Schooling, Experience, Career Interruptions, and Earnings

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Abstract

In this paper, I investigate how the interaction between schooling and work experience affects earnings. Different from the existing literature, in the construction of the experience variable I distinguish working and non-working periods after an individual leaves school. This distinction is important because, as demonstrated in the paper, the *potential experience* variable typically used in the previous literature produces a greater bias to the returns to experience for more educated workers. The empirical results using accurate measures of work history are remarkably different from those in the existing literature. Using different estimation strategies, I consistently find that more educated workers have a higher wage increase with actual experience but suffer a greater wage loss after unemployment periods. These results are puzzling with respect to existing theories of earnings dynamics. In order to rationalize them, I develop a novel model where high ability workers have greater returns to human capital. In addition, employers have imperfect information about workers and use past unemployment in the prediction of their unobservable quality. Under these assumptions, the model predicts that educated workers have a higher wage growth with experience but face greater wage losses with unemployment.

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1 Introduction

Economists have long recognized that schooling and experience are two of the most important aspects of earnings determination.[1] Given the importance of these two variables, a natural question is: how does their interaction affect earnings? In other words, do educated workers have a higher or lower wage increase as they accumulate experience? Which theories can explain this relationship?

In addition to the time spent at work, it is also well documented that individuals spend a significant portion of their time unemployed or out of the labor force during their careers, and these events have a persistent effect on a worker's life-time earnings.[2] Given the importance of non-working events throughout a worker's life cycle, it is also of considerable interest to investigate whether educated workers suffer greater or lower wage losses after out-of-work periods.

It is within this context that this paper examines how the interaction between schooling and work experience affects earnings. In contrast to the existing literature, I take into consideration that workers spend a significant amount of time not employed throughout their careers and that working and non-working periods are substantially different in terms of the interaction between workers and firms.

While considering the difference between working and non-working periods seems natural, this difference has been ignored in most of the existing literature. Table 1 presents some the most important papers that have addressed how the interaction between schooling and experience affects earnings. As can be seen in the table, in order to identify whether more educated workers have a higher or lower wage increase with experience, these papers have used rough measures of experience, such as age minus schooling minus six or years since transition to the labor force.[3]

As seen in the table, the overall finding in the literature is that returns to potential experience *do*

[1] The study of the impact of schooling and experience on earnings goes back to Becker (1962), Mincer (1962) and Ben-Porath (1967).

[2] Examples of papers studying the effect of career interruptions on earnings include Mincer and Polachek (1974), Corcoran and Duncan (1979), Mincer and Ofek (1982), Kim and Polachek (1994), Light and Ureta (1995), and Albrecht et al. (1999).

[3] Note also that these studies differ on how they define earnings. For example, Farber and Gibbons (1996) use earning in levels. There is also a difference between using annual or hourly wages as the dependent variable. Mincer (1974) uses annual earnings, but only finds evidence for parallel wage profile when controlling for weeks worked in the past calendar year. With the exception of Heckman et al. (2006), most recent papers have used hourly earnings as the dependent variable.

not change across educational groups in old datasets (Mincer, 1974), or *decrease* with educational level in the most recent datasets (Lemieux, 2006 and Heckman et al., 2006).[4] These results had a lasting influence on empirical work in the field of labor economics. For example, Mincer (1974) used his findings to justify the separability between schooling and experience present in the Mincer earnings equation, which has remained for decades the ''workhorse'' of empirical research on earnings determination.[5]

Despite the unquestionable value of the articles presented in table 1, in this paper I point out issues associated with the measures of experience they use. The first contribution of this paper is to demonstrate that potential experience used in Mincer (1974) confounds the impact of two distinct events on earnings: actual experience and past non-working periods. Furthermore, I demonstrate that if educated workers suffer greater wage losses after out-of-work periods, *potential experience* can produce greater bias to the returns to experience for more educated workers.

This result is at odds with the literature that discusses the bias associated with using potential experience variable (Filer, 1993, Altonji and Blank, 1999, and Blau and Kahn, 2013). According to this literature, potential experience generates *lower* bias to the returns to experience for demographic groups with higher employment attachment, such as more educated workers. In contrast, I demonstrate that potential experience can generate a *greater* bias to the returns to experience for workers with higher employment attachment if their earnings are more affected after career interruptions. To my knowledge, this is the first paper that addresses this matter.

The second contribution of this paper is to use the National Longitudinal Survey of Youth (NLSY) to estimate a model where earnings depend on work experience, past unemployment and non-participation periods, and their interaction with schooling. While there is an extensive literature the analysis the impact of career interruptions on earnings (Mincer and Polachek, 1974 and

[4] Altonji and Pierret (2001) also find negative coefficients for interaction between schooling and experience when including ability measures not observed by firms that are correlated to schooling on the earnings equation.

[5] The existing literature presents some possible explanations for the non-increasing effect of schooling on earnings. In the traditional Mincerian model, all workers have the same rate of returns to on-the-job investment, that is independent of their educational achievement. This independence between human capital investments at school and on-the-job can justify the parallel log earnings-experience profiles acroos educational groups. On the other hand, Farber and Gibbons (1996), and Altonji and Pierret (2001) claim that schooling is used by employers as a signal of a worker's ability. Therefore, schooling should not become more important for earnings as a worker accumulates work experience.

Mincer and Ofek, 1982), on the gender gap (Kim and Polachek, 1994 and Light and Ureta, 1995), and on race wage gap (Antecol and Bedard, 2004), to my knowledge this is the first paper that addresses how past working and non-working periods affect the wage coefficient on schooling.

The results from the estimation of the earnings model that fully characterize the work history of individuals are remarkably different from the standard specification using potential experience. Using my preferred estimation method, I find that for non-black males, the wage coefficient on schooling *increases* by 1.8 percentage points with 10 years of actual experience, but *decreases* by 2.2 percentage points with 1 year of unemployment. In other words, the earning differential between the more and less educated workers mildly rises with actual experience but significantly falls with unemployment. The periods a worker spends out of the labor force (OLF) do not significantly affect the wage coefficients on schooling. I also find qualitatively similar results for blacks and women, with the exception that I find a negative effect of the interaction between OLF periods and schooling on earnings for women.

I provide several robustness checks for these results. First, I estimate a non-parametric model where I do not impose restrictions on the relation between earnings, schooling, work experience, and career interruptions. Second, I change the earnings model so that the timing of career interruptions can also change the effect of schooling on earnings. Third, I take into consideration the possible endogeneity of work history, and estimate a model using an individual fixed effect assumption. In all these specifications, I consistently find that more educated workers have a higher wage increase with work experience but suffer greater wage losses after unemployment periods.

Given the novelty of these results, my third contribution is to propose a model that can rationalize the empirical findings of this paper. In the model, the productivity of a worker depends on his ability, schooling level and work experience. However, different from the articles in table 1, I assume that ability is complementary to schooling and experience in determining a worker's productivity. In other words, high ability workers have higher returns to human capital investiments at school and on-the-job.

The model also shares features with the employer learning literature (Farber and Gibbons, 1996

and Altonji and Pierret, 2001). Firms observe schooling and the work history of individuals but have imperfect information about their ability. Within this framework, employers have to make predictions about a worker's ability using the information available at each period. As low-ability workers are more likely to be unemployed throughout their careers, firms use information regarding past employment history of workers in the prediction of their unobservable ability.[6]

Based on the framework described above, the model can predict the empirical results of the paper. The intuition is as follows. High ability workers learn faster on-the-job and have a higher productivity growth as they accumulate work experience. As ability and education are positively related, the model predicts that educated workers have a higher wage increase with experience. In addition, employers use past unemployment as a signal that a worker is low ability. As a low ability workers have lower returns to schooling, the model predicts that more educated workers suffer greater wage losses when their low ability is revealed through unemployment.

The paper is organized as follows. In section 2, I discuss the issues of using potential experience when estimating a typical Mincer equation if career interruptions have an impact on earnings. In section 3, I describe the data and I show some descriptive statistics. Section 4 presents the main empirical results of the paper, and I provide some robustness checks. In section 5, I describe the model, and Section 6 concludes the paper.

2 Potential Experience and Career Interruptions in the Mincer Equation

The Mincer earnings equation has long been long used as the workhorse of empirical research on earnings determination. Based on theoretical and empirical arguments, Mincer (1974) proposed a specification where the logarithm of earnings is a linear function of education and a quadratic function of potential experience (age minus schooling minus six). Mincer also suggested that schooling

[6]While there are studies where employers use lay off information (Gibbons and Katz, 1991) or the duration of an unemployment spell (Lockwood, 1991 and Kroft et al., 2013) to infer a worker's unobservable quality, in this paper firms take into consideration the full work history of an individual.

and experience are separable in the earnings equation, meaning no interaction term between these two variables is required in the earnings equation. Notably, as discussed shown in table 1, Mincer founds evidence that potential experience profiles are nearly parallel across educational groups.

There is wide discussion on the potential pitfalls with the earnings specification proposed by Mincer (Murphy and Welch (1990) and Heckman et al. (2006)), including discussion of the issues associated with using the potential experience variable (Filer, 1993 and Blau and Kahn, 2013). In addition to the existing critiques, in this section I discuss new issues with using the potential experience variable when non-working periods affect earnings.

In order to give some perspective to this issue, I begin the analysis with the traditional case where earnings are affected only by actual experience and not by non-working periods.[7] The log-earnings generating process of worker i at time period t ($\ln w_{it}$) with level of schooling s is defined by the equation below. The parameter β_1^s identifies the impact of the increase of actual experience for workers with level of education s.

$$\ln w_{it} = \beta_0^s + \beta_1^s exper_{it} + \varepsilon_{it} \tag{1}$$

For expositional purposes, and different from Mincer's suggested specification, I assume that log earnings are a linear function of experience. As discussed in Regan and Oaxaca (2009), an inclusion of a quadratic and cubic term tends to exacerbate the type of bias that is discussed here.[8]

The object of interest of the paper is the interaction between schooling and experience. In terms of the equation above, I am interested in how the parameter β_1^s changes across different educational groups. Note that according to Mincer (1974) original specification, log-experience profiles are parallel across educational groups: $\beta_1^s = \beta_1$ for all s.

Equation (1) describes how log-earnings changes with actual experience, but individuals can spend some time not working after they leave school. I define $l_{\tau i}$ as an indicator variable that assumes a value of one if individual i worked at past time period τ. The actual experience variable

[7] In Mincer (1974), the potential experience variable is interpreted as a measure of on-the-job training.

[8] In the empirical section of the paper I include different functional forms for both actual experience and career interruptions.

is defined by the sum of past working periods after a worker left school:

$$exper_{it} = \sum_{\tau=g}^{t-1} l_{i\tau}$$

where g is the time at which an individual leaves school. I also assume that $l_{i\tau}$ is independent of the wage error term ε_{it} and $\mathbb{E}[l_{i\tau}] = p_s$, where p_s is a constant between zero and one that indicates the expected fraction of periods that a worker with s level of education stays employed after leaving school.[9]

In most datasets it is not possible to identify an individual's work history. For this reason, researchers have long used rough measures of experience which do not distinguish working and non-working periods, such as the potential experience variable. In the context described above, the potential experience variable $pexp_{it}$, is defined as the time period since an individual left school:[10]

$$pexp_{it} = t - 1 - g$$

In this framework, it is easy to show that the coefficient that expresses how earnings change with potential experience is a biased estimator of β_1^s, such that $\widetilde{\beta}_{pex} = p_s \beta_1^s$. In fact, this is typical attenuation bias associate with using the potential experience variable present in the literature (Filer, 1993 and Blau and Kahn, 2013). Note that while potential experience attenuates the returns to experience for all demographic groups, the attenuation bias is higher for demographic groups with lower employment attachment. That is the reason why using complete measures of actual experience is a special issue in the literature that studies the gender wage gap (Altonji and Blank, 1999).

Note that as educated workers tend to have a higher employment attachment than uneducated workers, such that $p_s > p_{s-1}$, this model predicts that potential experience underestimates the difference in the wage growth between educated and uneducated workers. In other words, if earnings are not affected by career interruptions, the potential experience generates a lower bias to the returns

[9] A discussion of the potential endogeneity of $l_{i\tau}$ is found in section 3.2.4.

[10] Mincer (1974)'s definition of age-6-schooling would also generate an error term regarding the correct measure of the time a worker left school. For simplicity, I will assume this term is orthogonal to all other variables of the model, and therefore, I ignore it here.

to experience for more educated workers. However, as I will show in section 3.2, this is the opposite to what it is observed in the data.

Suppose now that in addition to actual experience, non-working periods also have a long-term impact on wages.[11] A representation for the earnings equation in this framework would be:

$$\ln w_{it} = \beta_0^s + \beta_1^s exper_{it} + \beta_2^s interr_{it} + \varepsilon_{it} \tag{2}$$

where $inter_{it}$ is a measure of career interruptions of a worker since leaving school. Using the same notation as before, I define career interruptions as the accumulation of non-working periods since an individual left school:

$$interr_{it} = \textstyle\sum_{\tau=g}^{t-1}(1 - l_{i\tau})$$

Note that for simplicity, I assume that earnings are affected by the cumulative non-working periods. However, one can argue that the order and length of non-working periods have a different impact on earnings (Light and Ureta, 1995). In the empirical sections of the paper I also consider this possibility, but for exposition I assume that earnings are only affected by the accumulation of out-of work periods (Albrecht et al., 1999).

Under the earnings generating process described in (2), it is easy to show that a regression of earnings on potential experience identifies the following object:

$$\widetilde{\beta}_{pex}^s = p_s \beta_1^s + (1 - p_s)\beta_2^s$$

Note that in this framework $\widetilde{\beta}_{pex}^s$ confounds the effect of actual experience and career interruptions on earnings. In precise terms, the potential experience effect on earnings is a weighted average of β_1^s and β_2^s, with the weight being defined as the expected employment attachment of workers.

A few comments are needed on how this framework is related to the traditional potential experience bias when career interruptions do not have an impact on earnings, as presented in the

[11] Possible explanations for that are human capital depreciation (Mincer and Polachek, 1974 and Mincer and Ofek, 1982), firms using the information on past non-working periods as a signal of a worker's productivity (Albrecht et al., 1999), or even that workers accept a wage loss after career interruptions due to liquidity constraints, end of non-working benefits or disutility from leisure (Arulampalam, 2001). In section 4, I present a theory for why career interruptions affect wages.

discussion of model (1). First, if career interruptions have a negative impact on earnings ($\beta_2^s < 0$), the downward bias on estimating on the returns to actual experience is even greater than what the literature has been suggested (Filer, 1993 and Blau and Kahn, 2013).

Second, the potential experience bias can cause greater bias for groups with higher employment attachment. If demographic groups with high employment attachment are also more affected by career interruption (more negative β_2^s), it might be the case that $\widetilde{\beta}_{pex}^s$ is a more biased estimator of β_1^s than it is for groups with low employment attachment. In section 3.2 I demonstrate that i) educated workers have a higher employment attachment; ii) educated workers face much greater wage losses with career interruptions; and iii) potential experience produces a greater bias to the returns to actual experience for more educated workers.

3 Empirical Dynamics

3.1 Data

The data used in this paper are the 1979-2010 waves of the National Longitudinal Survey of Youth (NLSY) 1979. The NLSY is well suited for this study because it contains detailed information about individuals' work history since an early age, and follows them during a significant portion of their careers. The individuals in the sample were 14–22 years old when they were first surveyed in 1979, and they were surveyed annually from to 1979 to 1993 and biennially from 1994 to 2010.

The sample is restricted to the 2,657 non-black males from the cross-section (nationally representative) sample. This decision to restrict the sample was based on several reasons. First, this is a more stable demographic group during the decades of analysis. The labor market for women and blacks has passed through significant changes in the past 30 years. Second, reasons for career interruptions might differ by gender and race. Even though it is possible to differentiate unemployment from out-of-the-labor-force periods in the data, it is well know that reasons for non-participation in the labor market can substantially differ among demographic groups. Finally, most of the current studies presented in table 1 restrict the sample to non-black males, consequently this sample re-

striction allows a better comparison between my results and previous studies. Nevertheless, given the interest in women and blacks, I also present the main results of the paper for these groups, separately.

I define "year of leaving school" as the year when a worker has achieved his highest schooling level and I consider only workers that have been in the labor market after they left school.[12] Note that this definition for year of leaving school assures that career interruptions are not caused by a worker's decision to go back to school. However, it also ignores work experience that an individual might have accumulated before achieving his highest degree level. In order to show that the main findings of the paper are not sensitive to such previous work experiences, I also present robustness checks where I define "year of leaving school" as the year an individual reports to not be enrolled in school for the first time.

In the NLSY it is possible to identify week-by-week records of individuals' labor force status since 1978. I use these variables to calculate for each potential experience year (age minus schooling minus six) the share of weeks that each worker in the sample spent working, unemployed, out of the labor force, or in active military service. I use this information to present statistics on average employment attachment over the life cycle for high school graduates and workers with at least a college degree in figures 1 and 2, respectively. These figures reveal that both high school and college graduates spend on average a significant share of their time after leaving school not working, although career interruptions happen much more often for the former group.

A surprising finding from these figures is that non-black males spend a significant share of their time out-of-the labor force throughout their careers. Although the NLSY provides limited information on the reasons for non-participation of workers, I did some further investigation of the available data for why these group of workers are out-of-the labor force.[13] The results show that the reasons are very diverse, with the three most common reasons being individuals that did not want to work (20%), had a new job they were to start (19%) and were ill or unable to work (14%).

In addition to week-by-week information, NLSY also provides information on weeks between

[12] I dropped 75 individuals that did not have any observations after the year they left school.

[13] The data is limited due to the changes of questionnaires across years. These statistics are based on the years 1989-1993, when the most complete questionnaires on the reasons for non-participation are available.

interview years that an individual spent working, unemployed, out of the labor force, or in military service [14] These retrospective variables were used to construct the main work history variables used in the paper, as presented in table 2. More specifically, for each individual, work experience is defined as the cumulative number of weeks spent working since leaving school. In addition, cumulative unemployment, OLF, and military service years were defined as the number of weeks spent in each of these labor force conditions since leaving school. I then divide all variables by 52, so that the measurement unit is year.[15] Throughout the paper, potential experience is defined as age minus schooling minus six. This is the variable typically used in the literature (table 1) to measure experience, and as discussed before, it does not distinguish working and non-working periods throughout a worker's career. Note that because some individuals take more time to finish school than their schooling years, potential experience does not accurately measure the years a worker is in the labor market. For this reason, I also use time since leaving school as an alternative measure of experience that does not account for non-working periods. Note that time since leaving school is just the sum of the other cumulative work history variables.[16]

The wage is calculated as the hourly rate of pay (measured in year 1999 dollars) for the current or most recent job of a worker.[17] In order to perform the earnings equation estimation, I also restrict the observations to individuals employed at time of interview who work for hourly wages higher than $1 and less $100.[18] After these sample restrictions given above, the remaining sample consists of 2,484 individuals with 33,707 observations. All the statistics in the paper are unweighted.

[14] There is also information on the percentage of weeks that NLSY cannot be accounted for. I use this information as a control in all regressions.

[15] In section 3.2.3 I also explore the possibility that timing of career interruptions might affect earnings.

[16] An issue I faced while creating the work history variables is the fact that 7% of the individuals in the sample graduated before 1978 and there is no available information regarding their work history before this year. I try to overcome this problem by using information available on when a worker left school (a year before 1978) and impute the work history variables described in table 2 for these individuals, between the year of leaving school and the year 1978. The imputation method consists of calculating the number of work/unemployment/OLF/military service weeks for the 1978 calendar year, and the assumption that it was constant between the year of leaving school and 1978. An alternative approach is to drop the 196 individuals who graduated before 1978 from the analysis. The results of this second approach are quite similar to imputing the work history variable, so I decided to omit them in this paper, but they are available upon request.

[17] The hourly rate of pay is calculated in the NLSY from answers to questions concerning earnings and time units for pay. If a respondent reports wages with an hourly time unit, actual responses are reported as the hourly rate of pay. For those reporting a different time unit, NLSY uses number of hours usually worked per week to calculate an hourly rate of pay.

[18] There are 41 individuals who do not have any observations during the whole period of analysis with earnings within this interval.

Table 3 contains the main statistics of the sample used in the earnings equation estimations for different educational levels. This table highlights some important features of the data. First, the mean of the potential experience and time since leaving school variables are significantly greater than the mean of the work experience for all educational groups. This shows that even for non-black males – a group with considerably higher employment attachment – potential experience substantially overstates actual experience. However, as expected, the difference is higher for less educated workers. Second, the individuals in all the educational groups spend more time out of the labor force than unemployed throughout their career. Finally, the work history information reported in the NLSY is quite accurate: for only 0.8% of weeks since leaving school NLSY was not able to define the labor status of the workers in the sample.

3.2 Earnings Dynamics Estimation

There are two main earnings models that are estimated in this paper. The first model represents the typical earnings equation that has been widely used in the literature, which shows how the effect of schooling on wages changes with potential experience (see table 1). I refer to this model as the traditional model and define log-earnings of individual i in time period t as:

$$\ln w_{it} = \alpha_0 + \alpha_1 s_i + \alpha_2 (s_i \times pexp_{it}) + g(pexp_{it}) + \varepsilon_{it} \tag{3}$$

where $\ln w_{it}$ is the log of hourly earnings, s_i is years of schooling and $pexp_{it}$ is the potential experience, defined as "age - schooling - six" or "time since graduation", which do not distinguish working and non-working periods and $g(.)$ is as cubic function.[19] The primarily interest of the paper is estimating the parameter α_2 which identifies how the wage coefficient on schooling changes with potential experience. It is important to note that in previous work (table 1) this parameter has been consistently estimated as non-positive; I aim to test whether the same result is found in the sample used in this paper.

[19] Mincer (1974) uses log of annual wages and $g(.)$ function is defined as a quadratic function. But since the seminal paper from Murphy and Welch (1990), the convention is to use log of hourly earnings and define $g(.)$ a cubic (or even quartic) polynomial.

In addition to equation 3, I also estimate a wage model that fully characterizes the past employment and unemployment history of workers:

$$\ln w_{it} = \beta_0 + \beta_1 s_i + \beta_2(s_i \times exper_{it}) + \beta_3(s_i \times interr_{it}) + f(exper_{it}) + h(interr_{it}) + u_{it} \qquad (4)$$

where $exper_{it}$ is work experience and $interr_{it}$ is a measure of career interruptions since leaving school. The objects of interest are the parameters β_2 and β_3, which identify how the wage coefficient on schooling changes with work experience and past non-working periods respectively.

When modeling an earnings function that accounts for the work history of individuals, a researcher is confronted with some non-trivial choices. First, there is a question regarding the appropriate way to measure career interruptions. It has been shown that different labor force status of individuals during career interruptions might have different impact on subsequent wages (Mincer and Ofek, 1982 and Albrecht et al., 1999). For this reason, I will follow the literature and make the distinction between periods of unemployment, time spent out of the labor force, and military service periods.

Second, one can claim that the timing of career interruptions is also important for earnings determination. With respect to this issue, the literature has suggested different specifications, ranging from the simple accumulation of out-of-work periods since leaving school (Albrecht et al., 1999) to a less parsimonious model, which characterizes the number of weeks out of employment for every year since leaving school (Light and Ureta, 1995). For the main results of the paper I will follow Albrecht et al. (1999) and accumulate periods of unemployment and out-of-work since leaving school. However, in subsection 3.2.3 the analogous results using a less parsimonious model are also presented, where timing of non-working periods is important for earnings.

The final non-trivial choice is how to define the functions $f(.)$ and $h(.)$. In order to be consistent with the most recent literature on the earnings equation (Murphy and Welch (1990)), I define $f(.)$ as a cubic polynomial in the main tables of the paper. By analogy, I will also define $h(.)$ as cubic polynomial, although the coefficients of higher order terms are usually not significant. Nevertheless,

I will also present a less-restricted model, where I estimate both $f(.)$ and $h(.)$ non-parametrically in subsection 3.2.2 and the results are qualitatively similar to the ones presented with the cubic assumption.

3.2.1 Main Results

Throughout the paper I normalize the interactions between schooling and measures of work history variables such that coefficient of interactions represent a change in the wage coefficient on schooling with 10 years of experience, unemployment, or OLF periods. All the standard errors presented are White/Huber standard errors clustered at the individual level.

Columns (1) and (2) of table 4 show the estimation of the traditional earnings model as presented in equation (3). The main point of these estimations is to show that one can replicate the finding of the literature, as presented in table 1, using the sample restrictions of this paper. First, in column (1) I estimate that the effect of an extra year of schooling on earnings in the beginning of a worker career is 11% (0.006). Next, I estimate that interaction between schooling and potential experience is statistically insignificant. This result is in accordance with Mincer (1974), who found no effects of the interactions between schooling and potential experience on earnings (parallel or convergence of log earnings potential experience profiles across educational groups). Finally, in column (2) I estimate the same specification using time since leaving school as a measure of experience. This measure also does not distinguish working in non-working periods but accurately identifies the period in which a worker left school. Note that the results from these specifications are similar to the ones presented in column (1).

Column (3) provides the estimation of the career interruptions earnings model as presented in equation (4). As can be seen, the result from this specification is remarkably different from the ones using the traditional model. First, I estimate a lower schooling coefficient of 8% (0.005). Second, I find a positive and significant coefficient of 0.018 for the interaction between schooling and work experience, meaning that the effect of one additional year of education increases from 8% to 10%, after a worker accumulates *ten* years of work experience. Furthermore, I estimate a negative effect

of the interaction between past unemployment and schooling. Specifically, I estimate that the wage coefficient on schooling decreases by 2.1%, following *one* year of unemployment. Finally, I find a positive – but not significant – interaction between OLF periods and schooling.[20] But, as discussed in section 3.1, the interpretation for the impact of OLF periods on wage for this demographic group is challenging due to heterogeneous reasons that lead to this type of career interruption.

Columns (4) and (5) provide more robustness to the previous results. In column (4) tenure and its interaction with schooling are added to the model. The idea behind this addition is to investigate whether the main findings of the paper are due to the period a worker is attached to a particular employer, rather than general labor market experience. From these estimations, I find that: i) the coefficients of the career interruptions model are barely affected by the inclusion of these variables; and ii) the wage coefficient on schooling is not significantly affected by tenure. This result suggests that firm-specific mechanisms are not the main explanation for the empirical findings of the paper. This is the approach that is followed in section 4.

In column (5) Armed Forces Qualification Test score (AFQT) and its interaction with work experience are added to the earnings equation.[21] The AFQT score has been used in the employer learning literature (Farber and Gibbons, 1996 and Altonji and Pierret, 2001) as a measure of a worker's ability that is not easily observed by firms. According to this literature, when AFQT is included with its interaction with experience in the earnings equation, it causes the decreasing with experience (as described in table 1). Note that this result is not found in a model that accounts for career interruptions of workers: while there is a decline of β_2 from columns (3) to (5), the coefficient is still positive and significant. In addition, the other coefficients of interest remain practically unchanged with the inclusion of AFQT in the equation.

Figures 3, 4, and 5 illustrate how the wage coefficient on schooling changes with the work history variables used in the paper. In these figures I report the coefficients of schooling with a 95% confidence interval estimated from the same earnings model as presented in column (3) of table 4. The only difference is restricting the sample to workers within a specific range of work history

[20] I also reject with 99% confidence that the coefficient of the interaction between schooling and unemployment is equal to the coefficent of the interaction between OLF periods and schooling.

[21] AFQT is standardized by the age of the individual at the time of the test.

variable (as presented in the x-axis) and the omission of the interaction terms between schooling and work history variables from the equations.

Based on this approach, figure 3 shows a wage coefficient on schooling of 8% for workers with 0 to 4 years of work experience. However, this coefficient rises for workers with higher experience levels. In precise terms, I estimate the effect of schooling on earnings at 11% for workers with 16 to 20 years of work experience. In contrast, figure 4 shows that the wage coefficient on schooling tends to decrease for workers with higher levels of cumulative unemployment. In fact, I estimate that workers with 0 to 0.4 cumulative years of unemployment have a 10% wage coefficient on schooling, while workers with cumulative years of unemployment between 1.6 and 2 are rewarded only 4% for an extra year of education. Finally, figure 5 shows that the wage coefficient on schooling does not change significantly within OLF groups. All these results are consistent with the findings of table 4.

As discussed in section 3.1, the main group of interest for this work is non-black males. Nevertheless, one might be interested on the empirical results for other demographic groups. In table 5, I present the results of the career interruption model for black males, non-black females and black females in columns (1), (2) and (3) respectively. The main findings are similar to those for non-black males. For black males and non-black females, I estimate: i) a positive and significant effect of the interaction between work experience and schooling; and ii) a negative effect of the interaction between past unemployment and schooling on earnings. Neither work experience nor cumulative unemployment have a significant effect on the returns to schooling for black females. Finally, past OLF periods have a negative impact on the returns to schooling for both non-black and black females. However, it is well-known that reasons for non-participation periods are substantially different for males and females, which poses a challenge for comparing the results for these two groups.

Finally, table 6 provides robustness check that the main results of the paper are not sensitive to the definition of the year of leaving school. In precise terms, and different from the other results of the paper, in this table a worker enters the labor market when he first leaves school and the

accumulation of work, unemployed and OLF weeks start in this period. As discussed before, on one hand, some of the career interruptions can be justified by a decision of a worker to return to school after spending some time in the labor market. On the other hand, I can account for employment periods a worker had before returning to school in the construction of the work experience.

The table shows that the results using this definition for year of leaving school is very similar to the ones presented in table 4. In fact, in column (1) I estimate a 7% effect of schooling on earnings at the beginning of a workers career. Second, there is a positive and significant coefficient of interaction between schooling and work experience of 0.018. In contrast, there is a negative effect of the interaction between past unemployment and schooling of 0.151 and insignificant effect of OLF periods on the returns to schooling. In addition, in columns (2) and (3) I find similar results when including tenure and AFQT and its interactions with schooling and work experience respectively on the wage equation.

3.2.2 Earnings Profiles and Nonparametric Regressions

In this subsection I estimate a less restricted earnings model without imposing functional form assumptions on the relation between work experience, cumulative unemployment, and OLF years and earnings. In these estimations I also substitute years of schooling with educational degree dummies. This procedure allows the model to account for non-linearity in the relation between schooling and earnings. The earnings profiles are plotted with respect to work experience, cumulative years unemployed, and cumulative years OLF for different educational groups. The estimated non-parametric model is the following:

$$\ln w_{it} = f_s(exper_{it}) + h_s(cunemp_{it}) + g_s(colf_{it}) + \eta_{it} \tag{5}$$

where s represents educational group variables: less than high school, high school degree, some college and bachelor degree or more. As before $exper_{it}$ is work experience. I also define $cunemp_{it}$ as the cumulative years a work spent unemployed, and $colf_{it}$ as the cumulative years a worker spent OLF. Different from model (4), there is no imposition of any parametric restriction on $f_s(.)$

, $h_s(.)$ and $g_s(.)$. However, I still impose the additive separability of the work history variables in the model. The method used for the non-parametric estimation is the differentiating procedure described in Yatchew (1998).[22] I use locally weighted regressions using a standard tricube weighting function and a bandwidth of 0.5 when estimating f_s and 0.25 when estimating h_s and g_s.[23]

Figure 6 plots the estimate of $f_s(.)$ for different educational groups. The figure shows that the log earnings-work experience profiles have a concave shape as previously found in the literature (Murphy and Welch, 1992), with wages growing faster at the beginning of a worker's career. In contrast to previous literature, I estimate a much steeper wage growth for more educated workers, than for uneducated workers. In fact, the figure shows that the wage gap between individuals with at least a college degree and other workers tends to increase as workers accumulate actual experience. Similarly, the wage gap between high school graduates and workers with less than a high school education is smaller than it is for workers with zero work experience, but increases significantly as workers accumulate experience. These results are in accordance with the findings presented in table 4, namely that the wage coefficient on earnings increases, as workers accumulate actual experience throughout their careers.

Figure 7 presents the non-parametric estimation of the relation between log earnings and cumulative years of unemployment, defined by the function $h_s(.)$ in equation (5), for different educational groups. The figure shows that both college and high school graduates are negatively affected by unemployment periods, as wages decline with the accumulation of this variable. However, the rate of wage decline is substantively different across educational groups since workers with a bachelor's degree have a greater wage decline with unemployment. It is also notable that the wages of workers with less than a high school degree are not significantly affected by unemployment.

Finally, figure 8 plots the analogous estimation of the relation between log earnings and cumulative years that a worker spends out of the labor force, as described by the function $g_s(.)$. The

[22] In this method, I estimate each function $f_s(.)$, $h_s(.)$, $g_s(.)$ separately, imposing a functional form assumption for the non-estimated functions. In precise terms, when estimating $\hat{g}_s(.)$, I assume that $f_s(.)$ and $h_s(.)$ are cubic polynomial but impose no parametric restriction on $g_s(.)$. The same procedure is applied when estimating $\hat{f}_s(.)$ and $\hat{h}_s(.)$.

[23] The overall results of this graph are not sensitive to the choice of different bandwidths.

evidence shows that this relation is quite heterogeneous among the groups. While the earnings of workers with at least a college degree are almost not affected at all by the accumulation of OLF, workers with less than a high school degree face a substantial wage decrease with OLF periods. The interpretation of these results is difficult because non-participation periods have heterogeneous justifications among workers.

3.2.3 Timing of Career Interruptions

This section addresses whether accounting for timing of career interruptions in the earnings equation can affect the main findings of the paper. For this reason, instead of assuming that wages are affected by the cumulative unemployment and out-of-the-labor-force periods, I estimate the following log wage model separately by educational groups:

$$\ln w_{it} = \beta_0^S + \beta_1^S + f_s(exper_{it}) + \sum_{j=1}^{5} \gamma_j^s unemp_{it-j} + \sum_{j=1}^{5} \alpha_j^s olf_{it-j} + \eta_{it} \tag{6}$$

where s represents educational group variables: less than high school, high school degree, some college, and bachelor degree or more; $unemp_{it-j}$ is the number of weeks a worker spent unemployed in the calendar year that was j years before the interview and olf_{it-j} is the number of weeks a worker spent out of the labor force in the calendar year that was j years before the interview date. For example, for t =1993, the variable $unemp_{it-3}$ reports the number of weeks a worker spent unemployed in 1990 and olf_{it-3} the number of weeks a worker spent OLF in 1990.[24] I divide $unemp_{it-j}$ and olf_{it-j} by 52, allowing the coefficients to be interpreted as changes of year units. Finally, I limit the sample to observations of a worker 5 years after leaving school, so past work history variables reflect events that happened after a worker made the transition to the labor market.

Figure 9 plots the estimation of the coefficients γ_j^s with a 95% confidence interval for different s and j. The graph shows a few interesting facts. First, the weeks spent unemployed in the past

[24] These career interruption variables are constructed based on the week-by-week work history information provided by NLSY, which identifies with precision the periods of unemployment and OLF throughout a worker's career.

calendar year have the highest impact on earnings for all education groups, but the effects are much higher for workers with a bachelor's degree or higher. In precise terms, the estimation shows that spending the previous calendar year unemployed decreased the earnings of this group by 60%. Second, unemployment periods have a long-term impact on earnings, with a significant negative effect of unemployment weeks, which occurred 5 years prior to the interview. While the difference across educational groups is not as strong, this figure shows that educated workers are also more affected by older unemployment periods.

In figure 10, the analogous statistics for α_j^s are reported with a 95% confidence interval, showing that periods spent out of the labor force have a negative impact on the earnings of all workers. However, this effect is much lower than those estimated by unemployment periods, and tend to disappear with time. Finally, while it is estimated that college-graduate workers are more affected by past year OLF weeks than educated workers, the differences across educational groups are not as strong for OLF periods as they are for unemployment periods.

Figures 9 and 10 bring to light how unemployment and OLF periods affect the effect of schooling on earnings. In order to provide a more accurate test regarding whether the returns to schooling change throughout a workers' career – in a model where timing of career interruptions affect wages – I estimate the model below:

$$\ln w_{it} = \beta_0 + \beta_1 s_i + \beta_2(s_i \times exper_{it}) + f(exper_{it}) + \sum_{j=1}^{5} \lambda_j unemp_{it-j} \tag{7}$$

$$+ \textstyle\sum_{j=1}^{5} \pi_j(s_i \times unemp_{it-j}) + \sum_{j=1}^{5} \rho_j olf_{it-j} + \sum_{j=1}^{5} \psi_j(s_i \times olf_{it-j}) + \epsilon_{it}$$

where all the variables have the same definitions as before and s_i is a measure of years of schooling. In this framework, the coefficients of interest are β_2, which identifies how the wage coefficient on schooling changes with work experience, π_j which identifies how the wage coefficient on schooling changes with past unemployment periods j years before the interview and ψ_j which identifies how the wage coefficient on schooling changes with past OLF periods j years before the interview.

The result of the estimation of the earnings model 7 is presented in table 7. While I estimate

the model including olf_{it-j} and its interaction with s_i , for the sake of space these coefficients are omitted in the table. The result shows that ψ_j is not significant for any j. As can be seen in the table: first, the wage coefficient on schooling increases with work experience, even in a model where the timing of career interruption matters, as presented in columns (1) - (3). As can be seen, the estimated β_2 is not very different from the one estimated in table 4. Second, as column (2) shows, previous unemployment periods have a significant negative impact on earnings, with previous year unemployment having the highest impact. Third, column (3) shows that, although there is an estimated negative effect of all unemployment periods on the wage coefficient on schooling for all years, recent unemployment periods have a higher impact on earnings. The overall interpretation of these findings is that, while timing of unemployment and OLF might matter for earnings determination, this less-restricted model shows similar patterns, in terms of the effect of work experience and career interruptions on the wage coefficient on schooling, as the one presented in subsection 3.2.1.

3.2.4 Individual Fixed-Effects Estimates

An issue that emerged in models that fully characterize an individual's work history is the possible endogeneity problem of actual experience and career interruptions. The main argument is an omitted variable problem. It is possible that there are some variables not observed in the data that are related to both current wage determination and past employment. For example, workers with higher career aspirations might have higher employment attachment throughout their life-cycle earnings. In both cases, the seriousness of the endogeneity problem depends on how strong the correlation between current and past levels of the earnings residuals is, and whether past residuals are related to the employment attachment of workers.

A popular approach in the literature when dealing with possible endogeneity of work history is based on an individual fixed effect assumption (Corcoran and Duncan, 1979, Kim and Polachek, 1994, Light and Ureta, 1995 and Albrecht et al., 1999).[25] The basic idea of this approach is that the

[25]There are other suggestions in the literature with respect to ways of addressing the possible endogeneity of work history. Mincer and Polachek (1974) suggest using family characteristics, such as education of the partner or number of children, as instruments for previous working and non-working periods of married women. While it is questionable as to how exogenous these variables truly are, there is evidence that family characteristics have a weak relation to employment attachment of non-black males, the main group of interest of this work. Alternatively, Altonji

factor related to past employment attachment of workers – which causes the correlation of earnings residuals across time – is an individual-specific fixed component. In terms of the model presented in equation 4, the fixed effect assumption means that u_{it} can be written as a sum of an individual component ϕ_i and a transitory component η_{it}, both with mean zero and constant variance. While η_{it} is independent of an individual's work history, the work history variables can be correlated to ϕ_i.

Table 8 presents the main results of the estimation of the wage model described by equation (4) using an individual fixed effect estimation. Note that as schooling does not change overtime, I cannot identify β_1 when using this estimation strategy. However, it is possible to identify the effect of its interaction with other time-varying variables, such as work experience, tenure, and cumulative years OLF and unemployment. In order to make these new results comparable to the least square estimation, the same specifications are followed in this table as the one presented by the least square estimation of table 4.

The overall results from table 8 are qualitatively and quantitatively similar to those estimated by the least square estimation of table 4. Namely, the wage coefficient on schooling increases significantly as a worker accumulates work experience, and decreases as a worker accumulates unemployment periods. If anything, the fixed effect estimation shows a lower negative coefficient for the effect of unemployment on the returns to schooling. In other words, this new estimation leaves the conclusions based on the OLS regressions intact.

This result is not surprising in light of the findings of existing literature. Mincer and Polachek (1974), Blackburn and Neumark (1995), and Albrecht et al. (1999) have found that coefficients of the earnings model stay virtually unchanged when dealing with the possible endogeneity problem of work history variables. From these results, one can conclude that the endogeneity of work history appears to be less of a problem when estimating career interruptions models.

and Pierret (2001) suggest using potential experience ($pexp_{it}$) as an instrument for actual experience, in a model that earnings are not affected by unemployment periods. However, if career interruptions have impact on wages, the potential experience variable is not a validity instrument for actual experience. In this circumstance, $pexp_{it}$ is not redundant (or ignorable) in the log wage expectation, such that: $\mathbb{E}[\ln w_{it}|exper_{it}] \neq \mathbb{E}[\ln w_{it}|exper_{it}, pexp_{it}] = \mathbb{E}[\ln w_{it}|exper_{it}, interr_{it}]$.

4 Model

The dynamics estimated thus far are puzzling for conventional models of labor market dynamics. Unlike the past empirical literature, my research finds that more educated workers have a higher increase in earnings with actual experience, while suffering greater earnings losses after unemployment periods. This raises the question as to which economic reasons can explain this relationship. Is it possible to conciliate the existing theories for earnings dynamics with these novel empirical findings? In order to answer these questions, in this section I present an economic model that can rationalize the empirical findings of this paper.

4.1 The model environment

A worker enters the labor market in period 0 and lives for T periods. All firms are identical and the only input used in production is labor. Let y_{it} denote a worker's log-productivity in the t-th period after leaving school.

$$y_{it} = \theta_i g(s_i, x_{it}) \tag{8}$$

In this specification, θ_i is the worker's ability, $g(s_i, x_{it})$ is a worker's human capital, which is a function of the worker's schooling level s_i and work experience x_{it}. For exposition, I will omit x and s subscripts henceforth. I assume that both θ_i and $g(s, x)$ are positive, and $\partial g(s, x)/\partial s > 0$, $\partial g(s, x)/\partial x > 0$ and $\partial g(s, x)/\partial x \partial s = 0$. The important assumption is that ability and human capital are complementary in determining the log-productivity, which is captured in the multiplicative specification of (8).[26] An interpretation of the complementary assumption is that high ability workers can more effectively use their human capital at work and therefore have higher returns to schooling and experience.[27]

Furthermore, there are only two types of workers: high ability θ_H or low ability θ_L. While

[26] Note that this assumption makes the model different from the studies presented in table 1.

[27] Papers making similar assumptions include: Acemoglu and Pischke (1998), Gibbons and Waldman (2006), and DeVaro and Waldman (2012).

schooling and work experience are observed, ability is not observed by either employers or workers. All agents have to make their predictions about a worker's ability based on the information available at each period.

4.1.1 Information structure

The only available information regarding ability in period 0 is a worker's schooling level s. I define p_s as the fraction of workers with schooling level s that are high ability. I assume that p_s is different from zero and one, and it is strictly increasing with a workers schooling level, meaning that high ability workers are more likely to get more education. Note that in this version of the model, I do not model schooling decision of workers, but this assumption is consist with the signaling literature (Spence, 1973) where high ability workers have lower costs to acquire education. Nevertheless, later I sketch how the model could be enriched to allow for the endogeneity of schooling.

In addition to schooling, I assume that in every period some new information about a worker's quality becomes available to all firms.[28] This new information can be summarized by the signal $\tilde{y}_{it}$, which can be a good or bad signal, with high ability workers producing a good signal with probability γ_H and low ability workers producing a good signal with probability γ_L, such that $\gamma_H > \gamma_L$. As in Altonji and Pierret (2001), firms will use information on the worker's signals during the past $x-1$ *employed* periods to infer a worker's unobservable ability. I define $I_{it} = \{\tilde{y}_{i1}, ..., \tilde{y}_{ix-1}\}$ as the set of observed past signals.

Different from Altonji and Pierret (2001), an individual can be in one of two possible states at each period of his career: working or not working. Firms can also observe the employment history of an individual, which is characterized by the number of periods an individual was employed $x-1$ (work experience minus one) and the number of periods a worker was unemployed u since leaving school (career interruptions).[29] As will be clarified later, employment history gives extra information about a worker's ability and the timing of working and non-working periods will not

[28] This information consists on past on-the-job performance, new letters of recommendation, interviews, etc.

[29] Note that by definition $x + u = t$. Given the perfect linear combination between work experience, career interruption, and time since leaving school, one could define the information set available to firms as two of any of the three variables. For expositional purposes, I choose to present it as work experience and career interruptions. I also ignore the difference between unemployment and out-of-the-labor-force periods.

be important in the equilibrium of this simplified model.[30]

4.1.2 Timing and actions

At the beginning of each period the sequence of events and actions are as follows:

1. A fraction δ of individuals are unable to work. These are the workers that are moving for personal reasons or are not able to be matched to any employer.

2. The other fraction $(1-\delta)$ of workers are able to work and draw a new signal $\tilde{y}_{it}$ for the period.

3. The employers make job offers based on information available in the period and the new signal $\tilde{y}_{it}$.

4. A worker can either:

   - Choose to work in the period. In this case, a worker accumulates one period of work experience and keeps the signal for future wage offers.
   - Choose to not work in the period. In this case a worker accumulates one period of unemployment, while discarding the signal that will not be used for future wage offers.

Note that in the model unemployment can be involuntary or voluntary. Involuntary unemployment is caused by a worker who could not be matched to any employer in a given period (fraction δ), while voluntary unemployment results from a worker's decision to reject any job offer. I assume that firms cannot distinguish between these two types of career interruptions when making future wage offers. The idea is that (low performance) workers can always tell the employers that they did not work in a period because exogenous reasons were preventing them from working. Nevertheless, firms pay close attention to the accumulation of career interruptions, and workers are unlikely be able to justify the long periods of unemployment as involuntary.

[30] This mechanism is consistent with papers where employers use lay off information (Gibbons and Katz, 1991) or the duration of an unemployment spell (Lockwood, 1991 and Kroft et al., 2013) to infer a worker's unobservable quality. However, in this paper firms take into consideration the full work history of an individual.

4.1.3 Firms' decision

Firms do not discount the future and long term contracts are not allowed. As in Farber and Gibbons (1996) and Altonji and Pierret (2001), I assume that there is free entry of firms and all employers share the same information about a worker's productivity. As a consequence from competition among employers, the wage offered to a worker i in period t is equal to the expected productivity given the information available at the period and the new signal $\tilde{y}_{it}$:[31]

$$W_{it} = \mathbb{E}[\exp^{y_{it}} | x, u, s, I_{it}, \tilde{y}_{it}] \tag{9}$$

An alternative representation of the wage set up is to define $\mu(s, x, u, I_{it}, \tilde{y}_{it})$ as the employers' belief that a worker is high-type based on the information available up to that point. In this framework, I use equation (8) to show that the wage level of a worker in period t can be represented by:

$$W_{it} = \mu(s, x, u, s, I_{it}, \tilde{y}_{it}) \exp^{g(s,x)\theta_H} + [1 - \mu(s, x, u, I_{it}, \tilde{y}_{it})] \exp^{g(s,x)\theta_L} \tag{10}$$

The wage process presented in equation 10 shows the two different roles of work experience x in the model. On one hand, the term $g(s, x)$ represents the productivity increase of a worker as he accumulates work experience. This mechanism is defined as the human capital effect of working on earnings. On the other hand, accumulating employment periods also provides information about a worker's type, which is represented by the term $\mu(s, x, u, I_{it}, \tilde{y}_{it})$. This mechanism is referred to as the information effect of working on earnings. Furthermore, firms will also use information regarding career interruptions u in the assessment of a worker's type.

[31] Note that the information that a worker chose to work in period t is implicit in the term $\tilde{y}_{it}$.

4.1.4 Worker's decision

I assume that workers are risk neutral and discount the future using a discount rate $\beta > 0$. At each period a worker has access to the same information as firms.[32] In this framework, for individuals that are not exogenously unable to work, the work decision in the first $T-1$ periods of their career is defined by the following Bellman equation:[33]

$$V(s, x, u, I_{it}, \tilde{y}_{it}) = \max\{W_{it}(s, x, u, I_{it}, \tilde{y}_{it}) + \beta(1-\delta)\mathbb{E}[V(s, x+1, u, I_{it}, \tilde{y}_{it}, \tilde{y}_{t+1})],$$

$$b + \beta(1-\delta)\mathbb{E}[V(s, x, u+1, I_{it}, \tilde{y}_{t+1})] \tag{11}$$

where b is the utility flow for not-working. This Bellman equation highlights a trade-off associated with the employment decision.[34] On one hand, an individual can choose to work, be paid, and accumulate one year of experience. In this case, the signal $\tilde{y}_{it}$ is used for current and future wages offers. On the other hand, a worker could discard the signal, receive non-working benefits and accumulate one period of unemployment. In this case, firms will not be able to distinguish whether the unemployment period was due to a worker's choice or to an exogenous reason. Nevertheless, firms will use the extra non-working period information to update their beliefs about a worker's ability, and this unemployment information will be used for future wage offers.

4.2 Equilibrium

Equilibrium is characterized by a function of the state variables $S_{it} = \{s, x, u, I_{it}\}$ and signal $\tilde{y}_{it}$ to the firms' belief that a workers is high type μ_{it}, a wage offer W_{it} and an individual's decision to work in period t. From this general framework, it is possible to derive some predictions of an individual's optimal working strategy and how firms use past employment and unemployment information to

[32] As it would be clear in equilibrium, even if workers have better information regarding their own ability than firms, this information will be irrelevant for their working decisions.

[33] In period T, workers make the same decision but do not consider the future.

[34] Note that individuals are exogenously unable to work in period $t+1$ with probability δ. As the utility from this state is independent of previous work choices, this possibility should not affect an individual's decision to work in period t. In precise terms, the future expected utility of being exogenously unemployed is additive in both terms of the Bellman equation, and therefore is canceled out.

update their beliefs about a worker's type.

Proposition 1: For a given state S_{it}, if it is an optimal strategy for an individual to choose to work after a bad signal draw, it is also an optimal strategy to work in case of a good ability draw.

The justification is straightforward: the firms' belief that a worker is high type is greater after a good signal revelation than after a bad signal. As a result, present and future wage offers must be higher after a good signal than after a bad signal. For this reason, for any given state, a worker is better off taking the job after a good signal draw than he would be working after a bad signal draw.

This proposition has implications for the adverse selection and employer learning mechanism proposed by the model. Firms realize that workers with bad signals are more likely to be unemployed and workers with good signals are more likely to be employed. Even though firms cannot observe signals produced in the non-working periods, or ascertain whether unemployment was caused by an exogenous reason, they use information on career interruptions and employment periods to update their beliefs about a worker's ability.

4.2.1 Separating Equilibrium

The analysis is now restricted to a separating equilibrium where for any given state, individuals always choose to work after observing a good signal draw, and always decide to not work after observing a bad signal draw. This extreme case highlights the mechanisms of adverse selection and employer learning through work history that I want to stress with the model. It also simplifies the calculation of firms' beliefs and wage offers, and the derivations of the predictions of the model.

Some extra assumptions are required in order to guarantee the existence of such a separating equilibrium. First, I assume that high-ability workers always produce a good signal, such that $\gamma_H = 1$, while low-ability workers can produce both good and bad signals: $0 < \gamma_L < 1$. The direct implication of this assumption is that the decision to work after a bad signal is sufficient to reveal to employers that a worker is low type for the rest of his career.

Nevertheless, it might be optimal for an individual to work after it is revealed that he is low

ability. For this reason, I assume the productivity of a low ability worker is always lower than his non-working utility, such that $\exp^{g(H,T)\theta_L} < b$, where H is the highest schooling level a worker can achieve and therefore $g(H,T)$ is the highest human capital level a worker can possibly have. An interpretation of this assumption is that low-ability jobs are so much less rewarding, that workers would never reveal to firms that they are low ability.

Finally, for any state S_{it}, it must be optimal for an individual to choose to work after a good signal. For this reason I impose the following restriction on θ_H:

$$\widetilde{\mu} \exp^{g(0,0)\theta_H} + (1 - \widetilde{\mu}) \exp^{g(0,0)\theta_L} > b \tag{12}$$

where $g(0,0)$ is the lowest human capital level an individual can possibility have (zero schooling and zero actual experience) and $\widetilde{\mu}$ represents the lowest believe a firm can have that a worker is high type in this separating equilibrium. This term is a function of the parameters p_s, δ, and γ_L and T, and is derived in the appendix of the paper. An interpretation of this assumption is that high-performance jobs are very rewarding and an individual would always work after a good signal.

Under these assumptions, for any state S_{it} the optimal choice of an individual, that is not exogenously unable to work, is to be employed if $\tilde{y}_{it}$ is a good signal and to be unemployed if it is a bad signal. Note that the set of signals I_{it} becomes trivial, since individuals only work in good signal periods. In this case, the set I_{it} is equivalent to the employment periods x and therefore will be omitted henceforth.

Within this framework, it is easy to derive the fraction of workers that are employed and unemployed at each period, and the firms' equilibrium belief that a worker is high type. First, the fraction of high-ability individuals that are employed in each period is equal to the fraction of workers that were not exogenously unable to work: $\mathbb{P}(Work_{it}|\theta_H) = 1 - \delta$. In other words, because high ability workers always draw good signals, the only reason for this type of worker to be unemployed is being exogenously unable to work, which happens with probability δ.

In contrast, low ability workers can be unemployed due to both exogenous reasons or a bad signal draw. Therefore the probability that a low ability individual is working in a period is

$\mathbb{P}(Work_{it}|\theta_L) = \gamma_L(1-\delta)$. For $\gamma_L < 1$, high type worker are more likely to be employed than low type workers at any point of their career.

Note that working events are independent across time. As a consequence, the probability that a worker has x employment periods and u career interruptions conditional on high and low ability level respectively is characterized by a binomial probability function:

$$\mathbb{P}(X = x, U = u|\theta_H) = \binom{x+u}{x}(1-\delta)^x\delta^u \tag{13}$$

$$\mathbb{P}(X = x, U = u|\theta_L) = \binom{x+u}{x}(\gamma_L(1-\delta))^x(1-\gamma_L(1-\delta))^u \tag{14}$$

where $\binom{x+u}{x}$ is the binomial coefficient of x and $x+u$.[35]

In this framework, it is simple to characterize how employers learn about a worker's type throughout his career. The prior about a worker's type when he enters the labor market p_s is defined by the fraction of workers with education level s that are high type. However, as a worker progresses in his career, firms use information on his working and non-working periods to update their beliefs. Based on equations (13) and (14), I use the Bayesian rule to derive the firms' belief that a worker with experience x and career interruptions u is high type:

$$\mu^*(s,x,u) = \frac{\delta^u p_s}{\delta^u p_s + \gamma_L^x(1-\gamma_L(1-\delta))^u(1-p_s)} \tag{15}$$

Equation (15) presents features regarding how the firms' belief evolves as a worker progresses in his career. At the beginning of a worker's career firms have no information about a worker's history ($x = 0$ and $u = 0$). In this case, the belief that a worker is high type is defined solely by his schooling level, summarized by the prior p_s. As workers progress in their careers, and low ability workers are more likely to be unemployed, firms update their beliefs using information on x and u.

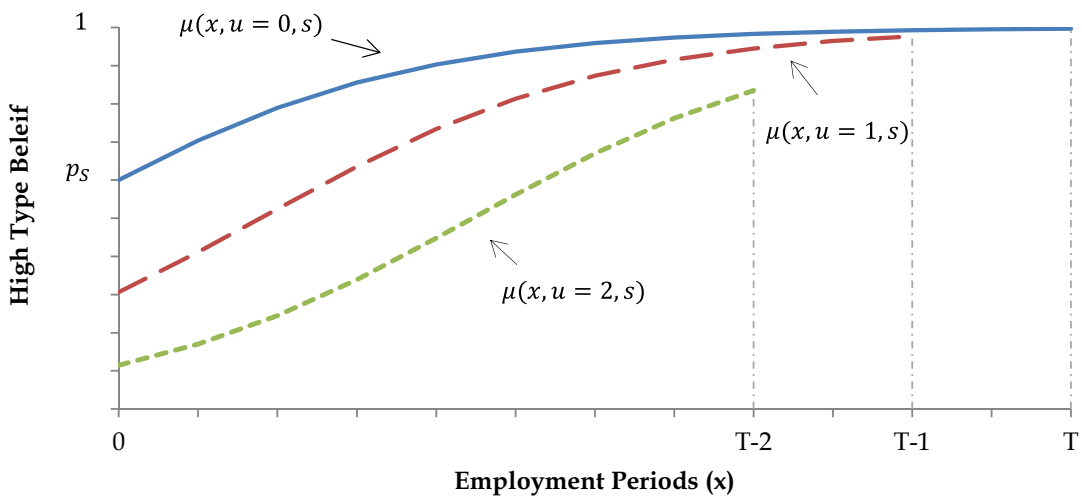
Proposition 2: $\mu^*(s,x,u)$ strictly increases with x and s and strictly decreases with u. Fur-

[35]Note, in this separating equilibrium, the timing of career interruptions is not important for the probability function. Therefore, firms will only use the cumulative values of work history variables to update their beliefs about a worker's type.

thermore, $\lim_{x\to\infty} \mu^*(s,x,u) = 1$ and $\lim_{u\to\infty} \mu^*(s,x,u) = 0$.

The idea of proposition 2 is simple. The adverse selection mechanism implies that firms use periods of past employment as a good signal of a worker's type, and past unemployment periods as a bad signal of a worker's type. For this reason, a firm's expectation that a worker is high type must increase with x and decrease with u. For T is large enough, firms should be able to recover a worker's type just by updating their beliefs, using previous working and non-working information.

The figure below illustrates how the work history of an individual affects firms' beliefs about his type. The blue line shows how the belief that a worker with zero career interruptions ($u = 0$) changes as he accumulates work experience x. The red line shows the analogous relation for a worker that suffers one period of career interruption ($u = 1$) in the beginning of his career, and is the green line of a worker that suffers with two periods of career interruptions ($u = 2$) in the beginning of his career. Note that the lines terminate at the end of a worker's career.



The graph shows that firms have a belief p_s that a worker with zero unemployment is high type at the beginning of his career (blue line). As the worker accumulates work experience, this expectation

raises to the point where firms are almost certain he is high type at the end of period T. In contrast, a worker who starts to accumulate work experience with one period of unemployment initiates the process from a lower level of expectation than p_s. However, as he gains work experience, firms use the new employment periods to update their beliefs, and the expectation about his type rises. Eventually, the employment information overcomes the signal of one period of career interruptions and $\mu^*(s, x, u)$ catches up with the expectation from a worker with no career interruptions. Finally, the green line shows that a worker with 2 periods of unemployment starts his career from a very low belief level. Although the worker is able to improve the firms' expectations as he accumulates employment periods, the new information is not such magnitude as to overcome the bad signal of two unemployment periods. As a result, the expectation that he is high type never catches up with that of workers with no career interruptions.

4.2.2 Wage determination

Having characterized how firms form and update their beliefs about a worker's ability in a separating equilibrium, I now turn to demonstrating that this learning process has important implications for wage setting. Using the firms' equilibrium belief that a worker is high type - derived in the past subsection - and the wage setting described by (9), one can write the equilibrium wage of a worker with schooling level s, work experience x and career interruptions u as follows:

$$W_{it}^* = \mu^*(s, x, u) \exp^{g(x,s)\theta_H} + [1 - \mu^*(s, x, u)] \exp^{g(x,s)\theta_L} \tag{16}$$

where $\mu^*(s, x, u)$ is the equilibrium belief that a worker is high type as defined in equation (15). From the equation above, it is easy to show that equilibrium wage levels are strictly increasing with respect to schooling and work experience and strictly decreasing with respect to unemployment period. Nevertheless, in this paper we are interested in how the interaction between schooling, work experience and past unemployment periods affects log earnings.

Proposition 3: Under the assumptions of the above model,

$$\frac{\partial^2 \ln W_{it}^*}{\partial x \partial s} > 0 \text{ for any } s, x \text{ and } u.$$

The proof of proposition 3 is presented in the appendix of the paper but the intuition follows from the assumption that ability and human capital are complementary in determining the log-productivity of a worker. More precisely, in the model, the work experience affects earnings in two ways. First, it increases a worker's log-productivity: workers learn more on the job and therefore become more productive as they accumulate x. The complementarity between ability and human capital implies that high ability workers have a higher log-productivity increase with work experience. Note that by assumption, the fraction of workers that are high ability increases with their schooling level. As a consequence, the model predicts that more educated workers have higher returns to experience.

The second way that work experience affects earnings is through a signaling effect. As described in the model, high ability workers are more likely to be employed in the course of their careers. As a consequence, the probability that a worker is high ability increases with his past employment periods. The complementarity between ability and human capital also implies that high ability workers have higher returns to schooling. Consequently, the model predicts that workers with high levels of work experience also have higher returns to schooling. To sum up, both human capital and signaling mechanisms imply that the interaction between schooling and work experience have a positive effect on log-earnings.

Proposition 4: Under the assumptions of the above model,

$$\frac{\partial^2 \ln W_{it}^*}{\partial u \partial s} < 0 \text{ for any } s, x \text{ and } u.$$

The proof of the proposition is also presented in the appendix of the paper, but the intuition is similar to the one just described. In the model, low ability workers are more likely to be unemployed throughout their careers. These workers are more likely to draw bad signals and therefore more likely to reject low wage offers. As a consequence, the fraction of workers that are low ability increases with u. Note that due to the complementarity between ability and human capital, low ability workers have lower returns to schooling. Consequently, the model predicts that educated workers are those who suffer the most when they have their low ability type revealed with unemployment. Put differently, the interaction between schooling and past unemployment periods have a negative

effect on log-earnings.

4.3 Some Extensions

In this subsection I discuss the general intuition of two possible extensions of the basic model presented so far.

4.3.1 Unemployment and Out of the Labor Force

A simplifying assumption used so far is that there are only two possible employment status: working and not working. However, in the empirical part of the paper I also distinguish the impact of unemployment and out-of the labor force periods on earnings. In fact, I find that: i) unemployment periods have a higher negative impact on earnings than out-of-the labor force periods; and ii) there is no significant difference across educational levels in terms of wage losses after OLF periods. A natural question is: how can one incorporate the distinction between unemployment and OLF into the model?

Note that in the model, non-working periods can be explained by a fraction δ of individuals that are unable to work due to exogenous reasons or by individuals that did not work after receiving a bad signal. As described before, firms cannot distinguish between these two types of career interruptions when making future wage offers. A simple way to incorporate OLF periods to the model is to assume that firms can identify a share of non-working periods caused by the exogenous reasons. For example, one can think that workers who were moving due to family reasons can demonstrate to potential employers that they did not work in a period because they were moving. As a consequence, an individual's work history would be also be characterized by the accumulation of non-working periods which are uncorrelated to worker's ability.

4.3.2 Schooling choices

In this paper employment and wage decisions happen after an individual leaves school. Nevertheless, I could also assume that workers have some knowledge of their own innate abilities and

make schooling choices at the beginning of their career. In this case, schooling would also be an endogenous variable of the model. A simple way to introduce schooling decisions is to assume that individuals make education choices in period zero in order to maximize their expected life time earnings, defined by the value function (11) in period zero. Even if costs of getting more education do not vary with ability, we would expect that high ability individual are more likely to achieve higher levels of education because these workers have higher returns to schooling. In this case, ability and schooling would be positively related, such as presented in the model.

5 Conclusion

In this paper I extensively examined whether educated workers have a higher or lower wage increase throughout their careers. Different from past work, I accounted for the fact that workers spend a significant amount of time not employed throughout their careers. This distinction is important because, as demonstrated above, the potential experience typically used in previous literature confounds the impact of two distinct events on the earnings: actual experience and past non-working periods. Not surprisingly, I found that these two events have different effects on wages across educational groups. I found that educated workers have a higher wage increase with experience but suffer a greater wage loss after unemployment periods. These results are robust to different specifications of the earnings equation, timing of the unemployment spells, and estimation methods.

In addition, I proposed a model that can rationalize the novel empirical results of this paper. In the model, the productivity of a worker is defined by his observed human capital and his unobserved ability. Firms update their predictions that a worker is high ability as new information becomes available throughout a worker's career. The innovation of the model is that firms can use past employment and unemployment periods in their assessment of a worker's ability. Under the assumption that human capital and ability are complementary in the determination of a worker's productivity, the model predicts that educated workers have a higher wage increase with work experience but suffer a greater wage loss after career interruptions.

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Theory Appendix

A Derivation of $\mu^*(x,u)$ and $\widetilde{\mu}$

In the model, firms use Bayesian rule to update their beliefs that a worker is high type based on the past employment history and schooling. For this reason we have that equilibrium belief that a worker is high type given this information is defined as:

$$\mathbb{P}(\theta_H|X=x,U=u,s)=\frac{\mathbb{P}(X=x,U=u|\theta_H,s)\mathbb{P}(\theta_i=\theta_H|s)}{\mathbb{P}(X=x,U=u|\theta_H,s)\mathbb{P}(\theta_i=\theta_H|s)+\mathbb{P}(X=x,U=u|s,\theta_L)\mathbb{P}(\theta_i=\theta_L|s)}$$

Substituting the work history probabilities presented in equations 13 and 14 and using the prior p_s that a worker is high type, one gets the equilibrium belief that a worker is high type given his work history and schooling level:

$$\mu^*(x,u)=\frac{\binom{x+u}{x}(1-\delta)^x\delta^u p_s}{\binom{x+u}{x}(1-\delta)^x\delta^u p_s+\binom{x+u}{x}(\gamma_L(1-\delta))^x(1-\gamma_L(1-\delta))^u)(1-p_s)}$$

dividing both the numerator and denominator by $\binom{x+u}{x}(1-\delta)^x$, I obtain the expression for the equilibrium presented in equation 15.

Based on this expression, it easy to see that the lowest possible belief that a worker is high type in a separating equilibrium is defined by workers that were unemployed during T periods and has zero schooling. Substituting these work history ($s=0$, $x=0$ and $u=T$) in equation 15, I obtain an expression for $\widetilde{\mu}$:

$$\widetilde{\mu}=\frac{\delta^T p_0}{\delta^T p_0+(1-\gamma_L(1-\delta))^T(1-p_0)}$$

B Proof of Preposition 3 and 4

The derivations of proposition 3 and 4 come directly from the wage equation presented in equation 16. Let's define μ_u^* as the derivative of the equilibrium belief with respect to u, μ_x^* is the derivative with respect to x, and μ_s^* is the derivative with respect to s. From equation 15 and assumptions of the model, it is easy to show that $\mu_x^*>0$and $\mu_s^*>0$ and $\mu_u^*<0$ for every x, s, and u. In other

words, the belief that a high type worker is strictly increasing with schooling level and past work experience and strictly decreasing with unemployment.

Using the expressions above and after some tedious algebra, one can show that:

$$\frac{\partial \ln W_{it}}{\partial s \partial x} = \frac{\exp^{g(x,s)(\theta_H+\theta_L)}(\theta_H-\theta_L)}{W_{it}^2}\{\mu_x^* g_s + \mu_s^* g_x + g_s g_x(\theta_H - \theta_L)\mu^*(1-\mu^*)\}$$

g_x is the derivative of the human capital function with respect to x and g_s is the derivative of the human capital function with respect to s. Note that by assumption of the model, the human capital function is strictly increasing schooling and experience, so that $g_s > 0$ and $g_x > 0$. Therefore, one can conclude that $\frac{\partial \ln W_{it}}{\partial s \partial x} > 0$ for every x, u, and s. Note also that the human capital effect of experience on earnings is represented by the term $\mu_s^* g_x$ and the signaling effect of experience on earnings is given by the term $\mu_x^* g_s$.

In the same way, one can show that:

$$\frac{\partial \ln W_{it}}{\partial s \partial u} = \frac{\exp^{g(x,s)(\theta_H+\theta_L)}(\theta_H-\theta_L)}{W_{it}^2}\mu_u^* g_s$$

As by assumption we have that $g_s > 0$ as it is easy to show from equation 15 that $\mu_u^*(x,u) < 0$, we can conclude that $\frac{\partial \ln W_{it}}{\partial s \partial u} < 0$ for every x, u, and s. The term $\mu_u^* g_s$ identifies that educated workers suffer the most when their low ability type is revealed.

Table 1 - Literature Review

Study	Data	Dependent Variable	Experience Specification	Sample	Main Findings
Mincer (1974)	U.S. Census, 1960	Log Annual Earnings[36]	Age-Schooling-6	White, non-farm, non student men up to age 65.	"Experience profiles of log earnings are much more nearly parallel."
Faber and Gibbons (1996)	NLSY 1979-1991	Hourly Wage (level)	Time since long-term transition to the labor force	Males and females after long-term transition to the labor force.	"The estimated effect of schooling on the level of wages is independent of labor-market experience."
Altonji and Pierret (2001)	NLSY 1979-1992	Log Hourly Wage	Age-Schooling-6[37]	White or black males with eight or more years of education.	"Wage coefficients on the variables that firms cannot observe and affect workers' productivity rise with experience while the coefficient on education falls."
Lemieux (2006)	CPS 1979–1981, 1989–1991, and 1999–2001	Log Hourly Wage	Age-Schooling-6	Men age 16 to 64 with 0 to 40 years of potential experience.	For 1979-1981 the experience profiles are parallel; For 1989-1991 and 1999-2001 the college-high school wage gap declines as a function of experience.
Heckman et al. (2006)	U.S. Census, 1940-1990	Log Annual Earnings	Age-Schooling-6	White and black males.	"The estimated profiles for white males from the 1940–1970 Censuses generally support the parallelism by experience patterns. Log earnings–experience profiles for the 1980–1990 Censuses show convergence for both white and black males."

[36] Mincer only finds insignificant effects of the interaction between schooling and experience when controlling for weeks worked in the past year.

[37] In Panel 2 of Table 1, the authors present their results using actual experience instrumented by potential experience. I discuss the validity of this approach in section 3.2.4.

Table 2 - Work History Variables

Variable	**Definition**
Potential Experience	Age - Schooling - 6
Time since leaving school	Weeks since leaving school /52
Work Experience	Weeks worked since leaving school /52
Cumulative Years OLF	Weeks OLF since leaving school /52
Cumulative Years Unemployed	Weeks Unemployed since leaving school /52
Cumulative Years in Military Services	Weeks in the Military Services since leaving school /52

Table 3 - Descriptive Statistics

	Education Level			
Variable	Less than High School	High School Degree	Some College	BA or More
Log Hourly Wage (1999 dollars)	2.00	2.25	2.44	2.80
Potential Experience	16.07	14.48	14.91	13.24
Time since graduation	14.21	14.14	12.46	11.52
Work Experience	11.04	11.87	10.86	10.68
Cumulative Years OLF	1.58	1.03	0.82	0.43
Cumulative Years Unemployed	1.41	0.76	0.40	0.24
Cumulative Years in Military Services	0.01	0.36	0.27	0.10
Cumulative Years Unaccounted	0.17	0.12	0.10	0.07
Individuals	224	1,083	508	669
Observations	3,432	16,750	6,138	7,387

Note: See Table 2 for definitions of the work history variables.

Table 4 - The Effect of Schooling, Experience, and Career Interruptions on Earnings

NLSY 1979 - Non-Black Males

Dependent Variable: Log Real Hourly Wage

Method: Least Squares

Model	(1)	(2)	(3)	(4)	(5)
Schooling	0.111	0.102	0.082	0.083	0.066
	(0.006)***	(0.005)***	(0.005)***	(0.005)***	(0.006)***
Schooling * Potential Experience/10	0.004				
	(0.004)				
Schooling * Time since Leaving School/10		0.007			
		(0.005)			
Schooling * Work Experience/10			0.018	0.014	0.014
			(0.003)***	(0.004)***	(0.004)***
Schooling * Cumulative Years Unemployed /10			-0.218	-0.207	-0.245
			(0.038)***	(0.038)***	(0.039)***
Schooling * Cumulative Years OLF /10			0.022	0.022	0.031
			(0.024)	(0.024)	(0.025)
Schooling * Tenure Years/10				0.002	
				(0.006)	
AFQT * Work Experience/10					0.020
					(0.008)**
Observations	33,707	33,707	33,707	33,181	32,162
R-squared	0.260	0.264	0.321	0.325	0.338
Tenure	No	No	No	Yes	No
AFQT	No	No	No	No	Yes
Other controls:	Cubic Polynomial of Potential Experience and Year Dummies	Cubic Polynomial of Time since Leaving School and Year Dummies	Cubic Polynomial of Work Experience, Cumulative Years OLF/Unemployment/Military; Uncounted Years; and Years Dummies		

*** p<0.01, ** p<0.05, * p<0.1

White/Huber standard errors clustered at the individual level are reported in parentheses.

Note: AFQT is normalized to have a standard deviation of 1. Difference in the number of observations between models (3) , (4) and (5) is due to 526 observations of individuals with missing tenure and 1,545 observations of individuals with missing AFQT information.

Table 5 - The Effect of Schooling, Experience, and Career Interruptions on Earnings, Other Demographic Groups

NLSY 1979 - Other Demographic Groups

Dependent Variable: Log Real Hourly Wage

Method: Least Squares

Sample	Black Males	Non-Black Females	Black Females
Schooling	0.106	0.092	0.111
	(0.015)***	(0.005)***	(0.012)***
Schooling * Work Experience/10	0.019	0.011	0.004
	(0.009)**	(0.004)***	(0.008)
Schooling * Cumulative Years Unemployed /10	-0.238	-0.155	-0.077
	(0.071)***	(0.047)***	(0.061)
Schooling * Cumulative Years OLF /10	-0.008	-0.049	-0.066
	(0.053)	(0.007)***	(0.017)***
Observations	4,228	29,543	4,004
R-squared	0.312	0.350	0.342
Controls:	Cubic Polynomial of Work Experience, Accumulated OLF/Unemployment/Military Years; Uncounted Years; and Years Dummies		

*** p<0.01, ** p<0.05, * p<0.1

White/Huber standard errors clustered at the individual level are reported in parentheses.

Table 6 - The Effect of Schooling, Experience, and Career Interruptions on Earnings - Leaving School Year as First Year a Responded Left School

NLSY 1979 - Non-Black Males

Dependent Variable: Log Real Hourly Wage

Method: Least Squares

Model	(1)	(2)	(3)
Schooling	0.070	0.070	0.057
	(0.005)***	(0.005)***	(0.006)***
Schooling * Work Experience/10	0.018	0.013	0.014
	(0.003)***	(0.003)***	(0.003)***
Schooling * Cumulative Years Unemployed /10	-0.151	-0.137	-0.167
	(0.027)***	(0.027)***	(0.028)***
Schooling * Cumulative Years OLF /10	-0.003	-0.000	-0.003
	(0.013)	(0.013)	(0.014)
Schooling * Tenure Years/10		0.009	
		(0.001)***	
AFQT * Work Experience/10			0.024
			(0.008)***
Observations	38,267	37,665	36,571
R-squared	0.311	0.318	0.325
Tenure	No	Yes	No
AFQT	No	No	Yes
Other controls:	Cubic Polynomial of Work Experience, Cumulative Years OLF/Unemployment/Military; Uncounted Years; and Years Dummies		

*** p<0.01, ** p<0.05, * p<0.1

White/Huber standard errors clustered at the individual level are reported in parentheses.

Note: Different from the other results, in this table I define year of leaving school as the first year a responded has left school. See section 3.1 for details. AFQT is normalized to have a standard deviation of 1. Difference in the number of observations between models (1), (2) and (3) is due to 602 observations of individuals with missing tenure and 1,696 observations of individuals with missing AFQT information.

Table 7- The Effect of Unemployment and Schooling on Earnings by Timing of Unemployment

NLSY 1979 - Non-Black Males, 1983-2010

Dependent Variable: Log Real Hourly Wage

Method: Least Squares

Model	(1)	(2)	(3)
Schooling	0.104	0.080	0.091
	(0.004)***	(0.004)***	(0.005)***
Schooling * Work Experience/10		0.021	0.016
		(0.003)***	(0.004)***
Weeks spent unemployed/52			
Last year	-0.219	-0.229	0.448
	(0.026)***	(0.025)***	(0.142)***
2 years ago	-0.13	-0.14	0.011
	(0.023)***	(0.023)***	-0.133
3 years ago	-0.085	-0.097	0.163
	(0.021)***	(0.021)***	-0.129
4 years ago	-0.101	-0.112	0.121
	(0.021)***	(0.021)***	-0.133
5 years ago	-0.112	-0.124	0.219
	(0.022)***	(0.022)***	(0.128)*
Schooling * Weeks spent unemployed/52			
Last year			-0.056
			(0.012)***
2 years ago			-0.012
			(0.011)
3 years ago			-0.022
			(0.010)**
4 years ago			-0.020
			(0.011)*
5 years ago			-0.029
			(0.011)***
Observations	31,711	31,711	31,711
R-squared	0.303	0.306	0.308

Controls: Cubic Polynomial of Work Experience, Weeks spent OLF in each of the past 5 year (and their interaction with schooling in model 3), Uncounted Years and Years Dummies

*** p<0.01, ** p<0.05, * p<0.1

White/Huber standard errors clustered at the individual level are reported in parentheses.

Note: The sample is restricted to observations 5 years after an individual's leaving school. Weeks spent in each labor status are constructed using annual aggregation of the week-by-week records.

Table 8 - The Effect of Schooling, Experience, and Career Interruptions on Earnings, Individual Fixed Effect

NLSY 1979 - Non-Black Males

Dependent Variable: Log Real Hourly Wage

Method: Fixed Effects

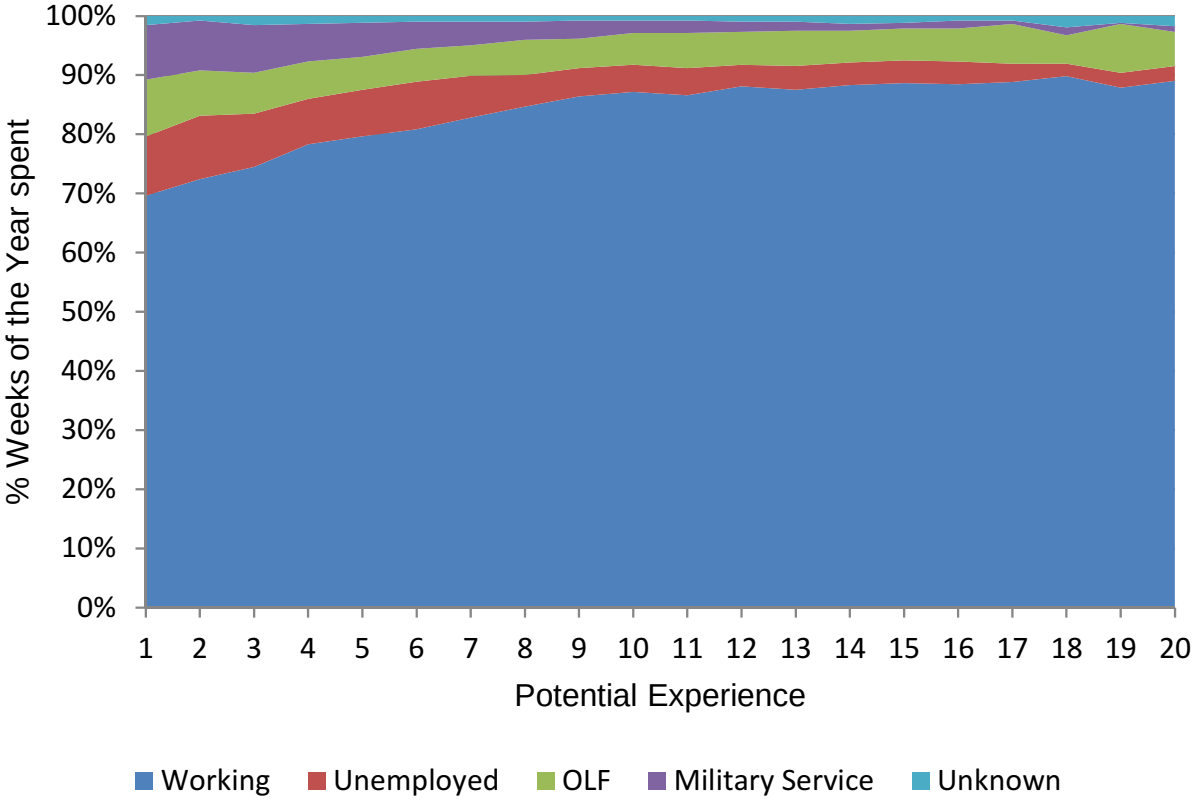
Model	(1)	(2)	(3)
Schooling * Work Experience/10	0.020	0.015	0.013
	(0.003)***	(0.004)***	(0.004)***
Schooling * Accumulated Unemployment Years/10	-0.095	-0.084	-0.114
	(0.036)***	(0.036)**	(0.036)***
Schooling * Accumulated OLF Years/10	-0.019	-0.019	-0.034
	(0.034)	(0.033)	(0.035)
Schooling * Tenure Years/10		0.007	
		(0.005)	
AFQT * Work Experience/10			0.025
			(0.007)***
Observations	33,707	33,181	31,672
R-squared	0.206	0.210	0.215
Tenure	No	Yes	No
Other controls:	Cubic Polynomial of Work Experience, Accumulated OLF/Unemployment/Military Years; Uncounted Years; and Years Dummies		

*** p<0.01, ** p<0.05, * p<0.1

White/Huber standard errors clustered at the individual level are reported in parentheses.

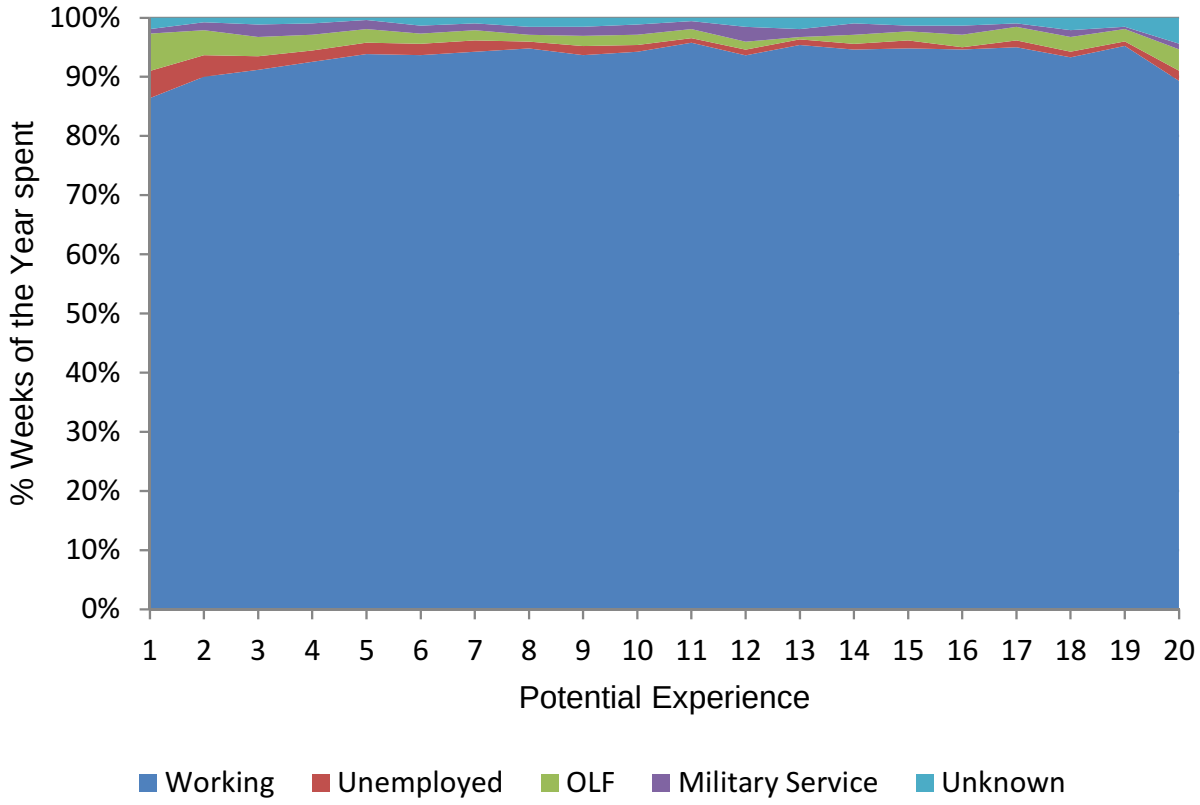
Note: AFQT is normalized to have a standard deviation of 1. Difference in the number of observations between models (1) , (2) and (3) is due to 526 observations of individuals with missing tenure and 1,545 observations of individuals with missing AFQT information.

Figure 1: Employment Attachment over the Life-Cycle - High School Graduates



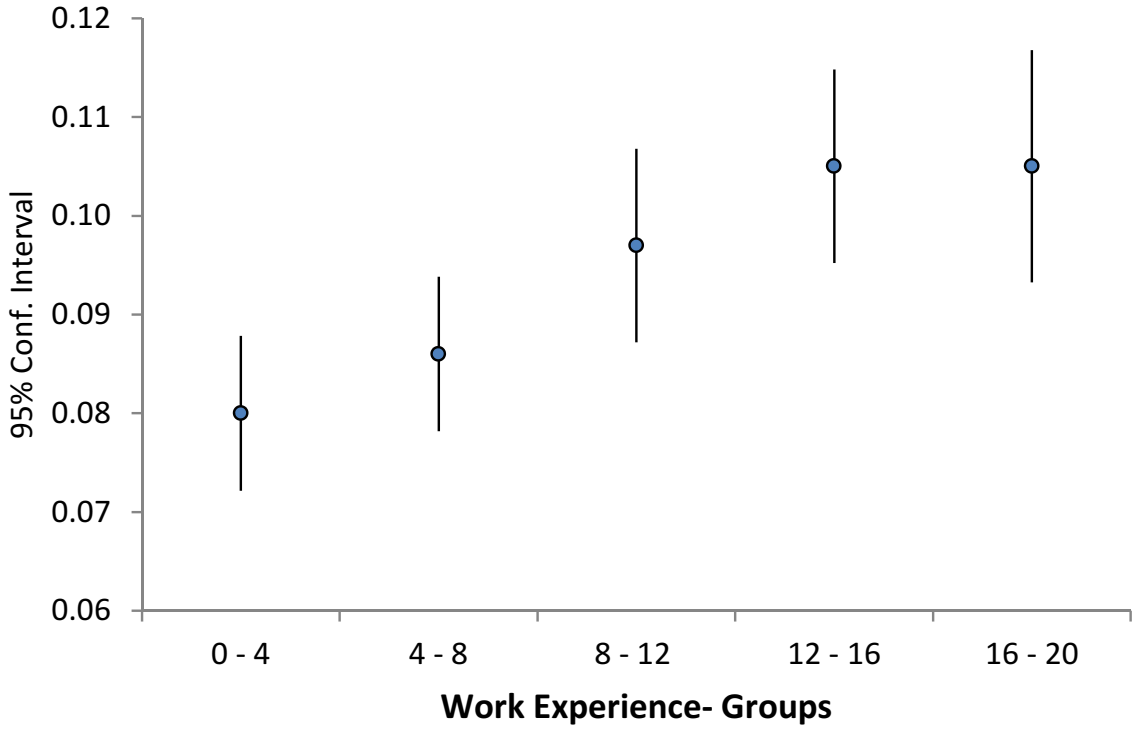
Note: Sample is restricted to observations after an individual left school. Weeks spent in each labor status are constructed using year aggregation of the week-by-week records.

Figure 2: **Employment Attachment over the Life-Cycle - BA or More Graduates**



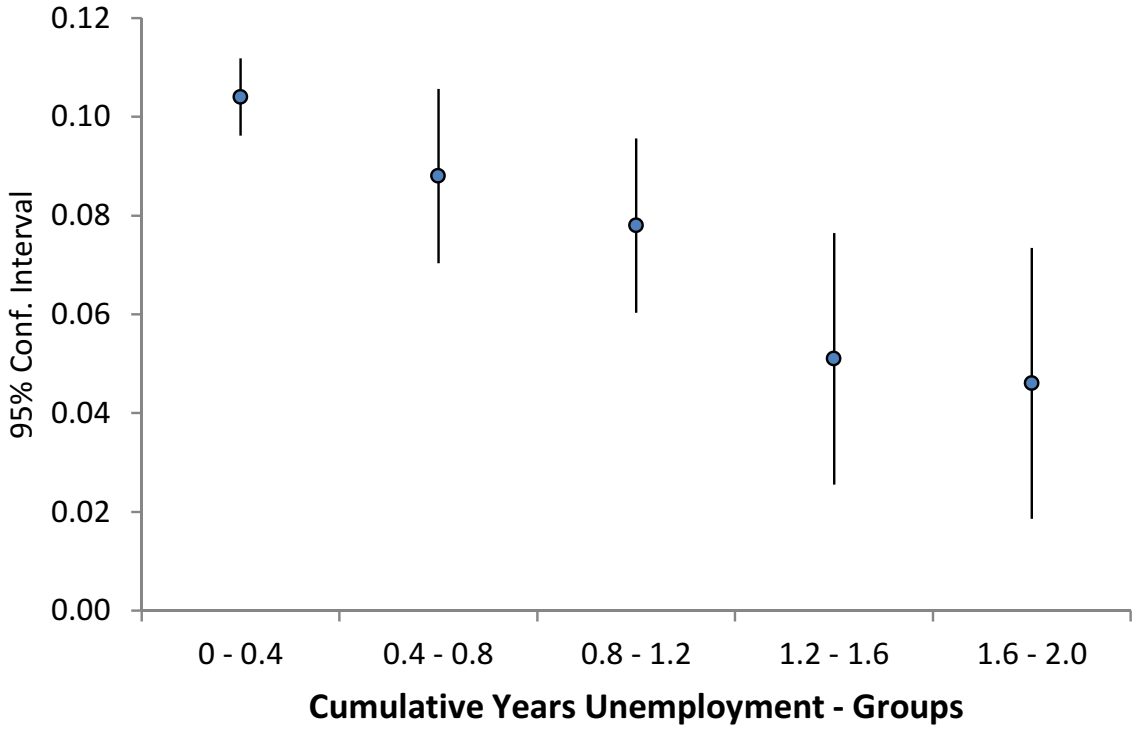
Note: Sample is restricted to observations after an individual left school. Weeks spent in each labor status are constructed using year aggregation of the week-by-week records.

Figure 3: **Earnings Coefficient on Schooling by Work Experience Groups**



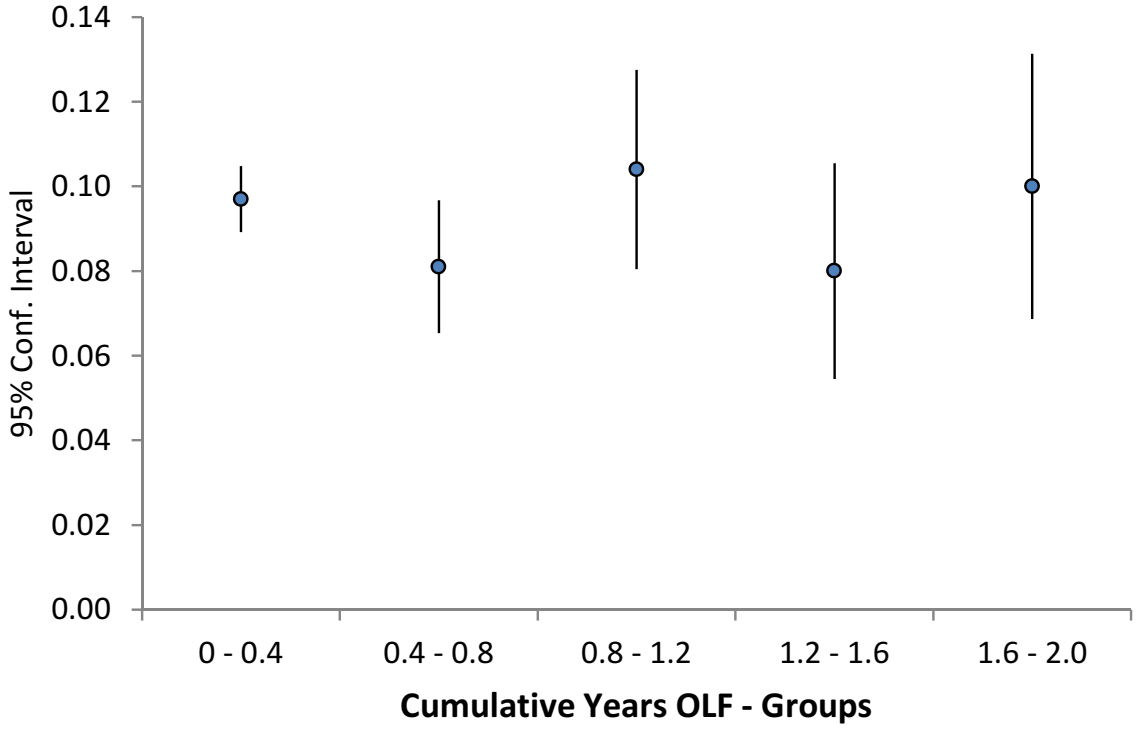
Note: Each circle represents the effect of schooling estimated by linear least squares within each of the 5 Work Experience groups. The controls used in the regressions are the same as those presented in column (2) of table 4. Confidence intervals are calculated using White/Huber heteroscedasticity standard errors clustered at the individual level.

Figure 4: **Earnings Coefficient on Schooling by Cumulative Years Unemployment Groups**



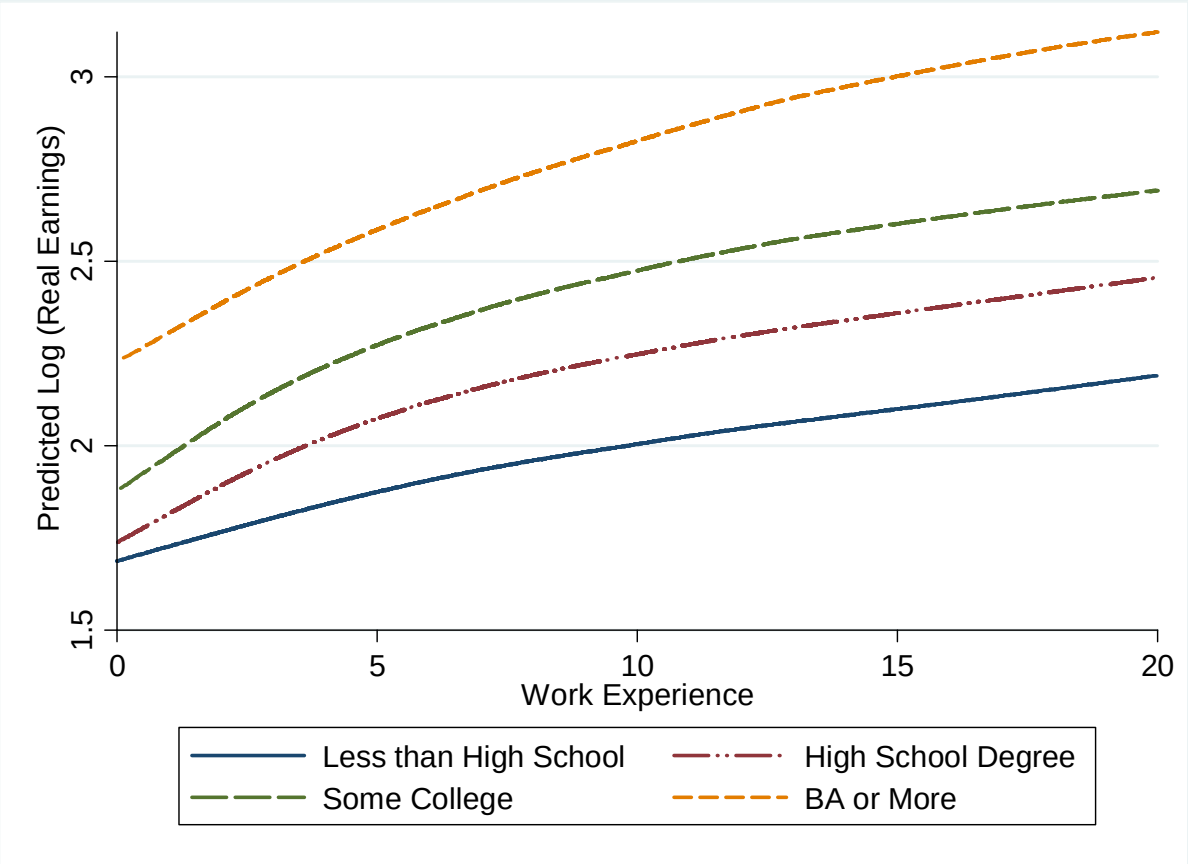
Note: Each circle represents the effect of schooling estimated by linear least squares within each of the 5 Cumulative Years Unemployed groups. The controls used in the regressions are the same as those presented in column (2) of table 4.Confidence intervals are calculated using White/Huber heteroscedasticity standard errors clustered at the individual level.

Figure 5: **Earnings Coefficient on Schooling by Cumulative Years OLF Groups**



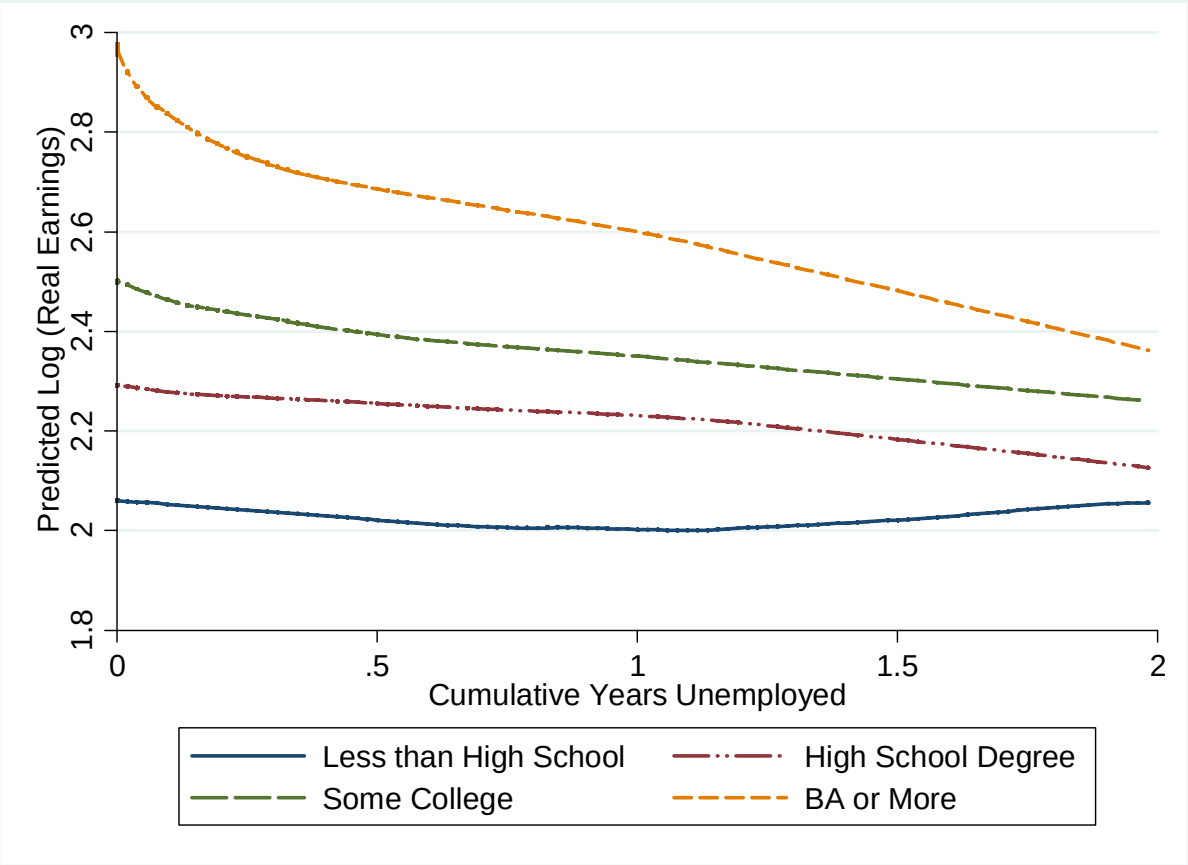
Note: Each circle represents the effect of schooling estimated by linear least squares within each of the 5 Cumulative Years OLF groups. The controls used in the regressions are the same as those presented in column (2) of table 4. Confidence intervals are calculated using White/Huber heteroscedasticity standard errors clustered at the individual level.

Figure 6: **Log Earnings - Work Experience Profile**



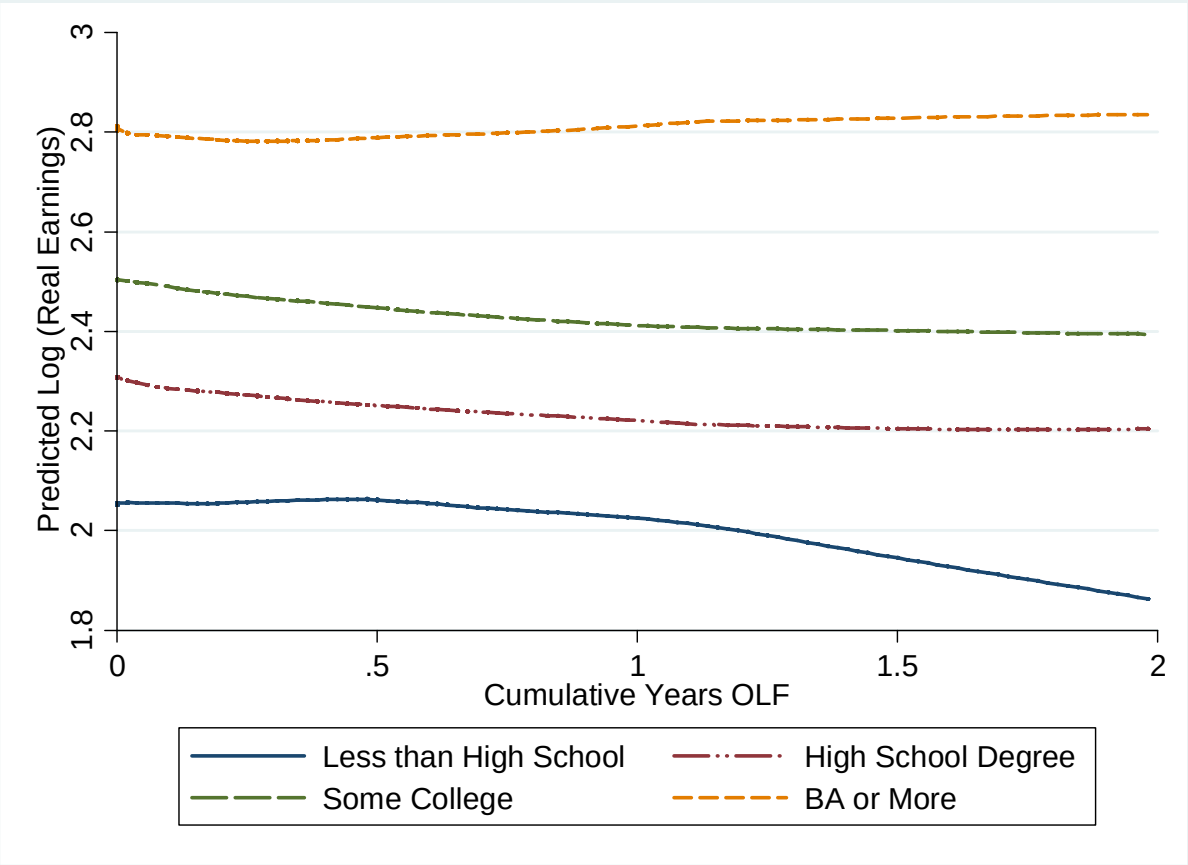
Note: The lines plot the predicted values from a locally weighted regression of log hourly earnings on work experience using a 0.5 bandwidth by each educational group. See section 3.2.2 for details.

Figure 7: Log Earnings - Cumulative Years Unemployed Profile



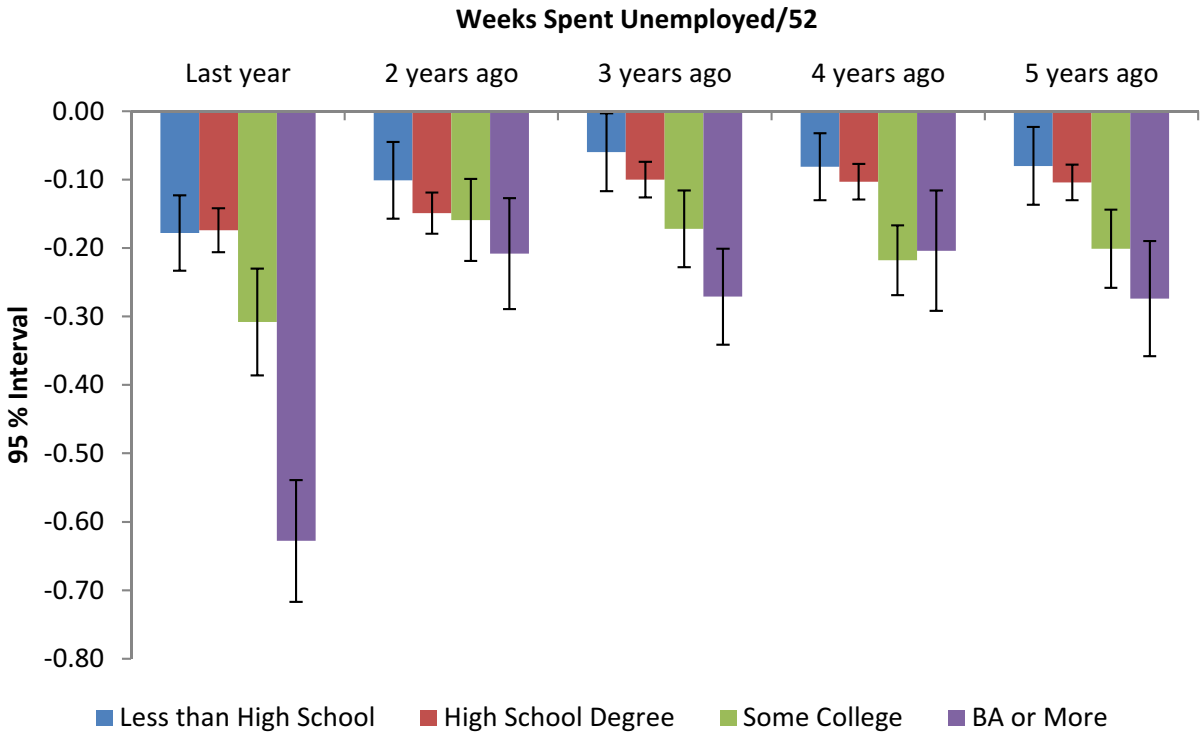
Note: The lines plot the predicted values from a locally weighted regression of log hourly earnings on cumulative years unemployed using a 0.25 bandwidth by each educational group. See section 3.2.2 for details.

Figure 8: Log Earnings - Cumulative Years OLF Profile



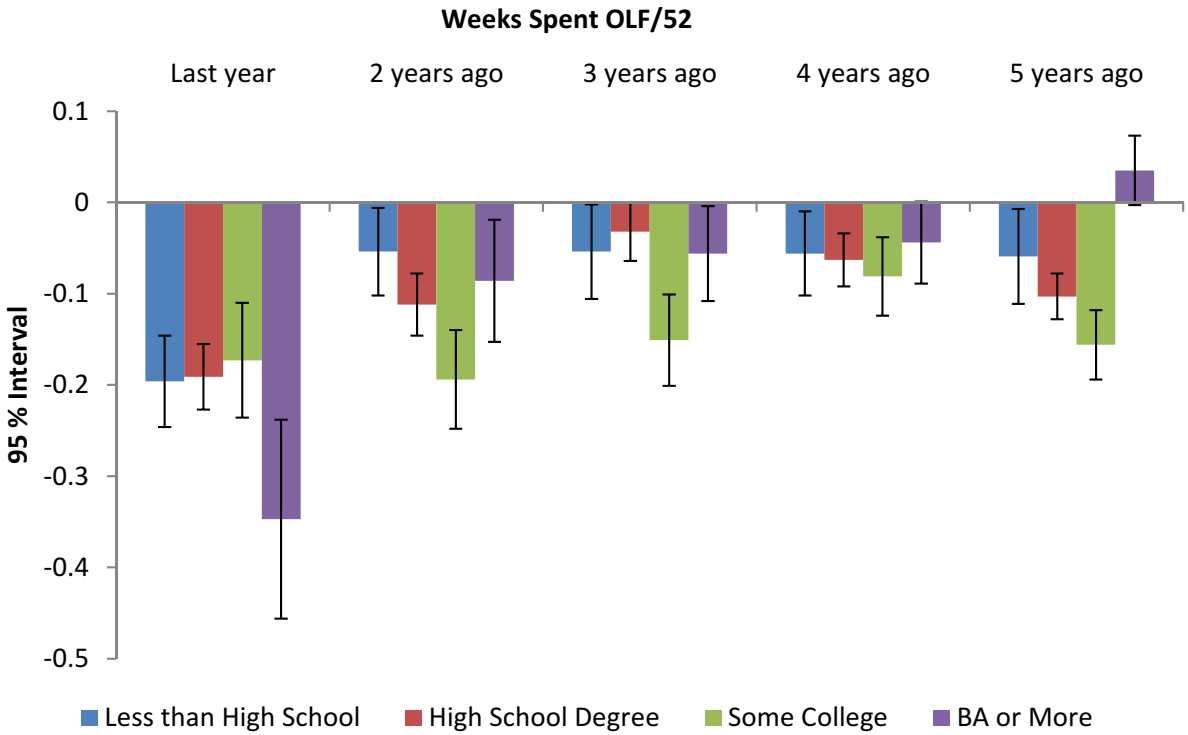
Note: The lines plot the predicted values from a locally weighted regression of log hourly earnings on cumulative year OLF using a 0.25 bandwidth by each educational group. See section 3.2.2 for details.

Figure 9: **The Effect of Unemployment on Earnings by Timing of Unemployment**



Note: Each bar represents the effect of weeks unemployed in each of the past 5 years conditional on weeks unemployment in the other 4 years. The model is estimated by linear least squares. The controls used are OLF periods, cubic polynomial of work experience, cumulative years military service; uncounted years, and years dummies. Confidence intervals are calculated using White/Huber heteroscedasticity standard errors cluster at the individual level. See section 3.2.3 for details.

Figure 10: **The Effect of OLF on Earnings by Timing of OLF periods**



Note: Each bar represents the effect of weeks OLF in each of the past 5 years conditional on weeks OLF in the other 4 years. The model is estimated by linear least squares. The controls used are unemployment periods, cubic polynomial of work experience, cumulative years military service; uncounted years; and years dummies. Confidence intervals are calculated using White/Huber heteroscedasticity standard errors cluster at the individual level. See section 3.2.3 for details.