Wage Progression Among Less Skilled Workers

Tricia Gladden and Christopher Taber[1]
Northwestern University

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[1]Gladden is associated with the department of economics at Northwestern, and Taber is associated with the department of economics and Institute for Policy Research. This paper was written for the conference "Labor Markets and Less Skilled Workers" sponsored by the Joint Center for Policy Research. We thank Joe Altonji, Gadi Barlevy, David Card, and Becky Blank, Hank Farber, Bruce Meyer, and Paul Oyer for comments. We also thank the Joint Center for Policy Research for financial support. All errors are our own.

Abstract

Despite the large amount of work in labor economics devoted towards wage progress we know surprisingly little about the mechanics of wage growth, particularly among low skilled workers. This paper takes a step in this direction by examining wage progression between and among moderate to low skilled workers. We find that once true labor market experience is taken into account appropriately, there are not large differences in earnings growth between low skilled workers and medium skilled workers despite the substantial difference in wage levels. In particular the return to experience for high school dropouts is almost exactly the same as the return for high school graduates. This return also does not differ across individuals from different family backgrounds. However, we do find differences between blacks and whites, and men and women.

1 Introduction

In the last thirty years we have witnessed a large increase in the "returns to skill." These changes in the wage structure have renewed interest in increasing the skill levels of low skill workers. Attempts to do this through job training programs have been largely unsuccessful as the wage gains from these programs tend to be quite modest (although the costs are often also small). In rethinking questions about subsidizing skill formation it is useful to step back and explore the issue of wage growth among low skilled workers. Despite the large amount of work in labor economics devoted to the wage process we know surprisingly little about the mechanics of wage growth, particularly among low skilled workers. This paper takes a step in this direction by examining wage progression between and among moderate to low skilled workers.

Conventional wisdom in the popular press and in political debate often reveals two conflicting views of wage growth among the poor and particularly among welfare mothers. One view postulates that work experience is crucial for this group, and that if they participated in the labor market, they would develop important skills that would lead to large increases in their earnings. At the same time another view stresses the "dead end jobs" into which low wage workers are locked. Proponents argue that in these jobs there is no opportunity for advancement and wages remain stagnant. We find that neither of these views is accurate and that once true labor market experience is taken into account appropriately, there are not large differences in earnings growth between low skilled workers and medium skilled workers despite the substantial difference in wage levels. Additional work experience for low skilled workers does appear to have positive effects on their future earnings, but it is not a magic bullet as the level of wage growth is modest and similar in magnitude to other groups.

Important policy questions that revolve around the wage growth of low skilled workers include the optimal design of the welfare system and the development of youth training and internship programs. Unfortunately, there are also serious econometric issues behind the wage growth process involving parameter heterogeneity and endogeneity issues. We do not attempt to directly address most of these problems here. This paper is primarily descriptive, laying out the patterns of wage growth for alternative groups of workers rather than trying to estimate the parameters of a structural model. These results should be useful in further research which will try to precisely establish the mechanisms of wage growth and design policies aimed at increasing the skill levels of low skilled workers. With this goal in mind, we develop a framework to differentiate between different types of wage growth and apply it to different groups of low wage workers. Since 66% of wage growth occurs during the first ten years of labor market experience (Murphy and Welch, 1992), we focus on the early part of the lifecycle. The National Longitudinal Survey of Youth is an ideal data set since it follows youth from their late teenage years until their early thirties. We use it to construct the weekly labor force experience of workers from 1978-1996. While the Current Population Survey (CPS) is not longitudinal, we take advantage of its repeated cross section nature to learn about some aspects of wage growth. Most of the past work on wage growth has focused on workers with strong attachments to the labor force. For example, Topel and Ward (1992) focus exclusively on males and do not distinguish on the basis of race or skill class. We perform a related analysis, but concentrate on low skill workers and examine interactions with schooling, family background, race, and gender.

Our goal is to measure the extent of wage growth among workers with different levels of schooling and from different family backgrounds using alternative econometric specifications. While, as in previous work, we do find interesting differences in wage growth by gender and race, we do not find that wage growth varies substantially between workers with different levels of schooling and family background. In performing this analysis we find that it is essential to account for actual labor market experience rather than potential experience. In performing this task, we attempt to correct for the endogeneity of actual experience in a number of ways. Our preferred specification instruments for actual experience using potential experience.

We also control for the contribution of job mobility to wage growth. The school to work transition for low skill workers is very erratic with many job changes and weak attachment to the labor force. Using a group of workers with high attachment to the labor force, Topel and Ward (1992) find that about one third of wage growth occurs at job changes. If job changes are also associated with wage growth for low skill workers, and if some groups of workers change jobs more than others, this may bias our estimates of returns to experience. To account for this possible bias, we estimate models controlling for the effects of job changes. We divide job changes into voluntary changes and involuntary changes and assess the impact of each on wage progression. We also look at the effects of job changes after an unemployment spells and compare them with moves directly from one job to another. We find that voluntary changes are associated with wage gains while involuntary job loss is associated with earnings losses. Most importantly, our results on the returns to experience by skill groups change very little when these controls are added.

In section 2 we discuss the data and the sample selection. We then lay out our general framework in section 3. Section 4 presents the results on the returns to experience among different workers, and in section 5 we control for the returns to mobility. Finally, we suggest lessons for policy makers and other conclusions in the final section.

2 The Data

We use data from two sources: the National Longitudinal Study of Youth (NLSY), and the Current Population Survey(CPS). The majority of our results are from the NLSY, and the CPS is used to check the robustness of these results.

The National Longitudinal Survey of Youth (NLSY) is a panel data set begun in 1979 with youth aged 14 to 22. We use the cross-sectional sample as well as the oversamples of blacks and hispanics. The survey is conducted annually[1] and respondents are questioned on a large range of topics, including schooling, wages, and work experience. We also use the work history files, which provide detailed information on job turnover and employment.

Our goal is to focus on low to moderate skilled workers, so we use the subsample of data with only 12 or fewer completed years of schooling. We also wish to focus on the early part of the career so we only include workers with ten or fewer years of potential experience (where potential experience is defined as Age-Education-6 for workers who leave school after grade 10, and Age-16 for other workers). One advantage of the NLSY is that it is a panel data set that reports the number of weeks worked for each year in the sample and obtains this information retrospectively for the years proceeding the sample. This allows us to construct an index of actual experience which the key variable in our analysis. We

[1] Until recently when it is conducted bi-annually. Our final year of data was 1996 with only the 1995 wave skipped.

calculate labor market experience in the following manner. A student is assumed to enter the labor force at the beginning of the calendar year that immediately follows the last year that he was enrolled in school. At the beginning of that year he has no experience, and experience accumulates each year by the annual weeks worked. We impute experience for missing years by taking the average of the number of weeks worked in the year immediately proceeding the missing year and in the year immediately following it.

One potentially difficult issue is precisely defining the time of entry into the labor force. We wish to define entry to be the date at which an individual leaves school and enters the labor force. To approximate this we use calendar years as our unit of time and assume that an individual begins his working life with zero experience and then begins the next year with a level of experience equal to the weeks worked in that calendar year. We have extensively explored the sensitivity of our main results to these assumptions and find that our results are very robust. This robustness comes in part from two aspects of our sample design. First, we do not include anyone who completes a year of post-secondary education. While a substantial number of high school graduates return to college after working in the labor force for some time, these people are not included in our data. Second, individuals who drop out of school and later receive a General Equivalency Degree (GED) are treated as dropouts. This assumption is justified by Cameron and Heckman (1993) who show that the earnings of GEDs is closer to dropouts than to high school graduates. However, the few students who drop out, complete a GED, and then attend college are not included in the sample. Thus, the only group of students who will be problematic are those who drop out of high school and return to conventional high school to complete a grade or get a standard high school diploma, but do not move on to college. Very few individuals have this pattern of schooling: only about 7% of high school non-completers and 1% of eventual high school graduates leave school for over a year and then return.

We use the NLSY work history data to compute job turnover for this sample. We compute the number of jobs an individual leaves voluntarily, and the number he leaves involuntarily, for each year he is in the sample. Voluntary job separations are defined as leaving a job for any reason other than being fired, laid off, or a business closing. We also distinguish job separations by whether they are followed by an unemployment spell of three or more weeks. We are interested in the impact of job separations on wage growth, and wages are recorded at each interview. Therefore, we count job separations over the period between two interviews. If a person is between jobs at the time of an interview, the separation is assigned to the interview year when he starts his next job.

One issue that arises when computing job turnover is determining which job changes to count. Many people in the sample hold more than one job at a time, or leave a job but return to it later. For our purposes, we decide not to count jobs that are obviously second jobs - that is, jobs that begin after and end before another job. It is reasonable to expect that these jobs would have little effect on wage growth, since they are not primary jobs. However, if a person leaves a job for three or more weeks, we count this as a job separation even if he eventually returns to it. The reasoning is that people often hold a job or search for another job while they are away from this employer, so returning to a job might represent job shopping that didn't work out. The results are not sensitive to whether or not these breaks in a single job are counted as separations.

To check the robustness of the results in the NLSY, we use the data from the March annual demographic supplement to the Current Population Survey. The data used was collected annually between 1964 and 1996. Because we are trying to get results comparable to the NLSY, we use only people born from 1957-1964. We exclude anyone who is still in school, or who has more than 12 years of education. The data on earnings, weeks worked, and hours worked refer to the calendar year preceding the March of the interview. Again, we look at workers who have been in the labor force ten or fewer years.

Because the CPS is a random sample each year, rather than a panel, actual work experience is not available. We impute actual experience using average weeks worked for various demographic and age groups. We break the sample into cells based on gender, race, level of education (12, 11, 10 , 9 or less) and year of birth. We then use the CPS to compute average weeks worked for these cells at each age. Actual experience is defined as the sum of these averages in each year since a person left school. Thus, for a 20 year-old born in 1963 and observed in the 1983 CPS, actual experience would be defined as the sum of average weeks worked by 18-year olds in his demographic group born in 1963 and observed in the 1981 CPS, and average weeks worked by 19-year olds from his demographic group born in 1963 and observed in the 1982 CPS.We discuss this imputation further below.

3 Framework

The question of precisely how to define a low skilled worker is not an easy one, particularly in combination with the phrase "wage growth." To be more specific, suppose we are examining wage growth of workers from age t_1 to age t_2. Let W_{t_1} and W_{t_2} be the wages earned at age t_1 and t_2 ignoring for now the question of labor supply. Consider four possible workers,

Worker	W_{t_1}	W_{t_2}
A	8	10
B	5	8
C	8	8
D	5	10

While we might be willing to say that worker A is a more highly skilled worker than B, the comparison is much more difficult when C and D are included. For example, if we classify skill groups by initial wages then D is classified as a low skill worker and C is classified as a high skill worker so we would find that low skill workers have the largest amount of wage growth. On the other hand if we define skill in terms of second period wages, then worker C is characterized as a low skill worker and D is a high skill worker so it looks as if high skilled workers have faster wage growth. This problem manifests itself any time we examine a variable that depends on income status ex-post. In particular, welfare receipt is likely to be correlated with W_{t_t} and W_{t_2} in some complicated manner that depends on the definition of receipt. While the question of wage growth levels among welfare mothers is extremely important, it is very difficult to examine directly since welfare status is endogenous to wage growth. To avoid this issue we focus on variables determined prior to labor force entry that are likely to be correlated with wages. Of primary interest is the relationship between schooling and wage growth as well as the relationship between family background and wage progression. We also consider the importance of race and gender. While these clearly are not pure measures of skill acquisition, they are good predictors of wages, so we can ask the more general question of whether groups who tend to have low levels of wages also have low wage growth. While thinking more seriously about the relationship between unobservable skill and growth is an important research question, we do not attempt to do that in this chapter.

In this section we explore whether different groups experience different levels of wage growth on the job. During the first ten years of labor force participation, work experience is approximately linear in a log wage regression, so we could run the regression,

$$w_{it} = \beta_{0j} + \beta_{1j} PE_{it} + u_{it},$$

where w_{it} is log wage for individual i at time t, j indexes a particular "skill group" defined by demographic characteristics and level of schooling for individual i, and PE_{it} is potential experience(Age-Education-6). By looking at β_{1j}, we can compare the level of wage growth across alternative groups. This would allow us to test whether one group experiences faster wage growth than another. There are a number of problems with this simple specification.

The primary issue involves the measure of experience. Since low wage workers tend to work less, higher wage workers will tend to have relatively more actual experience for each level of potential experience. Using the notation above, if group j has lower levels of actual experience for each level of potential experience than some other group, then the coefficient β_{1j} will tend to be biased downward relative to the coefficient for the other group. One advantage of the NLSY data is that we can measure the total number of weeks in which a worker has worked since entering the labor force. We could then run the regression,

$$w_{it} = \gamma_{0j} + \gamma_{1j} AE_{it} + \varepsilon_{it},$$

where AE_{it} represents actual experience which is defined as the total number of weeks worked divided by 52. If the goal is to measure whether a year of employment is the same for two groups then γ_{1j} is the appropriate parameter of interest. For the purpose of illustration suppose that,

$$AE_{it} = \alpha_j PE_{it} + v_{it},$$

then for each group j,

$$\beta_{1j} = \alpha_j \gamma_{1j}.$$

This expression helps clarify why β_{1j} is a biased estimator of γ_{1j}. Many workers have gaps between jobs and labor supply differs across demographic groups. Since most workers do not work every week after leaving school, actual experience will typically be less than potential experience. This means α_j will be smaller than one which will cause β_{1j} to be a downward biased estimate of the return to work experience.

Second, α_j may differ across groups, which will bias comparisons between groups. In particular, dropouts tend to work less than high school graduates, so the downward bias in β_{1j} will be greater for dropouts. Thus finding lower wage growth in terms of potential experience for dropouts versus high school graduates may be due to differences in labor supply rather than differences in the returns to experience. That is for two groups j and j',

$$\beta_{1j'} - \beta_{1j} = \alpha_{j'}\gamma_{1j'} - \alpha_j\gamma_{1j}.$$

A finding that $\beta_{1j'} > \beta_{1j}$ may be due to the fact that $\alpha_{j'} > \alpha_j$ rather than $\gamma_{1j'} > \gamma_{1j}$.

A serious potential problem arises in that actual experience will be positively correlated with u_{it} if high wage workers tend to work more. In the framework above, this problem leads one to worry that ε_{it} may be positively correlated with v_{it}. We deal with this potential problem in two ways. First, we allow ε_{it} to have a fixed effect θ_i,

$$w_{it} = \gamma_{0j} + \gamma_{1j}AE_{it} + \theta_i + \varepsilon_{it}.$$

This partly solves the problem in that by allowing AE_{it} to be correlated with θ_i we allow workers who tend to have higher wages to also tend to have higher labor supply.

This is still unsatisfactory. Fixed effects requires not only that AE_{it} is uncorrelated with ε_{it}, but also essentially assumes that it is uncorrelated with ε_{it-1}. However, actual experience is constructed from the sum of total weeks worked before t, so assuming that AE_{it} is uncorrelated with ε_{it-1} amounts to assuming that weeks worked in period $t-1$ is uncorrelated with ε_{it-1}. When one considers labor supply decisions, this assumption seems implausible. We would typically expect weeks worked to be positively correlated with the error term through labor supply decisions.

To deal with this problem we use potential experience as an instrumental variable for actual experience. This process is suggested by the set of equations above. Since potential experience is exogenous it seems reasonable to assume that it is uncorrelated with ε_{it}. It can be interpreted essentially as estimating β and α and using these estimates to form an estimate of γ.

A second issue with this type of estimation is that there has been a large change in the wage distribution over time and that low wage workers have seen a decline in their wages. In the NLSY panel, the average age of the sample increases with time so that PE_{it} will be correlated with time. It is important to control for these time effects.

$$w_{it} = \gamma_{0j} + \gamma_{1j} AE_{it} + \gamma_{2j} t_i + \varepsilon_{it},$$

where t_i represents calendar time. In this regression if every individual in the NLSY was born in the same year, time would be collinear with potential experience and we could not measure the effect using the instrumental variables approach. However, since the individuals in the NLSY were born from 1957-1964 there is some limited variation. Our work below essentially uses the variation across cohorts to separately identify the effects of potential experience and time.

One nice aspect of this instrumental variables strategy is that it can be performed with repeated cross section data rather than panel data. First notice that if the α_j were known, we would not need individual observations on actual experience to run the second stage regression. We could use variation across time, groups, and potential experience to estimate the β_j and form estimates of γ_j. Second, we do not need measures of actual experience to estimate the α_j. Notice that

$$E\left(AE_{it} \mid j, t, PE_{it}\right) = \alpha_j PE_{it}.$$

While we cannot construct actual experience for each individual in the sample, we can construct an estimate of $E\left(AE_{it} \mid j, t, PE_{it}\right)$. By definition when potential experience is zero, actual experience is zero. Assuming we have a measure of the number of weeks worked in year t for each individual, we can construct

$$\begin{aligned} E\left(AE_{it} \mid j, t, PE_{it} = 1\right) &= E\left(Weeks_{it} \mid j, t-1, PE_{it} = 0\right), \\ E\left(AE_{it} \mid j, t, PE_{it} = p+1\right) &= E\left(AE_{it} \mid j, t-1, PE_{it} = p\right) + E\left(Weeks_{it} \mid j, t-1, PE_{it} = p\right). \end{aligned}$$

Following the process iteratively we can form measures of the expected value of experience for each group and cohort. The biggest drawback of this approach is that the selection problem may be particularly severe. The formulation above assumes that each individual works at least one week in each year. If some individuals were working in some years, but not in others this strategy becomes problematic because we do not know the level of experience of the set of individuals who work in a particular period, only the average level of experience of their cohort. If the level of participation is high, this bias should not be severe. We use this strategy to estimate the model on CPS data to check the robustness of our NLSY results.

While very little previous research has formally explored the difference in wage growth between workers of different skill levels, there has been a substantial amount of work examining differences in wage growth between men and women, and between blacks and whites. Much of this work is surveyed in Altonji and Blank (1998). These studies typically find that black men and white women have profiles that are less steep than white men, and that these differences in slopes are smaller when accounting for actual experience rather than potential experience. Bratsberg and Terrel (1998) is a recent example that finds that the return to a year of experience is approximately two percent higher for white men than black men. In contrast, D'Amico and Maxwell (1994) find little evidence that black men have lower returns to experience than white men. Light and Ureta (1995) provide a recent example of the comparison between men and women. Thy use a rich model of actual experience and show that about 30% of the difference in the male/female wage gap can be explained by differences in the returns to experience for men and women as well as differences in the timing of experience.

4 Empirical Results

Figures 1 and 2 demonstrate the importance of accounting for actual experience when examining wage growth for low skill workers. On the left hand side of each figure we present the log wage growth of various types of workers by potential experience. On the right hand side we present log wage growth by actual experience.[2] In Figure 1, we differentiate by schooling and by demographic group. Wages grow faster for high school graduates when we measure wage growth in terms of potential experience. However, when we use actual experience, these differences virtually disappear. Similar results can be seen with the

[2] An individual achieves one year of actual experience with 52 weeks experience, two years with 104 weeks, etc.

demographic groups although the differences are not as striking.

In Figure 2 we obtain a similar result when examining wage growth among workers from different family backgrounds. To examine wage progression across levels of family income we divide the sample into four quartiles on the basis of their parent's income and plot the profile for each of the four groups. Once again we see the strongest wage growth for the highest wage group and the weakest for the lowest wage group. In looking at actual experience there is some evidence that higher family income may lead to faster wage growth, but it is clearly of smaller magnitude than with potential experience. In the next two panels we divide the sample by the level of parents education, and once again the difference between actual and potential experience is striking.

To get some intuition behind the difference, in Figure 3 we plot actual experience by potential experience for each of the four comparisons we made in the first two figures. Concentrating on the first panel we see that actual experience is growing much faster for high school graduates than for high school dropouts. This translates to a much faster rate of growth in wages for dropouts when experience is measure as actual experience rather than potential experience.

Next, we analyze the same issues more formally. Table 1 shows the effect on wage growth of experience and interactions of experience with demographic variables and schooling. The primary variable of concern with is the interaction between schooling and experience (Highest Grade$\times$ Potential/Actual Experience). The first column presents the results for potential experience. We see that there is a substantial difference in wage growth between schooling groups when we look at this coefficient. High school dropouts experience slower wage growth than high school graduates. Highest grade completed is normalized to be zero for a high school graduate, -1 for individuals with 11 years of schooling, etc. Thus the coefficient on potential experience for each demographic group can be interpreted as the return to experience for an individual with twelve years of schooling. The coefficient on the interaction implies that for white male high school graduates wages grow by 4.7% each year, but only 4.2% per year for white males with 10 years of education.

In the next column we apply our measure of actual experience rather than potential experience. As expected, for all four of the groups the measure of the return to experience rises. This is almost mechanical since many individuals work fewer than 52 weeks, but it is impossible to work more. The most striking feature of this column is that the experience/schooling interaction disappears. It becomes small and negative. One possible problem with using potential experience as an instrumental variable is that it may have a direct effect. If part of wage growth represents maturing then potential experience is not a valid instrument since it will be correlated with age. This would tend to bias down the IV estimate of the interaction between schooling and actual experience since dropouts have lower actual experience for each level of potential experience. While we cannot address this problem directly we can look at some indirect evidence by including potential experience and actual experience both in the same regression and interacting them will schooling and the demographic variables. These results are presented in column 3. Including the interactions with potential experience does little to affect the coefficient on the schooling/experience interaction. It changes only slightly from -0.0013 to -0.0015 and the standard error increases. The interaction between potential experience and education is also small and insignificant.

In the next column we present our preferred results where we instrument for actual experience with potential experience. Once again the coefficient on the schooling/experience interaction is small and insignificant. It appears that the whole difference in the return to experience between high school graduates and high school dropouts was due to labor supply differences. High school graduates work more weeks per year, so they tend to have more wage growth per year than dropouts, even though the return to a week of experience is the same for the two groups. It should be pointed out that the standard error on the schooling/experience interaction in our preferred set of results (column 4) is quite large, so while the point estimates indicate no effect, the confidence intervals are large enough to include some moderate amount of difference between low and high skilled workers. In columns five and six we present our fixed effects estimates for comparison. These results are similar to the others. When we look at potential experience it appears that the return to experience is higher for high school graduates, but this difference virtually disappears when we use actual experience.

While not our primary focus, the interactions between the racial/gender groups and experience are interesting as well. The effect of race on wage growth is fairly similar to that found by Bratsburg and Terrel (1998). Focusing on the IV results, black males experience approximately 1.4% less wage growth than white males. We also find that white women experience about 1.6% less wage growth than white men. A somewhat surprising result is the experience premium for black women. This indicates that black women experience wage growth which exceeds the growth rate for both black men and white women (though these differences are not statistically significant). We do not show Hispanic interactions, but find no strong evidence that either interaction is significant.

One weakness of the results in Table 1 is that we do not control for time effects. In Table 2 we remedy this problem and interact the time effects with schooling and demographic groups. This does not make a large difference when we look at the interaction between schooling and experience. Once again the coefficient on the schooling/experience interaction tends to be small and insignificant. The only exception is the fixed effect estimate which has a somewhat larger coefficient, although the standard error is also large. This slight positive result is driven by the coefficient on the schooling/time trend interaction which is negative, though insignificant. Since the returns to schooling are typically thought to have grown during this time period, this negative result is puzzling . The result on the returns to high school graduation is one difference between the CPS and NLSY(see MaCurdy, Mroz, and Gritz, 1998). Below we will check the robustness of our results by examining the CPS.

In Table 3, we present results on the interactions between experience and family background.[3] Rather than present the full sets of regression coefficients, we only present the coefficients on the interactions between the variable of interest and experience using the instrumental variable results (the specification in column 4). First we examine family income measured in thousands of dollars. In row one we see that the coefficient on both interactions is insignificant and extremely small. It indicates that increasing parents income by $10,000 is associated with only a 0.4% increase in wage growth. When we look at fathers income on earnings growth we see that fathers schooling is negatively associated with wage growth and once again the coefficient is insignificant and very small.[4] To increase the power

[3]Another variable that we have examined in the NLSY is the AFQT test score. Altonji and Pierret (1997) show that there may be interactions in this variable and experience. However, in our sample we found the results to be very sensitive to the specification. For example, as in Taber (1998) we get very different results depending on whether we use the wage from the NLSY "CPS job" versus annual earning divided by annual hours. We did not find this problem using the other variables we examine, so we do not use the AFQT score in any of the results.

[4]We also experimented with mothers income and get very similar results.

of our test we combine several measure of family background to create an index of family background and interact that with experience. SES1 is created by regressing schooling on fathers education, mothers education, and number of siblings, and creating a predicted value. SES2 is created by including family income in the regression as well. There is no evidence that family background is related to wage growth.

As discussed above, looking at interactions between welfare receipt and wage growth is problematic since welfare receipt is endogenous to wage growth and since the sample selection problem is likely to be substantial for this group. We run these regressions to document the results, but one must be very careful in interpreting them. Using data from the Panel Study of Income Dynamics, Moffitt and Rangarajan(1989) presents some evidence that mothers who are typical welfare recipients have steeper wage growth than typical non-recipient, but warns of selection bias. Burtless(1994) looks at the return to potential experience and finds that wages grow more slowly for welfare mothers than others. Looking at actual experience, we find similar results to Moffitt and Rangarajan(1989). Table 4 presents results using the same specification as in Table 3, but estimating only on women. The results indicate that welfare recipients actually have higher levels of wage growth than other workers. White women who experience a welfare spell at some point have wage profiles that are approximately 5.2% steeper then other workers. This effect is somewhat more pronounced for whites then blacks, but the difference between welfare mothers and others is substantial.

Given that our results are only partially robust to time trends, we next use the Current Population Survey data to look at the effect of the schooling/experience interaction on wage growth. These results are presented in Table 5. We construct the actual experience measure as discussed above. It is important to recognize that this measure is imperfect for a number of reasons. As mentioned above, the primary problem is that the group of people who belong to one group at one point in time might not belong to that group at another. This arises when thinking about both labor supply and schooling. When we construct the average experience for 21 year old high school graduates, some of those individuals will attend college eventually. Ideally we would not want to include these 21 year olds when we construct the actual experience for 25 year old high school graduates, but we can not avoid this problem since we do not know who will attend college. We have a similar problem with

GEDs. Secondly, the selection problem on labor market participation may be particularly important here. Ideally when looking at the expected experience of a 25 year old, we would want to condition on the expected actual experience of 25 year olds who are working at age 25. However when looking at 21 year old workers, we do not know which ones will participate in the labor force at age 25, so it is not clear whether we should use 21 year old labor force participants, or all 21 year olds. While we cannot avoid this problem, we can compare it with another approach. We estimate the expected level of actual experience for each group using the NLSY data and then perform our instrumental variable estimation using these predictions. The biggest problem with this approach is that the NLSY sampling framework may differ from the CPS framework.[5]

We present the CPS results in Table 5. The results are similar to the NLSY. Across all of the columns we see that the return to experience is somewhat larger in the CPS than NLSY. The potential experience results indicate that higher skilled workers receive higher returns to experience with the magnitude larger in the CPS than the NLSY. The most striking result is that, as in the NLSY, the instrumental variables point estimates of the schooling/experience interaction are negative and, in the CPS, quite large. Given the problems with this approach we want to avoid overstating the negativity, but at the very least we find no evidence that higher skilled workers receive higher wage growth. In fact our results suggest that high school dropouts may obtain somewhat higher returns to experience than high school graduates. The racial/gender interactions are of interest as well. While there is evidence that white women have less wage growth then white men, the difference is smaller here. There is no strong evidence of a black interaction. However, since the CPS does not oversample blacks, the standard errors on these coefficients are large. The biggest difference between the CPS and NLSY results is for black women. In this case we find that the point estimates for wage growth among black women are lower than for black men. A variable that plays a crucial role in this analysis is the time effects and interactions of the time effects. In the CPS we can use a cross section to control for time effects and examine synthetic cohorts. The results of this approach are presented in the final column. The point estimates indicate that high school graduates have substantially less wage growth than dropouts, but the standard errors are large enough that this effect

[5] See MaCurdy, Mroz, and Gritz (1998) for discussion.

is not statistically significant.

In interpreting the results on returns to experience it is important to keep in mind that they represent changes in log wages not changes in the wage levels. If higher wage workers experience the same amount of log wage growth as lower wage workers, then they experience greater levels of wage gains. This is important for two reasons. First, even though we say that there aren't big differences in wage growth between different workers, wage levels become more unequal with age. Thus, the fact that wage profiles are parallel in logs is not necessarily good news for low wage workers: four percent of zero is still zero. Second, the model is not inconsistent with our notion of human capital investment. Intuitively, if one thinks skill is useful in producing human capital, then one would expect human capital accumulation of skilled workers to exceed that of lower skilled workers. However, this is an argument about the level of human capital accumulation, not the rate of increase in accumulation. Heckman, Lochner, and Taber (1998) estimate a structural human capital accumulation model using the NLSY data. Even though the return to experience is similar for their two different skill groups, the estimates indicate that higher skilled workers are still more productive at human capital investment.

We have explored the sensitivity of the results above using many other specifications and found the basic results that there is no strong evidence of skill or family background interactions to be robust. Two important types of sensitivity analysis were performed. First, we tried a number of different definitions of labor market entry and schooling. Secondly we allowed for quadratic terms in the experience premium interacted in a number of ways. The qualitative results were robust across these different specification with only moderate variation in the estimated parameters.

5 Accounting for Job Turnover

In the previous sections we have treated employment as a strictly a positive influence on wage growth, and restricted nonemployment to have no effect. This seems problematic when one considers job matching. Topel and Ward (1987) show that about one third of wage growth occurs at job changes. Since it is often accompanied by unemployment spells, turnover will tend to be negatively correlated with employment. Furthermore, high school dropouts tend to change jobs more often than graduates, so this effect may bias our results. If the return to mobility is similar for low and medium skill workers, we may be overstating the return to experience for low skill workers. In this section we examine this possibility. The coefficients on these turnover variables are interesting in their own right and extend the work on returns to mobility to include low wage workers.

In this section we use a somewhat different specification. Let Δw_{it} denote the change in log wages from the beginning to the end of the year,

$$\Delta w_{it} = \gamma_{1j} \frac{Weeks_{it}}{52} + u_{it}.$$

Since total weeks worked is the first difference of actual experience, this equation is just a first differenced version of the regression above and can be thought of as another fixed effects estimator. We do not instrument here for two reasons. First, job changes should be considered to be endogenous to wages, so without instruments for job changes IV results would be difficult to interpret. Second, instrumenting does not substantially change our results. Our results in the previous section were robust to instrumenting, and the results in this section are as well.[6]

In order to account for the effects of mobility on wage growth we control for the number of job transitions. Let Tr_{it} denote the number of transitions made by individual i during year t. To measure the effect of transitions on wage growth we can include it in the regression,

$$\Delta w_{it} = \gamma_{1j} \frac{Weeks_{it}}{52} + \gamma_2 Tr_{it} + u_{it}.$$

Our goal is to examine the effect on γ_{1j} of including Tr_{it} in the regression.

When a worker changes jobs, the job match can end in two ways. One possibility is that the worker may be let go without finding a new job first. A second possibility is that the worker may terminate the job because he has a job prospect that is preferable. Typically we may expect wage gains to be positive for the second type of worker since he left the original job because his expected wage gain was large.[7] However we would expect wage losses for the first type of worker as a result of the loss in job-specific human capital and matching

[6] When we instrument for weeks worked but not turnover the coefficients are extremely close to those presented here.

[7] Although they also lose experience so the net effect could be negative.

capital. While it is impossible to know precisely the conditions under which the match was terminated, we do know whether the separation was voluntary or involuntary (from the standpoint of the worker). While the relationship is not perfect, we would typically expect that involuntary job changes are of the first type, and that voluntary job changes are often of the second. In our work below we distinguish between the returns to voluntary and involuntary job changes expecting positive effects for the voluntary changes. Similarly, we expect that job changes associated with unemployment spells are likely to be the first type of separation. We make this distinction as well, expecting wages to increase when a worker moves directly between jobs and to decrease when there is an unemployment spell.

There is a substantial literature examining the effects of job mobility (or job stability) on earnings using either regression analysis or structural modeling . Examples include Mincer and Jovanivich (1981), Flinn (1986), Antel (1991), Loprest (1992), Topel and Ward (1992), Wolpin (1992), Barlevy (1998), Gardecki and Neumark (1998), Light and McGarry (1998) and Neumark (1998). We extend this literature primarily by focusing on low wage workers.

In Table 6 we present the number of job changes for high school graduates and high school dropouts. As one would expect, dropouts have more turnover, but the difference is not huge. Using data from the first ten years of labor market experience, we find that in a typical year, dropouts experience no job changes 64% of the time and high school graduates experience no changes about 70% of the time. Most of this difference in total changes is due to a higher number of involuntary changes for dropouts. The distribution of voluntary changes is similar for the two groups with somewhat more turnover for the dropouts.

Table 7 presents our estimates of the effects of job changes on wage gains. The specification in this table is chosen to be close to Table 1. Since time effects are equivalent to intercepts we do not control for the direct effects of schooling and demographic groups. The specification in column two is closest to that in Table 1, and we see that the coefficient on the schooling/experience interaction (as measured by weeks worked) is very similar. Moreover, these results are extremely robust to the controls for job changes. Across all of the various specifications we once again find small and insignificant coefficients on the schooling/experience interaction. The robustness of this coefficient to these specifications comes from two aspects of weeks worked, 1) weeks are not that highly correlated with schooling status, and 2) weeks are not that highly correlated with turnover. Workers often change jobs with short unemployment spells. Using similar specifications we find very small effects when we look for an interaction between family background and experience. Once again we find no evidence of differences in the returns to schooling across skill groups.

While it is not our primary concern the coefficients on turnover are of interest in their own right. The importance of the distinction between voluntary and involuntary job changes is clear. From column four we see that a voluntary change is associated with an increase in wage growth of approximately 3%. In contrast involuntary changes lead to about 5% loss in wages. We also distinguish the return to the first voluntary job change in a year from the return to subsequent job changes in that year. We find that all of the benefit from job changes comes from the first change, and that subsequent changes may actually lead wages to fall (although the coefficient is not statistically significant). This provides some evidence that too much churning through jobs may be unproductive, but that for low wage workers some turnover is beneficial. In terms of involuntary job changes, we find that the second job change leads to a further decrease in wages, but that the loss attributed to the second change is smaller than the loss attributed to the first. Finally we distinguish job changes by the presence of an unemployment spell of at least three weeks. When workers move directly between jobs or are unemployed only a short period, their wages tend to rise with turnover, but when the unemployment spells are longer their wages fall.

6 Lessons for Policy Makers and Conclusions

Throughout this paper, we have emphasized that we are not producing structural estimates, but are describing the relationships between wage growth and other variables. The question that arises is what we learn from this exercise and whether it can be useful for policy makers. While there are still a number of issues that remain for future research, there are lessons from this work that should be helpful.

Our main result is that we find no evidence of differences in the experience profile across schooling groups and across individuals with different family backgrounds. The racial and gender interactions suggest that white men have the highest level of growth, followed by black women, black men, and then white women. These results are inconsistent with two views often expressed. (1) All low wage workers are not stuck in dead end jobs. High school dropouts whose parents have low income experience about the same amount of wage growth as other groups. (2) Work experience is not a magic bullet. The same evidence indicates that low skill workers will not have huge wage gains from work experience. There is no reason to believe that forcing to them to work will lead to a noticeable effect on the poverty rate.

We also looked at the effects of job turnover on wage progression for low skilled workers. The results here suggest that there is a positive return to some mobility. High school dropouts who change jobs once a year experience on average 3.4 percent higher wage growth in those years. In contrast, a second job change in a calendar year is not associated with additional wage growth. Furthermore, involuntary job changes lead to declines in wages. These results do not vary substantially with measures of family background. This information is important to keep in mind when considering welfare programs and internships. In terms of generating wage growth, it is productive to keep workers attached to the labor force so that they can receive the benefits of experience. However, it is also important to allow flexibility in choosing positions. A substantial amount of lifecycle wage growth comes with job changes so workers should not be discouraged from seeking new employers.

If our goal is to find policies that stimulate wage growth, this work suggests that: (1) We should encourage low skilled workers to work. Work experience does appear to lead to moderate amounts of wage growth even for low skilled workers. (2) We should try to keep low skill workers from being laid off. This is obvious in terms of the direct effect on the level of earnings, but it is also true in terms of wage growth. (3) We should encourage workers to shop for better jobs since a substantial amount of wage growth occurs at job changes. While none of these points are particularly surprising, it is important to document the magnitude of these effects for low skilled workers. The mechanisms of precisely how to design policies that maximize wage growth and precisely what the predicted impacts will be is an important topic for future research.

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Table 1
Regressions of Log Wages on Experience
High School Graduates and High School Dropouts
First Ten Years of Potential Experience
(Standard Errors in Parentheses)

	OLS	OLS	OLS	IV†	FE	FE
Highest Grade Completed	0.0047		0.0009		0.0045	
× Potential Experience	(0.0012)		(0.0021)		(0.0009)	
Highest Grade Completed		-0.0013	-0.0015	0.0018		0.0009
× Actual Experience		(0.0016)	(0.0026)	(0.0023)		(0.0013)
White Male	0.0466		0.0053		0.0481	
× Potential Experience	(0.0021)		(0.0059)		(0.0017)	
White Male		0.0546	0.0506	0.0588		0.0544
× Actual Experience		(0.0026)	(0.0066)	(0.0030)		(0.0019)
White Female	0.0301		-0.0123		0.0319	
× Potential Experience	(0.0025)		(0.0051)		(0.0018)	
White Female		0.0540	0.0641	0.0448		0.0420
× Actual Experience		(0.0031)	(0.0061)	(0.0038)		(0.0022)
Black Male	0.0307		-0.0093		0.0330	
× Potential Experience	(0.0027)		(0.0059)		(0.0022)	
Black Male		0.0482	0.0563	0.0426		0.0409
× Actual Experience		(0.0036)	(0.0071)	(0.0046)		(0.0028)
Black Female	0.0303		-0.0066		0.0364	
× Potential Experience	(0.0033)		(0.0049)		(0.0027)	
Black Female		0.0621	0.0670	0.0535		0.0463
× Actual Experience		(0.0046)	(0.0064)	(0.0068)		(0.0036)
Highest Grade Completed	0.0778	0.0477	0.0430	0.0496		
	(0.0047)	(0.0046)	(0.0048)	(0.0046)		
Hispanic Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Sample Size:						
Person-Years	32723	30808	30808	30808	32723	30808
Individuals	4956	4822	4822	4822	4956	4822

†The IV results instrument actual experience with potential experience

‡Schooling is Normalized to zero for High School Graduates.

Table 2

Regressions of Log Wages on Experience
High School Graduates and High School Dropouts
First Ten Years of Potential Experience
Including Time Trends
(Standard Errors in Parentheses)

	OLS	OLS	OLS	IV†	FE
Highest Grade Completed	0.0047		0.0005		
× Potential Experience	(0.0024)		(0.0029)		
Highest Grade Completed		-0.0014	-0.0011	0.0007	0.0025
× Actual Experience		(0.0021)	(0.0026)	(0.0043)	(0.0037)
White Male	0.0679		0.0233		
× Potential Experience	(0.0050)		(.0074)		
White Male		0.0632	.0503	0.0836	0.0746
× Actual Experience		(0.0046)	(.0066)	(0.0072)	(0.0100)
White Female	0.0275		-0.0119		
× Potential Experience	(0.0055)		(0.0069)		
White Female		0.0578	0.0633	0.0415	0.0662
× Actual Experience		(0.0048)	(0.0061)	(0.0096)	(0.0074)
Black Male	0.0408		-0.0004		
× Potential Experience	(0.0058)		(0.0075)		
Black Male		0.0560	0.0566	0.0567	0.0615
× Actual Experience		(0.0055)	(0.0071)	(0.0096)	(0.0098)
Black Female	0.0411		0.0021		
× Potential Experience	(0.0062)		(0.0068)		
Black Female		0.0673	0.0667	0.0707	0.0213
× Actual Experience		(0.0057)	(0.0064)	(0.0125)	(0.0094)
Highest Grade Completed	0.0002	0.0008	0.0006	0.0004	-0.0017
×Time	(0.0022)	(0.0016)	(0.0022)	(0.0022)	(0.0029)
Highest Grade Completed	0.08211	0.0437	0.0451	0.0470	
	(0.0148)	(0.0106)	(0.0144)	(0.0146)	
Demographic Time Interactions	Yes	Yes	Yes	Yes	Yes
Hispanic Interactions	Yes	Yes	Yes	Yes	Yes
Sample Size:					
Person-Years	32723	30808	30808	30808	30808
Individuals	4956	4822	4822	4822	4822

†The IV results instrument actual experience with potential experience

‡Schooling is Normalized to zero for High School Graduates.

Table 3
The Effects of Family Background
On Returns to Experience
High School Graduates and High School Dropouts
First Ten Years of Potential Experience†
(Standard Errors in Parentheses)

Variable	No Demographic Interactions*	Demographic Interactions*
Family Income♡ × Experience	00.00050	0.00040
	(0.00022)	(0.00029)
Highest Grade Completed By Father × Experience	-0.00054	-0.00082
	(0.00124)	(0.00143)
SES I	-0.01080	-0.01742
	(0.01213)	(0.01408)
SES II	0.00018	-0.00762
	(0.01395)	(0.01704)

†These results represent interaction between family background variables and experience in the Instrumental Variables specification where potential experience is used as an instrument for actual experience.

*Demographic interactions are full interaction between race and gender. The specification without interactions does include controls.

♡Family Income is Measured in Thousands of Dollars.

‡ Ses1 is consructed from a regression of schooling on parents education and the number of siblings.

§ Ses2 is consructed from a regression of schooling on parents education, family income, and the number of siblings.

Table 4
The Effects of Family Background
On Returns to Experience
High School Graduates and High School Dropouts
First Ten Years of Potential Experience
Women Only†
(Standard Errors in Parentheses)

Variable		No Demographic Interactions*	Demographic Interactions*
Welfare at Least			
One Year	Welfare×Experience	0.052404	0.05105
	× white female	(0.022067)	(0.02314)
	Welfare×Experience	0.04349	0.03992
	× black female	(0.02126)	(0.02266)
	Welfare×Experience	0.04066	0.03210
	×hispanic female	(0.02708)	(0.02820)
Welfare Two or			
more years	Welfare×Experience	0.05257	0.05141
	× white female	(0.02702)	(0.02761)
	Welfare×Experience	0.04377	0.04232
	×black female	(0.02635)	(0.02731)
	Welfare×Experience	0.05498	0.04468
	×hispanic female	(0.03693)	(0.03804)

†These results represent interaction between family background variables and experience in the Instrumental Variables specification where potential experience is used as an instrument for actual experience.

∗We include full interaction with race.

Table 5
Regressions of Log Wages on Experience
Current Population Survey
Sample of Whites and Blacks born 1957-1964
First Ten Years of Potential Experience
(Standard Errors in Parentheses)

Measure of Experience	Potential	Potential	Potential 1988 Cross Sec.	IV†	IV‡ NLSY 1st Stage	IV† 1988 Cross Sec.
Highest Grade§	0.0111	0.0056	-0.0034	-0.0027	-0.0073	-0.0123
×Experience	(0.0005)	(0.0008)	(0.0063)	(0.0016)	(0.0023)	(0.0139)
White Male	0.0738	0.0747	0.0572	0.0885	0.0948	0.0602
×Experience	(0.0009)	(0.0014)	(0.0091)	(0.0020)	(0.0025)	(0.0186)
White Female	0.0544	0.0467	0.0315	0.0784	0.0929	0.0721
×Experience	(0.0009)	(0.0014)	(0.0090)	(0.0025)	(00034)	(0.0190)
Black Male	0.0659	0.0587	0.0735	0.0882	0.0922	0.0961
×Experience	(0.0026)	(0.0040)	(0.0208)	(0.0069)	(0.0083)	(0.0312)
Black Female	0.0465	0.0327	0.0300	0.0747	0.0781	0.0904
×Experience	(0.0026)	(0.0041)	(0.0196)	(0.0115)	(0.0120)	(0.0623)
Highest Grade Completed	0.1129	0.0738	0.1466	0.0395	0.0214	0.0849
	(0.0017)	(0.0048)	(0.0088)	(0.0056)	(0.0065)	(0.0109)
White Female	-0.2110	-0.2729	-0.2206	-0.1871	-0.1444	-0.0740
	(0.0035)	(0.0108)	(0.0141)	(0.0114)	(0.0132)	(0.0226)
Black Male	-0.1687	-0.2272	-0.1942	-0.1314	-0.1513	-0.0426
	(0.0082)	(0.0239)	(0.0301)	(0.0267)	(0.0285)	(0.0336)
Black Female	-0.2874	-0.3926	-0.3020	-0.2373	-0.2454	0.0313
	(0.0084)	(0.0250)	(0.0290)	(0.0368)	(0.0458)	(0.1541)
Time Trend*	No	Yes	NA	Yes	Yes	NA
Sample Size	98044	98044	5734	98044	98044	5734

†The fourth and sixth columns construct average actual experience by cohort and instrument using potential experience.

‡The fifth column uses actual experience by cohort from the NLSY and instruments using potential experience.

§Schooling is Normalized to zero for High School Graduates.

∗The time trend is interacted with schooling and the demographic variables.

Table 6
Number of Job Changes per Year†
High School Graduates and High School Dropouts
First Ten Years in Labor Force

Type of Job Change	Number of Annual Changes	Total Sample Number	Total Sample Percent	Drop Outs Number	Drop Outs Percent	High School Graduates Number	High School Graduates Percent
All							
	0	28161	67.89	9140	63.82	19028	70.06
	1	9458	22.80	3581	25.00	5866	21.6
	2	2833	6.83	1149	8.02	1684	6.2
	3	730	1.76	308	2.15	424	1.56
	4	216	.52	106	0.74	111	.41
	5	83	.20	39	0.27	46	.17
Voluntary							
	0	32847	79.19	11118	77.63	21723	80.00
	1	7052	17.0	2578	18.0	4481	16.5
	2	1298	3.13	516	3.6	782	2.88
	3	241	0.58	89	.62	149	0.55
	4	441	0.10	20	.14	22	0.08
	5	2	0.005	1	.01	1	0.004
Involuntary							
	0	35765	86.22	11930	83.3	23846	87.8
	1	4853	11.7	1991	13.9	2852	10.5
	2	718	1.73	328	2.29	388	1.43
	3	124	0.30	64	0.45	60	0.22
	4	17	0.04	7	0.05	11	0.04
	5	4	0.01	1	0.01	3	0.01

†Each unit of observation here is a person year.

Table 7
Effects of Weeks Worked and Job Changes on Wage Gains
High School Graduates and High School Dropouts
First Ten Years of Potential Experience
(Standard Errors in Parentheses)

White Male×Weeks Worked	0.0514	0.0525	0.0531	0.0517	0.0516	0.0491
	(0.0027)	(0.0028)	(0.0029)	(0.0030)	(0.0030)	(0.0029)
White Female×Weeks Worked	0.0508	0.0515	0.0519	0.0480	0.0478	0.0496
	(0.0034)	(0.0034)	(0.0035)	(0.0035)	(0.0035)	(0.0035)
Black Male×Weeks Worked	0.0435	0.0450	0.0456	0.0465	0.0463	0.0433
	(0.0038)	(0.0039)	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Black Female×Weeks Worked	0.0374	0.0380	0.0383	0.0363	0.0362	0.0381
	(0.0048)	(0.0048)	(0.0049)	(0.0049)	(0.0048)	(0.0049)
Highest Grade Completed		0.0022	0.0020	0.0020	0.0019	0.0016
×Weeks Worked		(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
One Job Change†			0.0050			
			(0.0054)			
Two Job Changes‡			-0.0243			
			(0.0106)			
One Vol Job Change†				0.0311	0.0342	
				(0.0059)	(0.0065)	
Two Vol Job Changes‡					-0.0131	
					(0.0146)	
Invol Job Change†				-0.0501	-0.0467	
				(0.0068)	(0.0078)	
Two Invol Job Changes‡					-0.0012	
					(0.0185)	
One Job Change†						0.0352
without Unemployment Spell						(0.0067)
One Job Change†						-0.0335
with Unemployment Spell						(0.0058)
Sample Size:						
Person-Years	24789	21598	21598	21598	21598	21598
Individuals	4526	4149	4149	4149	4149	4149

†The one job change variables are indicators for at least one job change in a year.

‡The two job change variables are indicators for at least two job change in a year.

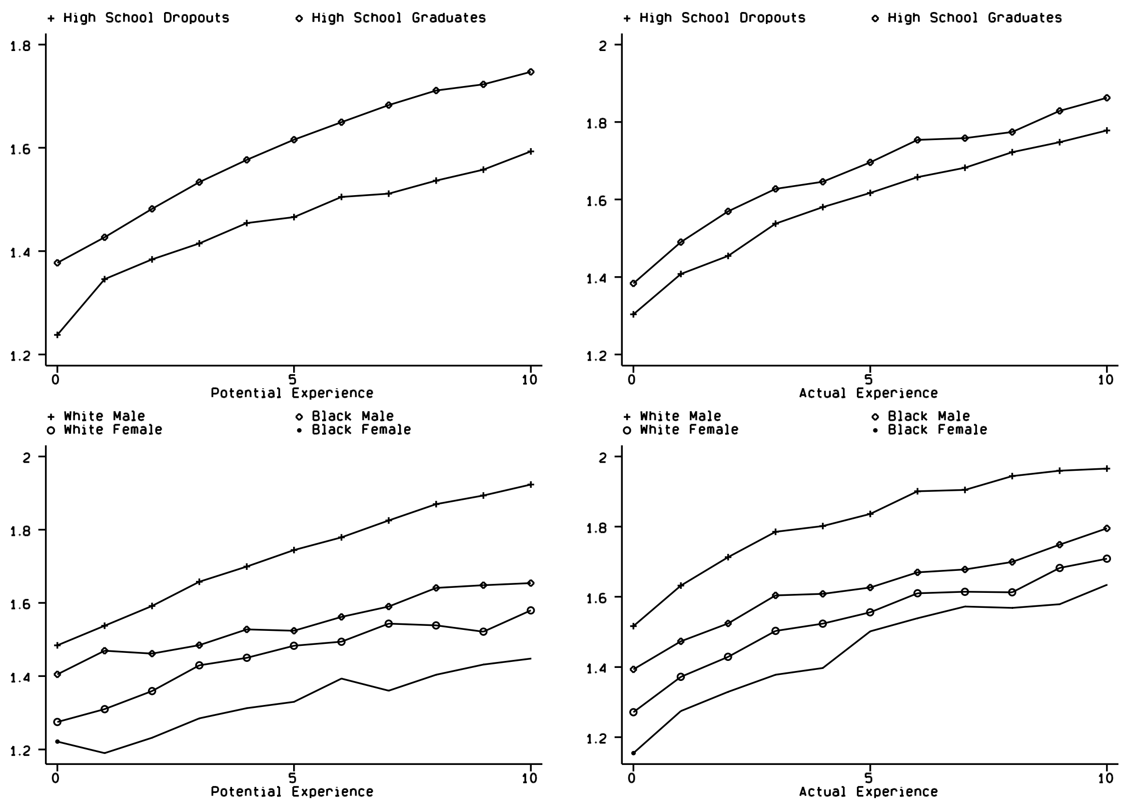

Figure 1: Wage Growth by Education and Demographics

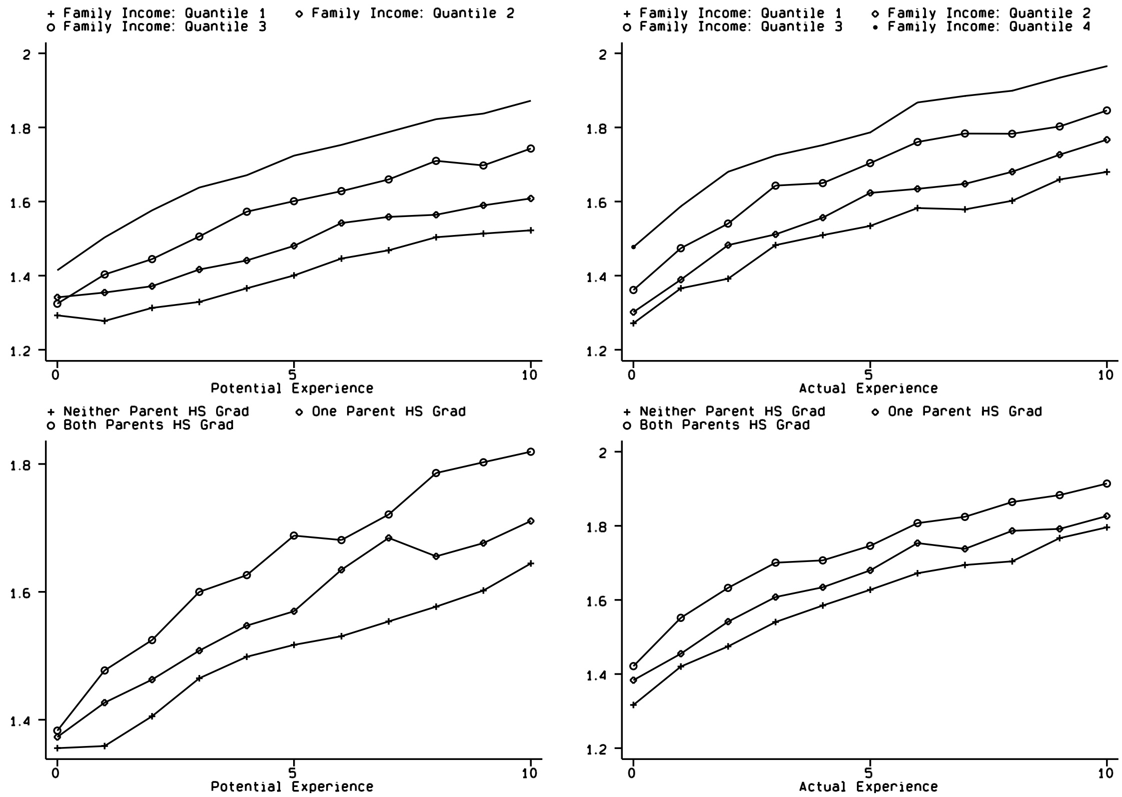

Figure 2: Wage Growth by Family Background

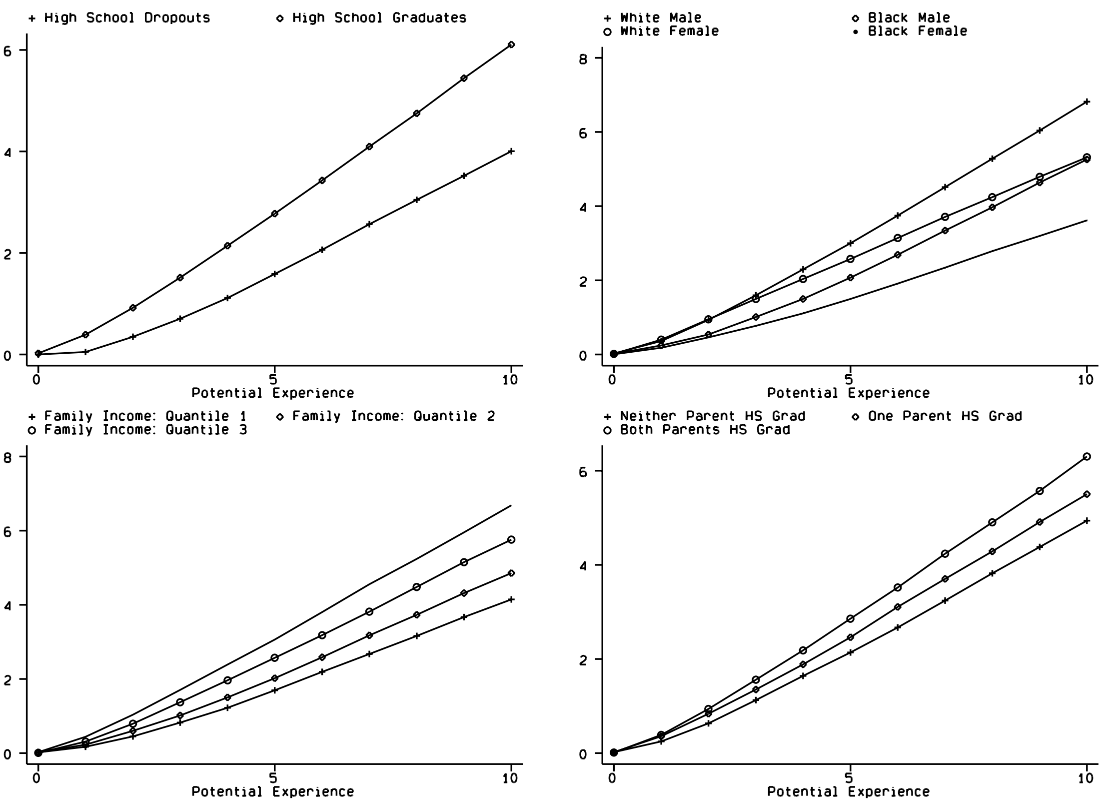

Figure 3: Actual Experience by Potential Experience