	0.65	246.84***	5.87*	0.53	75.79***
Sample	Employed	Employed	Employed	Employed	NILF	Unemp.
Destination	All	Unemp.	Emp.	NILF	Unemp.	NILF

"Exit" refers to leaving employment at a particular firm."PE" refers to potential experience, defined as (age − education − 6). Estimates include main effects and state, demographic, and month-year fixed effects. EE moves in Column (3) include movements into self-employment. Specifications are weighted using CPS sampling weights. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. The Wald test is for whether the PE $\leq$ 10 $\times$ U. Rate and PE > 10 $\times$ U. Rate coefficients are statistically distinct.

Table 4: Involuntary and Voluntary Separations to Unemployment

	(1) Pr(Involuntary) $\times$ 100	(2) Pr(Voluntary) $\times$ 100
PE $\leq$ 10	0.193***	0.322***
	(0.0444)	(0.0157)
PE $\leq$ 10 $\times$ U. Rate	0.140***	-0.0103**
	(0.00671)	(0.00321)
PE > 10 $\times$ U. Rate	0.125***	0.00814***
	(0.00559)	(0.00209)
N	10814088	10814088
R-sq	0.004	0.001
Wald	3.29	65.67***

The sample is restricted to employed individuals. "PE" refers to potential experience, defined as (age − education − 6). Estimates include main effects and state, demographic, and month-year fixed effects. Specifications are weighted using CPS sampling weights. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. The Wald test is for whether the PE $\leq$ 10 $\times$ U. Rate and PE > 10 $\times$ U. Rate coefficients are statistically distinct.

Table 5: Average Potential Experience of Hires

Outcome: Average PE of Hires	(1)	(2)
State Unemp. Rate	0.138**	0.123**
	(0.0479)	(0.0372)
N	549835	549835
R-sq	0.066	0.187
Occupation Fixed Effects:	No	Yes
Industry Fixed Effects:	No	Yes

Dependent variable is potential experience, defined as (age − education − 6). The sample excludes individuals with negative potential experience. Estimates include constant and state, demographic, and month-year fixed effects. Specifications are weighted using CPS sampling weights. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 6: Potential Experience within Cells

	(1)	(2)	(3)	(4)
Sample:	All	Employed	Unemployed	NILF
Panel A: Average Experience of Individuals within Cells				
State Unemp. Rate	-0.0106	0.0440*	0.174**	-0.142**
	(0.0252)	(0.0174)	(0.0560)	(0.0476)
N	16948516	10814088	653100	5481328
R-Sq	0.045	0.040	0.064	0.099
Panel B: Average Experience of Newly-Hired within Cells				
State Unemp. Rate	0.138**	0.174***	0.253***	0.0338
	(0.0479)	(0.0474)	(0.0672)	(0.0842)
N	549835	204594	138335	206906
R-Sq	0.066	0.052	0.058	0.109
Panel C: Ratio of Average PE of Hires to Average PE of Population in Cell				
State Unemp. Rate	0.00553**	0.00368	0.00415	0.00515*
	(0.00189)	(0.00265)	(0.00352)	(0.00252)
N	12214	12214	12214	12214
R-Sq	0.273	0.113	0.045	0.199

Dependent variable in first two panels is potential experience, defined as (age − education − 6). Estimates include constant and state, demographic, and month-year fixed effects. In Panel C, dependent variable is the ratio of the average potential experience of hires in the state-month-year to the average potential experience of the population in the state-month-year. Specifications are weighted using CPS sampling weights. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 7: Search Intensity

Outcome: Number of Methods of Search	(1)	(2)
PE ≤ 10	-0.293***	-0.171***
	(0.0220)	(0.0213)
PE $\leq 10 \times$ U. Rate	0.0266**	0.0227**
	(0.00810)	(0.00783)
PE $> 10 \times$ U. Rate	0.0186	0.0221*
	(0.0107)	(0.0100)
	565081	565081
R-sq	0.031	0.060
Demographic FE	No	Yes

Number of methods of search defined as the total distinct types of search methods an individual used in a particular month of unemployment. "PE" refers to potential experience, defined as (age − education − 6). The sample is restricted to unemployed individuals. Estimates include main effects and state and month-year fixed effects.Specifications are weighted using CPS sampling weights. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 8: Hiring and Worker Availability

	(1)	(2)	(3)	(4)
PE $\leq$ 10	9.377***	6.137***	8.089***	8.021***
	(0.807)	(0.660)	(0.316)	(0.326)
PE $\leq$ 10 $\times$ U. Rate	-1.903***	-1.928***	-0.490***	-0.482***
	(0.160)	(0.167)	(0.0332)	(0.0500)
PE $>$ 10 $\times$ U. Rate	-1.298***	-1.505***	0.0148	-0.0403
	(0.173)	(0.176)	(0.0364)	(0.0254)
N	561299	653100	5481328	4353020
R-sq	0.034	0.031	0.018	0.014
Wald Test	38.15***	51.59***	237.47***	130.32***
	Uenmp.	Unemp. and Avail.	NILF	NILF, Not in School

"Hired" refers to beginning a job at a new firm. "PE" refers to potential experience, defined as (age $-$ education $-$ 6). "Available" indicates the unemployed worker reports he could begin a job next week. "Not in School" indicates the worker not in the labor force is not currently in school. Estimates include main effects and state, demographic, and month-year fixed effects. Specifications are weighted using CPS sampling weights. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. The Wald test is for whether the PE $\leq 10 \times$ U. Rate and PE $> 10 \times$ U. Rate coefficients are statistically distinct.

Table 9: Hiring Over the Business Cycle: Age versus Education

Outcome: Pr(Hired) $\times$ 100	(1)	(2)	(3)	(4)
College	-1.633***	-1.648***	-1.608***	-1.576***
	(0.0814)	(0.0781)	(0.0706)	(0.0708)
No Col. $\times$U. Rate	-0.135***	-0.162***	-0.174***	-0.0567***
	(0.0179)	(0.0122)	(0.0108)	(0.0139)
Col. $\times$U. Rate	-0.0508***	-0.0784***	-0.0775***	0.0397**
	(0.00749)	(0.00612)	(0.00630)	(0.0121)
R-sq	0.001	0.001	0.002	0.002
State FE:	No	Yes	Yes	Yes
Demographic FE:	No	No	Yes	Yes
Month-Year FE:	No	No	No	Yes
N	16948516	16948516	16948516	16948516

"Hired" refers to beginning a job at a new firm. "PE" refers to potential experience, defined as (age $-$ education $-$ 6). "Col." and "No Col." refer to individuals with and without a college degree, respectively. Specifications are weighted using CPS sampling weights. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 10: Log Wages During Recessions for New Hires

Outcome: Log Weekly Wage	(1)	(2)	(3)	(4)
	Panel A: Aggregated Hires			
U. Rate	-0.0174***	-0.00797*	-0.0173***	-0.0244***
	(0.00287)	(0.00368)	(0.00452)	(0.00658)
R-sq	0.422	0.467	0.424	0.352
	Panel B: Disaggregated by Potential Experience			
PE $\leq$ 10	-0.138***	-0.178***	-0.176***	-0.0324
	(0.0129)	(0.0225)	(0.0232)	(0.0340)
PE $\leq$ 10 $\times$ U. Rate	-0.0262***	-0.0162***	-0.0217***	-0.0352***
	(0.00360)	(0.00394)	(0.00618)	(0.00568)
PE $>$ 10 $\times$ U. Rate	-0.0116**	-0.00350	-0.0176***	-0.0103
	(0.00348)	(0.00432)	(0.00415)	(0.00924)
R-sq	0.433	0.485	0.435	0.358
Wald Test	23.78***	15.55***	0.81	14.96***
N	112858	44415	30387	38056
Sample	All	Employed	Unemployed	NILF

"PE" refers to potential experience, defined as (age − education − 6). Wages are log weekly non-allocated wages, deflated to 1994. Estimates include constant and main effects, as well as state, demographic, month-year, occupation, and industry fixed effects. Specifications are weighted using CPS sampling weights. Standard errors are in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

A Online Appendix: Proofs

In this Appendix, I present proofs of the lemmas and propositions from the main text, as well as additional lemmas that are useful for obtaining the main results.

A.1 Optimal Hiring

I begin by characterizing the optimal hiring behavior after matching has already occurred. I begin with Lemma 3, which is helpful for the full characteriziation in Lemma 4.

Lemma 3 *The firm will only hire L-type workers if the optimal choice of H-type workers (N^*_{H}) is constrained by how many H-type workers the firm matched with in the hiring phase ($\hat{N}_{\mathrm{H}}$).*

Proof of Lemma 3. After the firm has matched with $\hat{N}_{\mathrm{L}}$ and $\hat{N}_{\mathrm{H}}$ low- and high-type workers, respectively, the firm's optimal hiring decision is constrained by non-negative employment for each type, and the number of matches of each type. Using wage expressions given by Equations 6 and 7, the constrained optimization problem can be written as

$$\begin{gathered}
\max_{N_{\mathrm{L}},N_{\mathrm{H}}} \frac{A(1-\beta)(\gamma N_{\mathrm{L}}+N_{\mathrm{H}})^{\alpha}}{1-\beta(1-\alpha)} - (1-\beta)(N_{\mathrm{L}}+N_{\mathrm{H}})k \\
+\mu_1(N_{\mathrm{L}}) + \mu_2(N_{\mathrm{H}}) - \mu_3(N_{\mathrm{L}}-\hat{N}_{\mathrm{L}}) - \mu_4(N_{\mathrm{H}}-\hat{N}_{\mathrm{H}}), \\
\mu_1 N_{\mathrm{L}} \le 0, \quad \mu_2 N_{\mathrm{H}} \le 0, \quad \mu_3(N_{\mathrm{L}}-\hat{N}_{\mathrm{L}}) \le 0, \text{ and } \mu_4(N_{\mathrm{H}}-\hat{N}_{\mathrm{H}}) \le 0 \\
N_{\mathrm{L}} \ge 0, \quad N_{\mathrm{H}} \ge 0, \quad N_{\mathrm{L}} \le \hat{N}_{\mathrm{L}}, \quad \text{ and } N_{\mathrm{H}} \le \hat{N}_{\mathrm{H}} \\
\text{where } \mu_i \ge 0 \text{ for each } i.
\end{gathered} \tag{10}$$

Maximizing with respect to N_{L} and N_{H} yields the following two first-order conditions:

$$\frac{\gamma\alpha(1-\beta)A(\gamma N^*_{\mathrm{L}}+N^*_{\mathrm{H}})^{\alpha-1}}{1-\beta(1-\alpha)} - (1-\beta)k + \mu_1 - \mu_3 = 0 \text{ and} \tag{11}$$

$$\frac{\alpha(1-\beta)A(\gamma N^*_{\mathrm{L}}+N^*_{\mathrm{H}})^{\alpha-1}}{1-\beta(1-\alpha)} - (1-\beta)k + \mu_2 - \mu_4 = 0 \tag{12}$$

which combine to the following condition:

$$(1-\beta)k\frac{1-\gamma}{\gamma} = \frac{1}{\gamma}\mu_1 - \mu_2 - \frac{1}{\gamma}\mu_3 + \mu_4. \tag{13}$$

Thus, if $N^*_{\mathrm{L}} > 0$, complementary slackness requires that $\mu_1 = 0$. By Equation 13, μ_4 must be positive, since the left side of the equation is strictly positive. Thus N^*_{H} must be constrained by $\hat{N}_{\mathrm{H}}$. ■

A.2 Characterization of the Hiring Regions

The four hiring regions can be shown formally using two cutoffs,

$$\tilde{N} := N \text{ such that } A(N)^{\alpha-1} = \frac{k(1-\beta(1-\alpha))}{\alpha} \text{ and} \tag{14}$$

$$\mathring{N} := N \text{ such that } A(N)^{\alpha-1} = \frac{1}{\gamma}\frac{k(1-\beta(1-\alpha))}{\alpha} \tag{15}$$

where $\tilde{N}$ is the optimal hiring decision if the choice of H-type hiring is interior and $\mathring{N}$ is the optimal hiring decision if the choice of L-type hiring is interior. These two cutoffs lead to the following optimal hiring lemma:

Lemma 4 *If the firm has matched with $\hat{N}_{\mathrm{L}}$ L-type workers and $\hat{N}_{\mathrm{H}}$ H-type workers, the optimal decision of how many workers to hire is given by:*

1. *If $\gamma\hat{N}_{\mathrm{L}} + \hat{N}_{\mathrm{H}} \leq \mathring{N}$ then $N^*_{\mathrm{H}} = \hat{N}_{\mathrm{H}}$ and $N^*_{\mathrm{L}} = \hat{N}_{\mathrm{L}}$;*
2. *if $\gamma\hat{N}_{\mathrm{L}} + \hat{N}_{\mathrm{H}} > \mathring{N}$ and $\hat{N}_{\mathrm{H}} < \mathring{N}$, then $N^*_{\mathrm{H}} = \hat{N}_{\mathrm{H}}$ and $N^*_{\mathrm{L}} = \frac{1}{\gamma}(\mathring{N} - \hat{N}_{\mathrm{L}})$;*
3. *if $\hat{N}_{\mathrm{H}} \geq \mathring{N}$ and $\hat{N}_{\mathrm{H}} \leq \tilde{N}$, then $N^*_{\mathrm{H}} = \hat{N}_{\mathrm{H}}$ and $N^*_{\mathrm{L}} = 0$; and*
4. *if $\hat{N}_{\mathrm{H}} > \tilde{N}$, then $N^*_{\mathrm{H}} = \tilde{N}$ and $N^*_{\mathrm{L}} = 0$.*

Proof of Lemma 4. Before examining the specific regions, I define two identities. First, suppose N^*_{H} is interior. Then by Lemma 3, $N^*_{\mathrm{L}} = 0$. So Equation 12 yields

$$N^*_{\mathrm{H}} = \Big(\frac{k(1-\beta(1-\alpha))}{\alpha A}\Big)^{\frac{1}{\alpha-1}}, \tag{16}$$

which is exactly $\tilde{N}$. So if the firm is unconstrained in hiring H-type workers, it will optimally choose $\tilde{N}$.

Next, suppose N^*_{L} is interior. By Lemma 3, N^*_{H} must be constrained by $\hat{N}_{\mathrm{H}}$. So from Equation 11,

$$\gamma N^*_{\mathrm{L}} + N^*_{\mathrm{H}} = \Big(\frac{k(1-\beta(1-\alpha))}{\gamma\alpha A}\Big)^{\frac{1}{\alpha-1}}, \tag{17}$$

which is equal to $\mathring{N}$.

Now consider the regions in turn.

First consider Region 1, where $\gamma\hat{N}_{\mathrm{L}} + \hat{N}_{\mathrm{H}} \leq \mathring{N}$, so both L-type and H-type hiring is constrained. In this case, the firm will hire all applicants with which it matched, so $N^*_{\mathrm{H}} = \hat{N}_{\mathrm{H}}$ and $N^*_{\mathrm{L}} = \hat{N}_{\mathrm{L}}$.

In Region 2, $\gamma\hat{N}_{\mathrm{L}} + \hat{N}_{\mathrm{H}} > \mathring{N}$ and $\hat{N}_{\mathrm{H}} < \mathring{N}$. Thus, $N^*_{\mathrm{H}} = \hat{N}_{\mathrm{H}}$. Since $\hat{N}_{\mathrm{H}} < \mathring{N}$, hiring of L-type workers is feasible. In particular, since $\gamma\hat{N}_{\mathrm{L}} + \hat{N}_{\mathrm{H}} \geq \mathring{N}$, by Equation 17 L-type hiring is unconstrained, so the firm will hire until $(\mathring{N} - \hat{N}_{\mathrm{H}})/\gamma$.

Next consider Region 3, where $\hat{N}_{\mathrm{H}} \geq \mathring{N}$ and $\hat{N}_{\mathrm{H}} \leq \tilde{N}$. From Equation 16, the firm cannot hire as many H-types as it would like, so it will be constrained by how many have matched with the firm, $\hat{N}_{\mathrm{H}}$. Will the firm hire any L-type workers? From Equation 17, if the firm is to hire a positive number of L-type workers, it must be that $\gamma N_{\mathrm{L}}^* + N_{\mathrm{H}}^* \leq \mathring{N}$. However, in Region 3 $\hat{N}_{\mathrm{H}} \geq \mathring{N}$. Since $N_{\mathrm{H}}^* = \hat{N}_{\mathrm{H}}$, N_{L}^* cannot be positive. Thus the optimal hiring in Region 3 is $\hat{N}_{\mathrm{H}}$ H-types and zero L-types.

Finally, consider Region 4, where $\hat{N}_{\mathrm{H}} > \tilde{N}$. From Equation 16, if the firm can hire as many H-types as it wants, it will hire $\tilde{N}$. So in this region, the hiring constraint does not bind, and the firm hires $N_{\mathrm{H}}^* = \tilde{N}$ and $N_{\mathrm{L}}^* = 0$. ■

A.3 Optimal Vacancy Posting

Before solving for optimal vacancy posting, I will prove one additional lemma to show the firm will never post vacancies such that it falls in Regions 2 and 4. Intuitively, in both Regions 2 and 4, the firm matches with extra workers that it chooses not to hire which is costly, due to the vacancy posting cost. Thus, the firm will maximize profits by choosing its vacancy posting carefully to avoid landing in these regions. Lemma 5 proves this intuition.

Lemma 5 *The firm will never choose to post vacancies such that the optimal hiring decision falls into Regions 2 or 4 from Lemma 4. Specifically, posting vacancies such that*

$$\frac{\mathring{N}}{\gamma q_{\mathrm{L}}(A) + q_{\mathrm{H}}(A)} < V < \frac{\mathring{N}}{q_{\mathrm{H}}(A)},$$

or such that

$$V > \frac{\tilde{N}}{q_{\mathrm{H}}(A)}$$

is strictly dominated.

Proof of Lemma 5.

First I will show that Region 4 is dominated by Region 3. Consider the largest vacancy posting that falls in Region 3: $V(\tilde{N})$. Suppose the firm posts $V(\tilde{N}) + \epsilon$, for some positive ϵ. From Lemma 4, we know the firm will only hire $\tilde{N}$ H-type workers, and no L-type workers. Thus, production and fixed employment costs ($\tilde{N}k$) are identical between $V(\tilde{N})$ and $V(\tilde{N})+\epsilon$ vacancies, however vacancy posting costs are strictly larger with more vacancy posting. Thus, Region 4 is dominated by Region 3.

Next I will show that Region 2 is dominated by Region 1 or Region 3, depending on the following condition:

$$\frac{c}{q_{\mathrm{H}}} \geq (1-\beta)k\frac{1-\gamma}{\gamma}. \tag{18}$$

First we consider Region 1. Let $V_1(\mathring{N}) = \frac{\mathring{N}}{\gamma q_{\mathrm{L}}(A)+q_{\mathrm{H}}(A)}$, which is the number of vacancies to arrive at the boundary point between Region 1 and Region 2. Now suppose the firm posts vacancies $V_1(\mathring{N}) + \epsilon$, for some small positive ϵ such that the $q_{\mathrm{H}}(A)V_1(\mathring{N}) + \epsilon < \mathring{N}$. This ensures that $V(\mathring{N}) + \epsilon$ falls in Region 2. From Lemma 4 we know that in Region 2, the firm will only hire $\mathring{N}$ total effective employees. Thus the firm will produce exactly the output it would have with vacancies $V_1(\mathring{N})$, however it will pay a higher vacancy cost since it posted more vacancies than strictly necessary. However, it will also pay a lower fixed cost of production, since it is producing with strictly more H-type workers and strictly fewer L-type workers. With some algebra, one can show that the profit is higher with vacancies $V_1(\mathring{N})$ compared with $V_1(\mathring{N}) + \epsilon$ if and only if Equation 18 holds.

Second we consider Region 3. Let $V_3(\mathring{N}) = \frac{\mathring{N}}{q_{\mathrm{H}}(A)}$, which is the number of vacancies to arrive at the boundary point between Region 2 and Region 3. Now suppose the firm posts vacancies $V_3(\mathring{N}) - \epsilon$, for some small positive ϵ such that the $q_{\mathrm{H}}(A)V(\mathring{N}) - \epsilon > \mathring{N}$. This ensures that $V_3(\mathring{N}) - \epsilon$ falls in Region 2. As with the comparison to Region 1, the the firm will produce exactly the output it would have with vacancies $V_3(\mathring{N})$. With some algebra, one can show that the profit is higher with vacancies $V_3(\mathring{N})$ compared with $V_3(\mathring{N}) - \epsilon$ if and only if Equation 18 does not hold.

Thus, if Equation 18 holds, any vacancy posting that falls in Region 2 is strictly dominated by posting at the boundary of Region 1. If Equation 18 fails, then any posting in Region 2 is strictly dominated by posting at the boundary of Region 3.

■

Proof of Proposition 1. From Lemma 5, the firm will only consider vacancies in Regions 1 and 3, as defined by Lemma 4. It is straightforward to show that the optimal vacancy posting from Region 3 dominates the optimal vacancy posting from Region 1 if and only if

$$\frac{c}{q_{\mathrm{H}}} \leq (1-\beta)k\frac{1-\gamma}{\gamma}.$$

This results in the following optimal vacancy posting schedule:

$$V^* : \begin{cases} \dfrac{\alpha A(1-\beta)}{1-\beta(1-\alpha)}(q_{\mathrm{H}}(A))^{\alpha}(V^*)^{\alpha-1} = (1-\beta)q_{\mathrm{H}}(A)k + c \\ \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \text{if } \dfrac{c}{q_{\mathrm{H}}} \leq (1-\beta)k\dfrac{1-\gamma}{\gamma} \\ \dfrac{\alpha A(1-\beta)}{1-\beta(1-\alpha)}(\gamma q_{\mathrm{L}}(A) + q_{\mathrm{H}}(A))^{\alpha}(V^*)^{\alpha-1} = (1-\beta)(q_{\mathrm{L}}(A) + q_{\mathrm{H}}(A))k + c \\ \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \text{otherwise} \end{cases} \tag{19}$$

■

B Online Appendix: Additional Tables

This Appendix includes a variety of additional results. Table B.1 provides summary statistics for the main samples. Table B.2 provides the estimates underlying Figure 2. Table B.3 gives several alternative specifications for the results in Table 1, including restricting results to individuals that are at least 20, restricting to hires into full time positions, restricting the sample to individuals who are not currently in school, and including time trends. All specifications tell a similar story to Table 1, with young workers experiencing substantially larger decreases in hiring rates with the state unemployment. In Columns (5) and (6), I separate hires from unemployment into layoffs and those who were not laid off. We see a larger decrease in the hiring rate for young workers for both samples; however, the coefficients for layoffs are not statistically distinct. Finally, in Columns (7) and (8), I run the specification separately for young and experienced workers. Here we again see results that confirm the main specification in Table 1.

Table B.1: Data Description

	All	Young	Experienced
Observations	16,948,516	24.6%	75.4%
Years Potential Experience	24.4	3.2	31.1
Age	43.3	21.9	50.3
Years Education	13.0	12.6	13.2
Female	52.1%	51.1%	52.5%
Non-White	16.2%	19.3%	15.2%
Hispanic	10.02%	12.7%	9.1%
Participation Rate	67.66%	66.88%	67.93%
Employment Rate	63.81%	60.84%	64.86%
Hired per Month	3.24%	5.86%	2.39%
Hired from Employment per Month	1.89%	3.11%	1.48%
Hired from Unemployment per Month	21.18%	23.45%	19.59%
Hired from Not in the Labor Force per Month	3.77%	7.26%	2.49%
Wage Observations	1,350,952	30.6%	69.4%
Real Log Weekly Wage	5.67	5.32	5.84

CPS monthly matched data, 1994 through September 2016. "Young" refers to individuals with less than or equal to ten years of potential experience, while experienced refers to individuals with more than ten years of potential experience. Sample restricted to civilian adults with non-missing age and education data who could be matched longitudinally. Wage data is only collected during outgoing-rotation group surveys, which occurs in 1/4 of the months.

In Tables B.4 and B.5 I replicate Table 5 for individual major occupation and industry groups, respectively. Although most cells are under-powered, across a variety of job classifications I show that the average potential experience of new hires has a positive point estimate. Exceptions are in management occupations and the transportation industry; however, transportation occupations show positive point estimates. Thus, it does not appear to be the case that the increase in the average potential experience of hires is due to cyclical composition changes in the jobs that hire.

In Table B.6, I interact education with two age categories: 30 and under, and over 30. Here we see that for individuals 30 and under without a college degree the hiring rate falls by approximately 0.3 percentage points with each additional percentage point of state

Table B.2: Hiring Over the Business Cycle: Detailed Potential Experience Categories

Outcome: Pr(Hired) × 100	(1)	(2)	(3)	(4)
PE < 0 × U. Rate	-0.493***	-0.283***	-1.950***	-0.581***
	(0.0241)	(0.0366)	(0.112)	(0.0302)
0 ≤ PE < 1 × U. Rate	-0.452***	-0.302***	-1.984***	-0.526***
	(0.0371)	(0.0270)	(0.180)	(0.0493)
1 ≤ PE < 2 × U. Rate	-0.296***	-0.235***	-1.879***	-0.482***
	(0.0256)	(0.0186)	(0.164)	(0.0619)
2 ≤ PE < 3 × U. Rate	-0.207***	-0.179***	-1.916***	-0.450***
	(0.0294)	(0.0282)	(0.210)	(0.0563)
3 ≤ PE < 4 × U. Rate	-0.173***	-0.151***	-1.999***	-0.427***
	(0.0347)	(0.0212)	(0.254)	(0.0753)
4 ≤ PE < 5 × U. Rate	-0.133***	-0.114***	-2.181***	-0.412***
	(0.0337)	(0.0201)	(0.278)	(0.100)
5 ≤ PE < 6 × U. Rate	-0.0858***	-0.124***	-1.643***	-0.339***
	(0.0240)	(0.0192)	(0.201)	(0.0820)
6 ≤ PE < 7 × U. Rate	-0.0851***	-0.113***	-1.886***	-0.200**
	(0.0184)	(0.0186)	(0.251)	(0.0590)
7 ≤ PE < 8 × U. Rate	-0.0940***	-0.0929***	-2.035***	-0.326***
	(0.0268)	(0.0198)	(0.250)	(0.0901)
8 ≤ PE < 9 × U. Rate	-0.0370	-0.0668**	-1.712***	-0.223*
	(0.0285)	(0.0208)	(0.289)	(0.0891)
9 ≤ PE < 10 × U. Rate	0.00137	-0.0289	-1.708***	-0.169*
	(0.0211)	(0.0147)	(0.216)	(0.0721)
10 ≤ PE < 15 × U. Rate	0.0242	-0.00495	-1.588***	-0.110*
	(0.0164)	(0.0107)	(0.209)	(0.0466)
15 ≤ PE < 20 × U. Rate	0.0484**	0.0261*	-1.474***	-0.182***
	(0.0173)	(0.0111)	(0.204)	(0.0483)
20 ≤ PE < 25 × U. Rate	0.0534***	0.0186	-1.328***	-0.0801
	(0.0143)	(0.0112)	(0.177)	(0.0405)
25 ≤ PE < 30 × U. Rate	0.0546***	0.0236*	-1.287***	-0.000331
	(0.0125)	(0.00983)	(0.139)	(0.0307)
30 ≤ PE < 35 × U. Rate	0.0581***	0.0340**	-1.374***	0.0388
	(0.0133)	(0.0118)	(0.168)	(0.0326)
35 ≤ PE < 40 × U. Rate	0.0552*	0.0382**	-1.455***	0.0317
	(0.0209)	(0.0132)	(0.212)	(0.0490)
40 ≤ PE < 45 × U. Rate	0.0706***	0.0444***	-1.260***	0.0688*
	(0.0110)	(0.0111)	(0.141)	(0.0273)
45 ≤ PE× U. Rate	-0.506***	-0.329***	-1.870***	-0.564***
	(0.0322)	(0.0331)	(0.239)	(0.0443)
N	16948516	10814088	653100	5481328
R-sq	0.011	0.005	0.033	0.025
Sample	All	Employed	Unemployed	NILF

"Hired" refers to beginning a job at a new firm. "PE" refers to potential experience, defined as (age − education − 6). Estimates include main effects and state, demographic, and month-year fixed effects. Specifications are weighted using CPS sampling weights. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

unemployment rate, but for individuals 30 and under with a college degree the net rate change is zero. On the other hand, for individuals over 30, in the specification with full controls we see no difference in hiring rates by college education, with both groups experiencing a small

Table B.3: Alternative Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PE $\leq$ 10	3.850***	1.951***	2.336***	4.990***	4.016**	9.588***		
	(0.0729)	(0.0496)	(0.0548)	(0.116)	(1.413)	(0.805)		
PE $\leq$ 10 $\times$ U. Rate	-0.138***	-0.157***	-0.175***	-0.233***	-2.040***	-1.918***		
	(0.0166)	(0.0109)	(0.0121)	(0.0186)	(0.386)	(0.164)		
PE $>$ 10 $\times$ U. Rate	0.0197	-0.00403	-0.00669	0.0707***	-1.845***	-1.299***		
	(0.0114)	(0.00910)	(0.00782)	(0.0141)	(0.324)	(0.175)		
U. Rate							-0.126***	-0.00271
							(0.0281)	(0.0123)
R-sq	15392007	16948516	15607133	16948516	85539	567561	4453483	12495033
N	0.007	0.004	0.004	0.009	0.031	0.034	0.006	0.002
Sample:	No Teens	FT Hires	FT hires,	State	Layoff	Unemp.	Young	Exp.
			Not in School	Time Trends		Not Layoff		
Wald Test	252.52***	614.03***	475.01***	572.13***	0.77	55.92***		

"Hired" refers to beginning a job at a new firm. "PE" refers to potential experience, defined as (age − education − 6). Estimates include main effects and state, demographic, and month-year fixed effects. "No Teens" restricts the sample to individuals aged 20 or older. "FT Hires" are restricted to hires into jobs of at least 35 hours per week. "Not in School" is restricted to individuals who are not in school in the first month of the sample. "Layoff" are unemployed individuals that report being on layoff. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table B.4: Average Potential Experience of Hires by Occupation

	(1)	(2)	(3)	(4)	(5)
Occupation	Management	Professional	Service	Sales	Office Support
State Unemp. Rate	-0.177	0.118	0.0985	0.169	0.0309
	(0.124)	(0.0749)	(0.0689)	(0.0970)	(0.0860)
N	36983	76892	136435	71744	78111
R-sq	0.074	0.072	0.106	0.126	0.117
	(6)	(7)	(8)	(9)	(10)
Occupation	Agriculture	Construction	Installation	Production	Transport
State Unemp. Rate	0.157	0.291**	0.224	0.464***	0.176
	(0.185)	(0.0979)	(0.179)	(0.0887)	(0.101)
N	10250	42626	14402	37441	44951
R-sq	0.219	0.055	0.051	0.068	0.056

Dependent variable is potential experience of new hires into a particular major occupation category, defined as (age − education − 6). The sample excludes individuals with negative potential experience. Estimates include constant and state, demographic, and month-year fixed effects. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table B.5: Average Potential Experience of Hires by Industry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry	Ag.	Mining	Constr.	Trade	Transport	Info.	Financial
State Unemp. Rate	-0.00749	0.423	0.306**	0.222**	-0.303*	0.0400	0.0608
	(0.188)	(0.354)	(0.0922)	(0.0769)	(0.114)	(0.144)	(0.147)
N	11728	2918	46830	92578	22150	11066	27208
R-sq	0.190	0.200	0.055	0.088	0.061	0.117	0.078

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Industry	Prof.	Ed/Health	Leisure	Other Services	Public	Dur. Mfg.	Non-Dur. Mfg.
State Unemp. Rate	0.116	0.109	0.0639	-0.0190	0.0714	0.151	0.279
	(0.114)	(0.0802)	(0.0551)	(0.128)	(0.124)	(0.0980)	(0.151)
N	59540	92723	83409	29210	18127	30806	21542
R-sq	0.067	0.069	0.106	0.128	0.093	0.063	0.076

Dependent variable is potential experience of new hires into a particular major industry category, defined as (age − education − 6). The sample excludes individuals with negative potential experience. Estimates include constant and state, demographic, and month-year fixed effects. Specifications are weighted using CPS sampling weights. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

but statistically significant increase in hiring rate of about 0.05 percentage points. Thus, the fall in hiring is entirely borne by young individuals without a college degree.

In Table B.7, I replicate Table 9 using alternative samples, including restricting results to individuals that are at least 20, restricting hires into full time positions, restricting the sample to individuals who are not currently in school, and including time trends. Results are consistent with the preferred sample in Table 9.

Table B.6: Hiring Over the Business Cycle: Age versus Education

Outcome: Pr(Hired) $\times$ 100	(1)	(2)	(3)	(4)
$\leq$ 30	5.616***	5.613***	5.572***	5.578***
	(0.139)	(0.142)	(0.144)	(0.144)
$\leq$ 30 $\times$ Col.	-3.433***	-3.431***	-3.387***	-3.379***
	(0.178)	(0.173)	(0.178)	(0.178)
$>$ 30 $\times$ Col.	-0.319***	-0.336***	-0.325***	-0.289***
	(0.0629)	(0.0618)	(0.0525)	(0.0525)
$\leq$ 30 $\times$ U. Rate	-0.368***	-0.394***	-0.404***	-0.292***
	(0.0222)	(0.0202)	(0.0195)	(0.0206)
$>$ 30 x U. Rate	-0.0313*	-0.0566***	-0.0634***	0.0498**
	(0.0153)	(0.0112)	(0.0101)	(0.0154)
$\leq$ 30 $\times$ Col. $\times$ U. Rate	0.274***	0.273***	0.282***	0.285***
	(0.0202)	(0.0199)	(0.0212)	(0.0212)
$>$ 30 $\times$ Col. $\times$ U. Rate.	-0.00674	-0.00682	0.00123	0.000122
	(0.0125)	(0.0121)	(0.00878)	(0.00872)
R-sq	0.008	0.008	0.009	0.009
State FE:	No	Yes	Yes	Yes
Demographic FE:	No	No	Yes	Yes
Month-Year FE:	No	No	No	Yes
N	16948516	16948516	16948516	16948516

"Hired" refers to beginning a job at a new firm. "PE" refers to potential experience, defined as (age − education − 6). "Col." and "No Col." refer to individuals with and without a college degree, respectively. "$\leq$ 30" and "$>$ 30" are individuals younger and older than 30, respectively. Specifications are weighted using CPS sampling weights. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table B.7: Age versus Education, Alternative Specifications

Outcome: Pr(Hired) × 100	(1)	(2)	(3)	(4)
≤ 30	4.464***	1.980***	2.595***	5.578***
	(0.0878)	(0.0646)	(0.0720)	(0.143)
$\leq 30 \times$ Col.	-2.264***	-0.154	-0.768***	-3.376***
	(0.115)	(0.135)	(0.134)	(0.179)
$> 30 \times$ Col.	-0.284***	-0.212***	-0.210***	-0.295***
	(0.0494)	(0.0307)	(0.0308)	(0.0536)
$\leq 30 \times$ U. Rate	-0.172***	-0.177***	-0.206***	-0.271***
	(0.0173)	(0.0129)	(0.0138)	(0.0207)
> 30 x U. Rate	0.0210	-0.00294	-0.00551	0.0705***
	(0.0123)	(0.00927)	(0.00814)	(0.0152)
$\leq 30 \times$ Col. $\times$ U. Rate	0.137***	0.100***	0.121***	0.285***
	(0.0163)	(0.0136)	(0.0140)	(0.0212)
$> 30 \times$ Col. $\times$ U. Rate.	0.00220	0.0146**	0.0142**	0.00114
	(0.00826)	(0.00461)	(0.00465)	(0.00891)
N	15392007	16948516	15607133	16948516
R-sq	0.007	0.003	0.004	0.009
			FT hires	State
Sample:	No Teens	FT Hires	Not in School	Time Trends

"Hired" refers to beginning a job at a new firm. "PE" refers to potential experience, defined as (age − education − 6). "Col." and "No Col." refer to individuals with and without a college degree, respectively. "≤ 30" and "> 30" are individuals younger and older than 30, respectively. Estimates include main effects and state, demographic, and month-year fixed effects. "No Teens" restricts the sample to individuals aged 20 or older. "FT Hires" are restricted to hires into jobs of at least 35 hours per week. "Not in School" is restricted to individuals who are not in school in the first month of the sample. Specifications are weighted using CPS sampling weights. Standard errors in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

C Online Appendix: Heterogeneity by Occupation

So far I have shown that, on average, young workers and more-experienced workers are affected differently by an increase in the state unemployment rate: for young workers the hiring rate falls and real wages fall, while for more-experienced workers the hiring rate is unaffected and real wages fall by much less. However, it is possible that these two phenomena are occurring in different types of jobs. I thus replicate these two sets of results for major occupation groups.

In the top panel of Figure C.1 and the first column of Table C.1 I modify the specification in Equation 1 such that the dependent variable is an indicator for hiring into a particular occupation. As before, I include state, month-year, and demographic fixed effects, and cluster standard errors at the state level. Each row of Table C.1 corresponds to a separate regression. Here the same pattern from Table 1 holds within all occupation categories, with a statistically significant decrease in the hiring rate for young workers and either no significant change or a small increase in the hiring rate for experienced workers. Thus, for all major occupations, firms hire fewer young workers and no fewer experienced workers.

Although the aggregated regressions in Table 1 show a small but statistically significant increase in the hiring rate of experienced workers with the state unemployment rate, Table C.1 shows there is substantial variation by occupation. In the bottom panel of Figure C.1 and the second column of Table C.1, I replicate Column (1) from Table 10, again calculated separately for each major occupation. Here we see strong decreases in log wages for young workers across occupations. While many occupations exhibit wage decreases for experienced workers, for all occupations young workers show more negative point estimates.

Table C.1: Cyclical Hiring and Wages within Occupations

Occupation		Change in Hiring		Change in Log Wages	
	PE $\leq$ 10 × U. Rate	-0.00720***	(0.00191)	-0.0139	(0.0182)
Management	PE > 10 × U. Rate	-0.00122	(0.00170)	-0.00780	(0.0128)
	Difference	17.82***		0.37	
	PE $\leq$ 10 × U. Rate	-0.0136***	(0.00321)	-0.0529***	(0.0117)
Professional and related	PE > 10 × U. Rate	0.00144	(0.00221)	-0.0287*	(0.0118)
	Difference	30.37***		7.43**	
	PE $\leq$ 10 × U. Rate	-0.0652***	(0.00647)	-0.0278***	(0.00552)
Service	PE > 10 × U. Rate	0.0164*	(0.00689)	-0.0131*	(0.00617)
	Difference	112.41***		6.93*	
	PE $\leq$ 10 × U. Rate	-0.0517***	(0.00537)	-0.00695	(0.0108)
Sales and related	PE > 10 × U. Rate	0.00632*	(0.00254)	-0.00254	(0.0122)
	Difference	161.3***		0.12	
	PE $\leq$ 10 × U. Rate	-0.0421***	(0.00300)	-0.0262***	(0.00693)
Office and admin. support	PE > 10 × U. Rate	0.00746**	(0.00244)	-0.00395	(0.00773)
	Difference	162.4***		8.18**	
	PE $\leq$ 10 × U. Rate	-0.00274	(0.00245)	-0.0801	(0.0417)
Farming, fishing, and forestry	PE > 10 × U. Rate	0.00670***	(0.00160)	-0.0591*	(0.0255)
	Difference	11.83**		0.68	
	PE $\leq$ 10 × U. Rate	-0.0268***	(0.00377)	-0.0326**	(0.0111)
Construction and extraction	PE > 10 × U. Rate	0.00545	(0.00327)	-0.0147	(0.00984)
	Difference	178.85***		2.96	
	PE $\leq$ 10 × U. Rate	-0.00659***	(0.00127)	0.00498	(0.0224)
Installation	PE > 10 × U. Rate	0.000279	(0.000943)	-0.00408	(0.0154)
	Difference	52.81***		0.33	
	PE $\leq$ 10 × U. Rate	-0.0149***	-0.00346	-0.0517***	(0.0123)
Production	PE > 10 × U. Rate	0.00195	-0.00267	-0.0247*	(0.0115)
	Difference	52.81***		9.11**	
	PE $\leq$ 10 × U. Rate	-0.0224***	(0.00363)	-0.0292	(0.0162)
Transportation	PE > 10 × U. Rate	0.00481	(0.00241)	-0.00530	(0.0127)
	Difference	155.41***		6.99*	

Each column represents a separate specification, with each row a separate regression. In Column (1) the dependent variable is a dummy variable for whether the individual was hired into that particular occupation (scaled to 100), while in Column (2) the dependent variable is log wages for individuals hired into the occupation. "PE" refers to potential experience, defined as (age − education − 6). Estimates include constant and main effects, as well as state, demographic, and month-year fixed effects. Specifications are weighted using CPS sampling weights. Standard errors are in parentheses, clustered at the state level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. "Difference" indicates whether a Wald test for the difference in the point estimates for unemployment rate for young versus experienced is statistically significant.

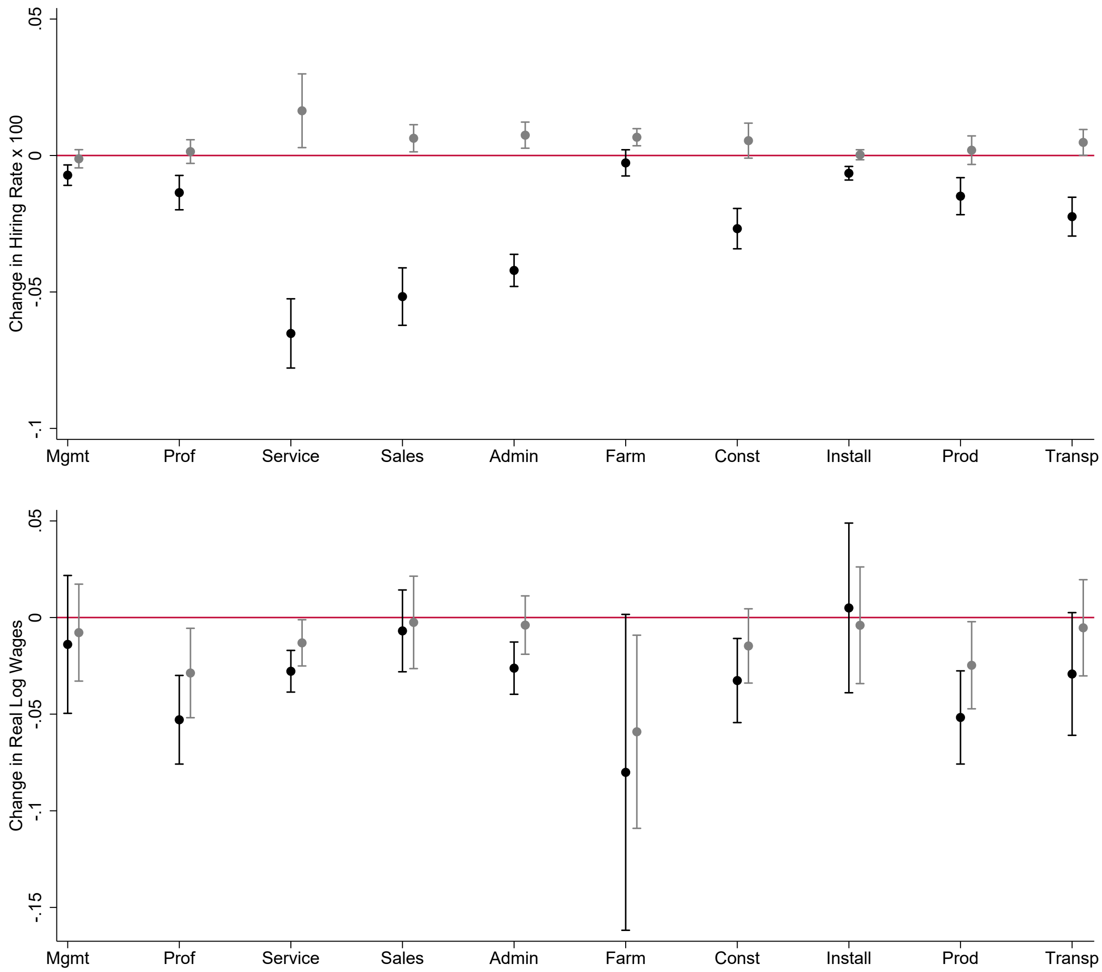


Figure C.1: Each point in the top and bottom panels represents the change in the hiring rate or log wages (respectively) for each additional percentage point in the state unemployment rate from separate regressions by occupation, as described in Table C.1. Grey lines represent young workers and black lines represent experienced workers, where "young" is defined as potential experience (age − education − 6) less or equal to 10 years and "experienced" as potential experience above 10 years. Specifications are weighted using CPS sampling weights. Error bars represent 95% confidence intervals, based on standard errors clustered at the state level.