The Relationship Between Wage Growth and Wage Levels

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Abstract

Increasing labor force participation among low skill workers has been a major goal of policy makers over the last decade. Examples of policies that share this goal include expansions in the Earned Income Tax Credit and the Personal Responsibility and Work Opportunity Reconciliation Act. A largely ignored consequence of these policies would be additional work experience for low skilled workers. One of the most robust findings in labor economics is that wages increase with work experience. However very little of this work has focused on wage growth among low wage workers. As a result, we have very little information on the impact of additional labor force participation on future wages for this group.

We use a correlated random effects model to estimate the relationship between wage levels and wage growth. That is we let log wages take the form

$$w_{it} = \theta_i + \beta_i E_{it} + u_{it},$$

where w_{it} represents log wages, θ_i and β_i are individual specific random coefficients, E_{it} is a measure of experience, and u_{it} is an error term. Our goal is to estimate the relationship between the permanent component, θ_i, and the random coefficient on experience, β_i. We estimate models with both potential experience, which we define as years since leaving school, and actual experience, which we define as the total number of weeks worked since leaving school. We allow experience to be arbitrarily correlated with both θ_i and β_i. Our estimates of $cov(\theta_i, \beta_i)$ vary across specifications from small and insignificant negative effects to moderately sized and statistically significant negative effects. Consider a worker who earns approximately 50% less than a median worker early in life. We estimate that this individual will experience faster wage growth later in life ranging from about zero to one percentage point per year. Contrary to the popular perception, wage growth among low skill workers appears to be at least as high as that for a medium skilled worker.

1 Introduction

Increasing labor force participation among low skill workers has been a major goal of policy makers over the last decade. Examples of policies that share this goal include expansions in the Earned Income Tax Credit and the Personal Responsibility and Work Opportunity Reconciliation Act. A largely ignored consequence of these policies would be additional work experience for low skilled workers. One of the most robust findings in labor economics is that wages increase with work experience. However very little of this work has focused on wage growth among low wage workers. As a result, we have very little information on the impact of additional labor force participation on future wages for this group. One possible explanation for this hole in the literature is that there are serious econometric issues behind the wage growth process involving parameter heterogeneity, endogeneity, and selection issues. We attempt to fill some of these holes and address these issues in this paper. A second explanation for the lack of research is that policy makers may believe that low wage workers are locked into "dead end jobs" in which wages stagnate. We find no evidence to support this claim. Our results suggest that wage growth among low skill workers is similar to wage growth among median workers. If anything, wages actually grow faster for low skill workers.

We use a correlated random effects model to estimate the relationship between wage levels and wage growth. That is we let log wages take the form

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This paper builds on our previous work (Gladden and Taber, 2000) in which we measure the variation in wage growth across members of different skill classes. As an example of the type of analysis we performed, suppose that there are two groups of individuals whose wage growth we would like to compare. Let g_i be a dummy variable that distinguishes between the groups. We focus on the comparison across different levels of schooling, so g_i could be a dummy variable indicating whether the worker obtained a high school diploma.[1] We construct a measure of actual weeks of experience rather than potential experience. We then estimate the regression,

$$w_{it} = \beta_0 + \beta_1 g_i + \beta_2 AE_{it} + \beta_3 AE_{it} g_i + \beta_4 t + \beta_5 t g_i + u_{it},$$

where AE_i represents actual experience. However, this yields the potential problem that actual experience may be positively correlated with u_{it} if high wage workers participate in the labor force at a higher rate. We deal with this potential problem in a few ways. The key parameter of interest in this work is β_3 where g_i represents high school graduation. Using a number of different methods, we consistently find that β_3 is small in magnitude and insignificant. We also look for differences in earnings growth between other groups. We find no evidence that family income or other measures of family background affect wage growth. We do find that demographics relate to growth in the manner found by previous research. White men tend to have larger returns to experience than white women and than black men. Interestingly, we find that black women actually receive higher returns to experience than white women and than black men.

Several authors have studied the relationship between wage growth and welfare receipt. 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 warn of selection bias. Burtless(1994) looks at the return to potential experience and finds that wages grow more slowly for welfare mothers than others. Corcoran and Loeb (1999) examine actual experience in the NLSY and find

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[1] Our sample included no individuals who had completed a year of post-secondary education.

that welfare recipients have slightly less wage growth than other workers.

The main weakness of our previous work is that we only examine the relationship between wage progression and observable measures of skill. These observables explain only a small amount of wage dispersion. While the measures of skill are statistically significant, the R^2 in our regressions are approximately 0.15. This leaves a tremendous amount of wage variation that cannot be explained by our measures of skill. Our goal here is to assess the relationship between unobservable skill and wage growth, or more specifically the relationship between wage growth and wage levels. We build on the substantial literature on the covariance structure of wages in labor economics including Abowd and Card (1989) and more recent work by Baker (1997), Baker and Solon (1998), and Lillard (1999). This literature attempts to understand the evolution of wages over the lifecycle.

Although it is not the focus of their studies Baker (1997) and Lillard (1999) both find a negative relationship between wage levels and growth. This work differs from ours along many dimensions. First, both authors use the PSID and do not focus on earnings growth early in the lifecycle which is crucial for identification in our framework. Second, they do not focus on low skill workers. Third, they follow the larger literature on earnings dynamics which has largely ignored the information that can be provided by actual experience as opposed to potential experience. Our previous work indicates that this is a major limitation along some dimensions. We showed that in terms of observables it is crucial to consider the role of actual experience in explaining differences in wage growth among different workers, so it is reasonable to expect that this would also be true when measuring unobservable heterogeneity in wage growth across workers.

2 Economic/Econometric Framework

While it may be an interesting avenue for future research, our goal is not to formally estimate a precisely specified structural model. We keep the framework simple and focus on data description. However, there is a "structural interpretation" to our specification. We present it here with the aim of aiding the reader in interpreting the results.

Assume that human capital is generated in a learning by doing process,

$$H_{it} = F_i(E_{it}, H_{i0})$$

where for individual i, E_{it} is the level of experience at the beginning of time period t, and H_{i0} is the level of human capital with which the individual begins their life. The human capital investment decision is made purely at the extensive margin (work/no work). We have not allowed for investment at the intensive margin as in Ben Porath (1967) or Heckman, Lochner, Taber (1998). Heckman and Lochner (2000) discuss the differences between these models and attempt to distinguish between them.

People rent their human capital at the makret rate R_{it}, so they are paid wages $R_{it}H_{it}$. We assume that the human capital production function has a separable form,

$$H_{0t} = g_i(E_{it}) f_i\left(H_{i0}\right).$$

Then letting w_{it} denote log wages,

$$w_{it} = \log(f_i\left(H_{i0}\right)) + \log(g_i(E_{it})) + \log(R_{it}).$$

In the simplest specification we assume that $\log(g_i)$ is linear with coefficient β_i, define $\theta_i = \log(H_{i0}) + E(\log(R_{it}))$, and define $u_{it} = \log(R_{it}) - E(\log(R_{it}))$, then we can write the expression as,

$$w_{it} = \theta_i + \beta_i E_{it} + u_{it}.$$

We also follow Lillard and Reville(1999) and consider a quadratic version of $\log(g_i)$ in which

$$w_{it} = \theta_i + \beta_i \left(E_{it} - \gamma E_{it}^2\right) + u_{it}.$$

The goal of this work is to learn about the evolution of income inequality over the lifecycle, namely about the joint distribution of (θ_i, β_i).

In doing so we examine two separate measures for experience. The first is potential experience which is measured as the number of years since the worker entered the labor force. The second is actual experience which is the number of weeks that a worker has actually worked. If human capital growth is due to learning on the job, this second measure is more appropriate.

3 The Data

We use data from the National Longitudinal Study of Youth (NLSY). It 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[2] and respondents are questioned on a large range of topics, including schooling, wages, and work experience.

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 who have been working for ten or fewer years. 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 a measure of actual experience which is the key variable in our analysis. We calculate labor market experience in the following manner. A student is assumed to enter the labor force at the beginning of the calendar year immediately following 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. Ideally, we would 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. The problem of individuals returning to school does not appear to be problematic in our sample. 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

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

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.

4 Regression Results

There are a number of econometric issues that arise in estimating this model. The first problem is that actual experience is endogenous. We have every reason to believe that the amount that an individual works should be related to both wage levels and growth, (θ_i, β_i). Second, u_{it} is likely to be serially correlated. Third, there may be a substantial amount of selection bias since many low skilled workers will not work in some years. We will address these issues in the next section, but we begin with a descriptive analysis. Throughout this section we treat actual experience as exogenous and assume that (θ_i, β_i) and experience are independent of u_{it}.[3]

Perhaps the simplest specification of the model would be a one factor model in which the lowest wage workers always remain the lowest wage workers as they age. In this case one could examine the distribution of β_i directly by examining wage profiles at different quantiles. In that case, each quantile would represent a quantile of β_i. We present this type of quantile comparisons in Figure 1. We trace wage profiles along four quantiles: the tenth, twenty-fifth, median, and the seventy-fifth. Figure 1a presents the profiles by “potential” experience which is measured as the number of years since the respondent left school and entered the labor market. We see a tremendous difference between the groups. While the initial levels are different, the most remarkable feature of the figure is the difference in the slopes of the profiles. While median wages grow substantially, there is basically no evidence of wage growth among the 10^{th} quantile of workers. Misreading this figure could lead one to conclude that there is little wage growth among low skill workers.

There are a number of problems with this interpretation. First, this figure does not follow the same workers over time. As a result, the pattern in quantiles could arise as a

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[3] We are also assuming that experience is uncorrelated with u_{it}. This assumption is supported loosely by our previous research in which we show that fixed effects estimates are very close to instrumental variables estimates. We also address it below.

result of increasing earnings inequality. Second, potential experience is not the appropriate measure for low skill workers since they typically have weaker attachment to the labor force. We address this second problem explicitly by examining actual experience rather than potential experience. These profiles are presented in Figure 1b.[4] The results are striking. Including actual experience wipes out virtually all of the differences in slopes between the different quantiles. However, there is still some evidence that the slope is steeper for higher wage workers. This could arise from either steeper wage profiles for high wage individuals, or increasing dispersion in earnings over the lifecycle. That is, one can not tell whether it represents the poor becoming worse off, or represents increases in the unconditional variance of wages. The main lesson from this figure is that most of the difference in the slopes of potential experience appears to be explained by differences in actual experience.

Our primary goal is to estimate long run earnings prospects for worker with low earnings who are encouraged to become more active participants in the labor force. In particular, if we condition on low wage workers with low attachment to the labor force, what is their expected returns to experience? Consider a welfare mother of age t^* who currently earns low wages. Suppose we can subsidize a job for one year for this woman. Her expected long run benefit from this additional labor market experience is captured in her value of β_i. In evaluating policies aimed at increasing labor supply for low wage workers the question (in this context) is the magnitude of β_i. Large values would indicate that this type of policy is likely to have a lasting impact on the earnings of poor workers and could be a sound investment. On the other hand, if the benefits of work experience are small then some other type of human capital investment would be more appropriate.

There are at least two reasons why a relationship between current wages and future wage growth may exist. The first possibility is that pre-market skills are related to wage growth. If low wage workers are stuck in jobs that are not only low paid, but also have little avenue for advancement then we would expect that individuals with low values of θ_i would also have low values β_i. On the other hand, if work experience is a panacea that

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[4] In creating the figure we group people based on interval values of their actual experience. For example, individuals with 1.2 years of actual experience are categorized as one year. The figure presents quantiles based on this stratification.

propels poor workers out of poverty then we would expect these two effects to be negatively correlated. This question is closely related to our previous work except that it looks at the relationship between wage growth and wage levels directly rather than through observable measures of skill.

A second reason why wage growth may be related to current wages is that previous wage growth may be correlated with future wage growth. An individual may have low wages at a point in time because they have had low wage growth in the past. The fundamental question is whether we expect this low wage growth to persist. Consider an individual who has worked considerably until age 25, but has experienced only minor amounts of wage growth. There are essentially two explanations. One possibility is that this is an individual is a slow learner and has not accumulated much human capital; the other possibility is that he has simply had bad luck. These alternatives lead to very different predictions of future wage growth. Under the first story this individual will continue to experience slow wage growth and his wages will be low even if he works extensively. In the second case, there is no reason to expect that this individual should experience any less wage growth than anyone else with similar levels of experience. In general, our goal is to understand how wage levels relate to future wage growth and to understand the mechanism that leads to that level of growth.

With this goal in mind we perform a preliminary exercises in order to understand the importance of these relationships. Figures 2a and 2b presents the progression of wages conditioning on the initial wages. We produced the figure by classifying individuals based on their initial wages. The four groups are 1) workers whose initial wage is in the bottom 10% of initial wages, 2) workers whose initial wage is between the 10^{th} and 20^{th} percentile, 3) workers with initial wages between the 20^{th} and 40^{th} percentiles, and 4) workers with an initial wage between the 40^{th} and 60^{th} percentiles. Since our goal is to compare low wage workers with medium wage workers we ignore the high end. These figures show that in both cases low wage workers first recover and then experience rates of wage growth similar to the other groups.

We next attempt a more formal analysis. In the context of the model our goal is to discover the relationship between θ_i and β_i. First consider the use of potential experience

$$w_{it} = \theta_i + \beta_i PE_{it} + u_{it},$$

where potential experience increases by one each year.[5] A simple method of examining this relationship is to look at the covariance between wage differences and initial wage levels,

$$\begin{aligned} cov(w_{it+1} - w_{it}, w_{i0}) &= cov\left(\beta_i + u_{it+1} - u_{it}, \theta_i + u_{i0}\right) \\ &= cov(\theta_i, \beta_i) + cov\left(u_{it+1} - u_{it}, u_{i0}\right). \end{aligned}$$

If we choose t sufficiently large the second term of this equation should be small.

We estimate the model by regressing changes in log wages on initial log wages. The results of this regression are presented in Table 1. We have restricted the time period (t) for the wage difference to be at least seven years. One can see that the point estimate is actually negative and borderline significant at conventional levels. Since the first wage may be problematic, we run the same regression for the second wage with similar results. The magnitude of the effect is small and fairly precisely estimated. Workers who earn 0.5 log wage points less than the median experience approximately 0.005 (one half of a percentage point) more wage growth per year than the median worker. Since a 0.5 log wage change seems large to us, the change of 0.005 relative to the level of 0.04 seems small, particularly relative to the differences across racial groups.

Figure one demonstrated the importance of incorporating actual experience. We can incorporate it into our specification as,

$$w_{it} = \theta_i + \beta_i AE_{it} + u_{it},$$

where actual experience is measured as total weeks of experience at the beginning of the current calender year. One potential problem in using actual experience is that we would expect it to be correlated with wage levels and wage growth. We put no restriction on this relationship.[6] In order to obtain estimates we do assume that u_{it} is independent of

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[5] Note that the figure suggests that wage growth is approximately linear during the first ten years. Since the analysis is simpler we do not include a quadratic term in the wage equation at this point. We will relax this assumption below.

[6] Heckman and Vytlacil (1998) consider a similar type of situation with a random slope coefficient that may be correlated with its covariate. They discuss this model in the context of instrumental variables.

$(\theta_i, \beta_i, AE_{it})$, but we put no restrictions on the joint distribution of $(\theta_i, \beta_i, AE_{it})$. In this case notice that

$$\begin{aligned} cov(w_{i0}, \frac{w_{it+1} - w_{it}}{AE_{it+1} - AE_{it}}) &= cov\left(\beta_i + \frac{u_{it+1} - u_{it}}{AE_{it+1} - AE_{it}}, \theta_i + u_{i0}\right) \\ &= cov\left(\theta_i, \beta_i\right) + cov\left(u_{i0}, \frac{u_{it+1} - u_{it}}{AE_{it+1} - AE_{it}}\right). \end{aligned}$$

Once again if t is large, the second term should be small. We implement this approach by regressing $\frac{w_{it+1} - w_{it}}{AE_{it+1} - AE_{it}}$ on initial wages and wages one year out. These results are presented in Table 2. This gives a very similar story to Table 1: fairly small negative effects that are borderline significant. The point estimates suggest that workers who earn 0.5 log wage points less than the median experience wage growth that is about one percentage point higher. While nontrivial, this seems like a fairly small effect to us.

Since actual experience is measured in weeks, the denominator $AE_{it+1} - AE_{it}$ is simply weeks worked in calender year t (divided by 52). We are assuming that weeks worked is uncorrelated with the error term during that period t. This seems inconsistent with standard labor supply models. In this case one may worry about our assumption that

$$cov\left(\frac{u_{it+1} - u_{it}}{AE_{it+1} - AE_{it}}, \theta_i\right) = 0.$$

Since $AE_{it+1} - AE_{it}$ is a measure of weeks worked and $u_{it+1} - u_{it}$ is essentially the unexplained difference between wages at the end of the year and at the beginning, the nature of this relationship is uncertain. However if $AE_{it+1} - AE_{it}$ is correlated with both θ_i and $u_{it+1} - u_{it}$, it is unlikely that this covariance would equal zero.

We see no way to identify this model allowing for an arbitrary relationship between $(\theta_i, \beta_i, AE_{it})$ and between AE_{it} and u_{it}. However, we can achieve identification using the following alternative assumptions. Suppose that

$$E(\beta_i \left(AE_{it+1} - AE_{it}\right) \mid w_{i0}) = E(\beta_i \mid w_{i0}) E(AE_{it+1} - AE_{it} \mid w_{i0})$$

and

$$(u_{it} \mid w_{i0}) = 0.$$

In this case we can identify

$$\begin{aligned}
E(\frac{w_{it+1}-w_{it}}{E(AE_{it+1}-AE_{it}\mid w_{i0})} \quad \mid \quad w_{i0}) &= E\left(\frac{\beta_i AE_{it+1}-AE_{it}}{E(AE_{it+1}-AE_{it}\mid w_{i0})}+\frac{u_{it+1}-u_{it}}{E(AE_{it+1}-AE_{it}\mid w_{i0})}\mid w_{i0}\right)\\
&= \frac{E\left(\beta_i AE_{it+1}-\beta_i AE_{it}\mid w_{i0}\right)}{E(AE_{it+1}-AE_{it}\mid w_{i0})}\\
&= E\left(\beta_i \mid w_{i0}\right)
\end{aligned}$$

Notice that we have put no restriction on the distribution between AE_{it} and w_{i0}, the distribution between $(AE_{it+1}-AE_{it})$ and w_{i0},or the distribution between θ_i and β_i. The assumption that, conditioning on initial wage, β_i is independent of weeks worked is somewhat unattractive since one may expect that individuals with higher β_i would work more weeks. However, allowing for arbitrary correlation between β_i, experience and the error term is not feasible.

We estimate this model by first regressing $AE_{it+1}-AE_{it}$ on w_{i0}. We call the predicted value from this regression $AE_{it+1}\widehat{\ -\ }AE_{it}$. We then regress

$$\frac{w_{it+1}-w_{it}}{AE_{it+1}\widehat{\ -\ }AE_{it}}$$

on initial wages and other covariates. These results are presented in Table 3. Once again our estimates of $cov(\theta_i,\beta_i)$ are small negative numbers that are borderline significant at conventional levels.

In Tables 1, 2, and 3 we use different assumptions on the model to estimate the relationship between wage levels and wage growth. While individually, each model may be problematic, the problems are quite different across specifications. Thus, it is reassuring that the basic results seems to be robust to the underlying assumptions that are made.

In Table 4 we present results in which we stratify the data on the basis of gender. In this case the point estimates are closer to zero for women than for men. However, these results are not statistically significantly different from each other. Given that much precision is lost when we separate women from men, we will continue to use the pooled sample. We should note that across specifications, cov(θ_i,β_i) has a larger negative effect for men than for women.

These results beg the larger question of whether there is any evidence of heterogeneity in β_i. To address this we use a similar strategy but regress wage growth on initial wage growth instead of wage levels. In Table 5 we regress wage growth later in life on wage growth in the first two periods. That is we regress $w_{it+1} - w_{it}$ first on $w_{i1} - w_{i0}$ and then on $w_{i2} - w_{i1}$. In Table 6 we perform a similar exercise regressing $\frac{w_{it+1}-w_{it}}{AE_{it+1}-AE_{it}}$ on $\frac{w_{i1}-w_{i0}}{AE_{i1}-AE_{i0}}$ and $\frac{w_{i2}-w_{i1}}{AE_{i2}-AE_{i1}}$. To see the logic behind this notice that

$$\begin{aligned} cov(\frac{w_{it+1}-w_{it}}{AE_{it+1}-AE_{it}}, \frac{w_{i1}-w_{i0}}{AE_{i1}-AE_{i0}}) &= cov\left(\beta_i + \frac{u_{it+1}-u_{it}}{AE_{it+1}-AE_{it}}, \beta_i + \frac{u_{i1}-u_{i0}}{AE_{i1}-AE_{i0}}\right) \\ &= var\left(\beta_i\right) + E\left(\frac{cov\left(u_{it+1}-u_{it}, u_{i1}-u_{i0}\right)}{AE_{it+1}-AE_{it}}\right). \end{aligned}$$

Again if we choose t large enough we should be able to identify $var(\beta_i)$.

The results here are hard to interpret. We typically find variances that are negative and insignificant. With potential experience and second year gains we find a statistically significant effect. We attempted to judge the magnitude of this result by simulating how the variance of log wages would change with a change in actual experience. These simulations led us to conclude that a small variance in β_i can have a large effect on earnings inequality since it is a permanent effect. As a result we conclude that this parameter is not estimated precisely enough to draw strong conclusions from our findings.

5 Generalized Method of Moments Results

5.1 Methodology

A substantial literature has developed in economics that attempts to uncover the autocovariance of wages over the lifecycle. For example, Baker (1997) postulates a specification similar to ours,

$$w_{it} = \theta_i + \beta_i PE_{it} + u_{it},$$

where PE_{it} is a measure of potential experience, and θ_i and β_i are random across individuals but are fixed for an individual over time. Using panel data one can hope to separate the distribution of (θ_i, β_i) from the distribution of u_{it}. Without any assumptions on u_{it} this is impossible. However, with reasonable assumptions we can identify aspects of the joint distribution of (θ_i, β_i). Typically u_{it} is thought to be stationary, and Baker finds that an ARMA(1,2) fits the Panel Study of Income Dynamics (PSID) data well. Our primary goal is to uncover the relationship between the levels of wage growth and wage levels. Baker (1997) has some evidence on this relationship, but does not explicitly explore or discuss it. He also typically estimates a negative covariance between wage levels and wage growth. Lillard and Reville (1999) use a similar model and estimate it using maximum likelihood. They also find evidence of a negative relationship, but do not discuss it.

We have explored a number of different types of models and a number of different assumptions about the error structure. In this paper we present results from 3 different models: an AR(1), and ARMA(1,1) and an ARMA(1,2). We define the ARMA(1,2) model as:

$$u_{it} = \rho u_{it-1} + \varepsilon_{it} + \mu_1 \varepsilon_{it-1} + \mu_2 \varepsilon_{it-2},$$

where ε_{it} is a zero-mean and i.i.d. For an ARMA(1,1), $\mu_2 = 0$, and for an AR(1), $\mu_1 = \mu_2 = 0$.

Identification is achieved in a manner similar to the regression example above. Consider the covariance between w_{i0} and $(w_{i4} - w_{i3})$. Notice that,

$$\begin{aligned} w_{i4} - w_{i3} &= \beta_i 4 + u_{i4} - \beta_i 3 - u_{i3} \\ &= \beta_i + \rho u_{i3} + \varepsilon_{i4} + \mu_1 \varepsilon_{i3} + \mu_2 \varepsilon_{i2} - u_{i3} \end{aligned}$$

Thus

$$\begin{aligned} cov\left(w_{i0}, (w_{i4} - w_{i3})\right) &= cov\left(\theta_i + \varepsilon_{i0}, \beta_i + (\rho - 1)\, u_{i3} + \varepsilon_{i4} + \mu_1 \varepsilon_{i3} + \mu_2 \varepsilon_{i2}\right) \\ &= cov(\theta_i, \beta_i) + cov(\varepsilon_{i0}, (\rho - 1)\, u_{i3}) \\ &= cov(\theta_i, \beta_i) + \rho^3 \,(\rho - 1)\, var(\varepsilon_{i0}) \end{aligned}$$

If ρ is close zero or one, this last term will be small, and hence $cov\left(w_{i0}, (w_{i4} - w_{i3})\right)$ will be close to $cov(\theta_i, \beta_i)$. Exact identification of $cov(\theta_i, \beta_i)$ can be achieved through additional years of data. We estimate this covariance using generalized method of moments. Identification rests on the assumption about the time series properties of u_{it}. Regardless of the specification, as t increases $cov\left(w_{i0}, (w_{it} - w_{it-\tau})\right)$ will become closer and closer to $cov(\theta_i, \beta_i)$. By exploring different assumptions about the u_{it} process we are able to obtain a more robust estimate of $cov(\theta_i, \beta_i)$.

We can obtain estimates of $var(\beta_i)$ in a similar manner. Notice that,

$$\begin{aligned}
cov\left(\left(w_{i1}-w_{i0}\right),\left(w_{i5}-w_{i4}\right)\right) =& cov\left(\beta_i+u_{i1}-u_{i0},\beta_i+\left(\rho-1\right)u_{i4}+\varepsilon_{i5}+\mu_1\varepsilon_{i4}+\mu_2\varepsilon_{i3}\right)\\
&= var(\beta_i)+cov(u_{i1}-u_{i0},\rho\left(\rho-1\right)u_{i3})\\
=& var(\beta_i)+\rho^2\left(\rho-1\right)\left(\rho\left(\rho+\mu_1\right)+\mu_2\right)\left(\rho+\mu_1-1\right)var(\varepsilon_{i0})\\
&+\rho\left(\rho-1\right)\left(\rho\left(\rho+\mu_1\right)+\mu_2\right)var(\varepsilon_{i1}).
\end{aligned}$$

Once again if ρ is close to one or zero these last two terms will be close to zero, and as t gets large, these last terms will become smaller and smaller.

We generalize the model to accommodate actual experience,

$$w_{it}=\theta_i+\beta_i AE_{ie}+u_{it},$$

where we use exactly the same assumptions about the error terms, but now the measure of experience is actual experience rather than potential experience. For the reasons mentioned above, we allow the relationship between actual experience and (θ_i,β_i) to be completely general. Since this assumption did not seem particularly important above (i.e. in comparing Table 2 to Table 3), we will also assume that actual experience is independent of u_{it}. The results above can be easily generalized,

$$\begin{aligned}
cov\left(w_{i0},\frac{w_{i4}-w_{i3}}{AE_{i4}-AE_{i3}}\right) =& cov\left(\theta_i+u_{i0},\beta_i+\frac{\left(\rho-1\right)u_{i3}+\varepsilon_{i4}+\mu_1\varepsilon_{i3}+\mu_2\varepsilon_{i2}}{AE_{i4}-AE_{i3}}\right)\\
=& cov(\theta_i,\beta_i)+E\left(\frac{1}{\left(AE_{i4}-AE_{i3}\right)}\right)cov(u_{i0},\left(\rho-1\right)u_{i3})\\
=& cov(\theta_i,\beta_i)+E\left(\frac{1}{AE_{i4}-AE_{i3}}\right)\rho^3\left(\rho-1\right)var(u_{i0})
\end{aligned}$$

and

$$\begin{aligned}
cov\left(\frac{\left(w_{i1}-w_{i0}\right)}{AE_{i1}},\frac{\left(w_{i5}-w_{i4}\right)}{AE_{i5}-AE_{i4}}\right) =& cov\left(\beta_i+\frac{u_{i1}-u_{i0}}{AE_{i1}},\beta_i+\frac{\left(\rho-1\right)u_{i4}+\varepsilon_{i5}+\mu_1\varepsilon_{i4}+\mu_2\varepsilon_{i3}}{AE_{i5}-AE_{i4}}\right)\\
=& var(\beta_i)+E\left[\frac{1}{AE_{i1}\left(AE_{i5}-AE_{i4}\right)}\right]\\
&\left[\rho^2\left(\rho-1\right)\left(\rho\left(\rho+\mu_1\right)+\mu_2\right)\left(\rho+\mu_1-1\right)var(\varepsilon_{i0})+\right.\\
&\left.\rho\left(\rho-1\right)\left(\rho\left(\rho+\mu_1\right)+\mu_2\right)var(\varepsilon_{i1})\right].
\end{aligned}$$

We can use essentially the same methods to compute moments using various years of data and to estimate the parameters of interest, $var(\beta_i)$ and $cov(\theta_i, \beta_i)$

A major advantage of this methods of moments framework is that it allows us to address the sample selection problem in a straight forward manner. We do not have data on earnings in every year for every sample member, but since the parameters β_i and θ_i do not vary over time we can use the data we have for their estimation. As long as almost all sample members work at least four years at some point in the panel, identification of the moments of interest is feasible. To see how this works consider the model above with $\rho = 0$. In this case, with no selection, calculating an estimate of

$$cov\left(w_{i0}, \frac{w_{i2} - w_{i1}}{AE_{i2} - AE_{i1}}\right)$$

yields a consistent estimate of $cov(\theta_i, \beta_i)$. However, the sample selection bias may be severe in this case. We can only construct this covariance for those individuals in the sample who work in years zero, one, and two. In a sample of low wage women, there are likely to be a considerable number of sample members who do not work in at least one of these three years. To estimate $cov(\theta_i, \beta_i)$ in this case, for those women missing one or more of the first three wages we could use the first three years that the women actually work. In this case we do not require that woman work the first three consecutive years, but rather that they work in any three years of the sample. The selection bias is likely to be much smaller under this criterion as the restriction here is much less severe. When we allow ρ to be nonzero, the algebra becomes much more complicated, but the basic principle that delivers identification still holds.

5.2 Preliminary Results

Before estimating $cov(\theta_i, \beta_i)$ and $var(\beta_i)$ using the full ARMA approach, we wanted to construct some simple estimates of $cov(\theta_i, \beta_i)$ using a variety of moments to explore the robustness of our estimates. This specification also provides a nice intersection between the GMM and regression approaches. We assume that there is some $\tau < t$ such that u_{is} is uncorrelated with $(u_{it} - u_{it-\tau})$ for $s = 0, 1,$or 2 and $s < t - \tau$. We also assume that experience is uncorrelated with wage growth in the first two periods, and that u$_{it}$ is independent of experience. These assumptions allow us to generalize the results above:

$$\begin{aligned} cov\left(w_{is}, \frac{w_{it} - w_{it-\tau}}{AE_{it} - AE_{it-\tau}}\right) &= cov\left(\theta_i + \beta_i E_{is} + u_{is}, \beta_i + \frac{u_{it} - u_{it-\tau}}{AE_{it} - AE_{it-\tau}}\right) \\ &= cov(\theta_i, \beta_i) + E\left(\frac{1}{AE_{it} - AE_{it-\tau}}\right) cov(u_{is}, u_{it} - u_{it-\tau}) \\ &= cov(\theta_i, \beta_i) \end{aligned}$$

These assumptions provide many moments that can be used to estimate $cov(\theta_i, \beta_i)$, each of which is constructed using three wages.

However, two problems occur with using only three wages to construct an estimate. In practice, using data from different years - for instance $cov(w_0, w_{i,8} - w_{i,7})$versus $cov(w_0, w_{i,8} - w_{i,6})$ - can lead to different estimates of the parameters of interest. This is predictable given the regression results presented above. An additional problem with this approach is sample selection. Few of the individuals in our data have all 11 wages. This occurs for 4 reasons: some individuals started working before 1979, the year of the first NLSY interview. Some individuals left school later than 1986, and so could not have worked for 10 years before our last year of data, 1996. Many individuals, especially women, have some years in which they do not work. Finally, some individuals drop out of the sample.

By constructing moments that are weighted sums of several covariances, we are able to minimize this problem. We can construct:

$$\frac{1}{k_i}\left[\sum_{s=0}^{2}\sum_{t=6}^{10}\sum_{\tau=1}^{3} cov\left(w_{is}, \frac{w_{it} - w_{it-\tau}}{E_{it} - E_{it-\tau}}\right)\right] = cov(\theta_i, \beta_i)$$

where k_i is the number of covariances for which an individual has non-missing values for the three necessary wages. To minimize the influence of the initial condition and the ARMA process on our estimates, we use covariances of $w_0, w_{1,}$ and w_2 with wage gains in the 6th through 10th periods. Gains are taken over 1, 2 and 3 year periods.

Unfortunately, this method does not completely solve the problem of sample selection. In our NLSY sample, there are 5546 individuals with 12 or fewer years of school. Only about 3000 of these individuals leave school after 1976 so that we can observe one of their first three wages, and continue in the sample 6 or more years after leaving school. If we assume that there is no cohort effect, and that attrition from the sample does not cause sample selection, we could get consistent estimates using these 3000 individuals. However, only about 2200 of these individuals have non-missing wage observations for one of the first three observations, and non-missing wage observations for two or more wages in periods 6-10. Thus, we still have a selected sample.. The basic problem is that we are estimating the effect of work experience on wage growth, and this is impossible to measure for people who do not work.

The results using this method are presented in Table 7 for potential experience and Table 8 for actual experience. We find that: (1) Point estimates of $cov(\theta_i, \beta_i)$ are negative. This finding is robust. Similar to those above, the estimates range from tiny and insignificant to moderate and significant. Our findings indicate that workers with a lower initial wage level have somewhat higher wage growth levels later. (2) For the majority of specifications, the magnitude of the negative effect is greater when actual, rather than potential experience, is used. This indicates that low skill workers are working less than moderately skilled workers, but they are getting a somewhat higher rate of wage growth for the amount of time that they do work.

5.3 GMM Results

In practice, the method we use to estimate the full model requires estimating estimating eight parameters: $var(\beta_i)$ and $cov(\theta_i, \beta_i)$; the three ARMA parameters(μ_1, μ_2,and ρ); $var(\varepsilon_{it})$ and $var(\nu_{it})$ (the variance of the initial condition which is discussed below); and $cov(\beta_i, \beta_i E_{i1})$ and $cov(\beta_i, \beta_i E_{i2})$. The last two covariances allow us to use the covariance between wage gains and period 1 or period 2 wages to identify $cov(\theta_i, \beta_i)$ without assuming that actual experience is independent of β_i.

Estimation is implemented using moments similar to those discussed above. In order to construct the moments, it is necessary to make an assumption about the error structure of the initial period. This is potentially important since first period earnings take a crucial role in identification of the covariance. We assume that the initial error consists of a transitory and a permanent component. Thus, the structure of the error terms is somewhat different for the first few periods: In the case where we assume an ARMA(1,2) error structure:

$$
\begin{aligned}
u_{i0} &= \varepsilon_{i0} + v_{i0} \\
u_{i0} &= \rho u_{i0} + \varepsilon_{i1} + \mu_1 \varepsilon_{i0} \\
u_{it} &= \rho u_{it-1} + \varepsilon_{it} + \mu_1 \varepsilon_{it-1} + \mu_2 \varepsilon_{it-2},\ t > 1
\end{aligned}
$$

There is no theoretical justification for any particular form of the initial condition. Estimates using data from earlier periods where the influence of the initial condition is strong may be biased, but we hope that the form assumed is flexible enough to avoid serious biases. These results do not control for important observables such as race and gender. However, the regression results above indicate that these observables are not likely to change our basic findings.

An important aspect of the estimation is in the selection of moments. Theoretically, only 8 moments are required to identify the parameters. However, different moments can lead to different results. In practice we construct all of our moments using weighted sums as discussed above. We use as much data as possible in order to minimize sample selection bias.

Tables 9-13 present the GMM results. In tables 9 and 10 we use moments selected to maximize the number of individuals with enough wage observations to be included. For example, to estimate $cov(\theta_i, \beta_i)$ we create a moment by summing all feasible covariances between $w_0, w_{1,}$ and w_2, and $(w_t - w_{t-1})$, $(w_t - w_{t-2})$ and $(w_t - w_{t-3})$, where t=6-10. Other moments are created in a similar fashion.

Table 9 presents estimates using potential experience with varying assumptions about the error structure. Table 10 presents the analogous results using actual experience. In general, these estimates indicate that $var(\beta_i)$ is small and insignificant. The estimates of $cov(\theta_i, \beta_i)$ are typically negative, with point estimates that range from small to moderate. Again, the point estimates tend to be larger in models using actual experience, reflecting the fact that low-skill workers tend to work less.

In both Tables 9 and 10, column one presents results assuming that the error structure is iid, and that experience is uncorrelated with β_i. These results are comparable to the preliminary results presented above. The final three columns in each table present results from models assuming AR(1), ARMA(1,1) and ARMA(1,2) error structures. The AR component is clearly significant, and its estimation is robust to various specifications. However, the MA error structures are more problematic. First, when estimating the ARMA(1,1) model, for most specifications we obtain positive point estimates of the covariances between growth and levels. The result is driven by the large estimate of $var(\nu_{it})$ (the variance of the initial condition), the large positive estimate of ρ, and the negative estimate of μ_1. For example, the covariance between initial wages and wage gains in the 6^{th} year in the labor force can be written as:

$$cov\left(w_{i0}, \frac{w_{i6} - w_{i5}}{AE_{i6} - AE_{i5}}\right) = cov(\theta_i, \beta_i) + E\left(\frac{1}{AE_{i6} - AE_{i5}}\right) cov(u_{i0}, u_{i6} - u_{i5})$$

For the ARMA(1,1) error structure, $cov(u_{i0}, u_{i5} - u_{i6})$ can be written as:

$$cov(u_{i0}, u_{i6} - u_{i5}) = var(\varepsilon_{it}) \times (\rho^4 - \rho^3) \times (\rho^2 + \rho \times \mu_1) + var(\nu_{it}) \times (\rho^6 - \rho^5).$$

For the parameter estimates in column 5 of Table 10, the numerical value of $cov(u_{i0}, u_{i6} - u_{i5})$ is about -0.03, which is large compared with our estimates of $cov(\theta_i, \beta_i)$. The high value of ρ combined with the large estimate of $var(\nu_{it})$ implies that even 6 years out there will still be a substantial negative correlation between u_{i0} and $u_{it} - u_{it-1}$. Thus, the ARMA(1,1) estimates still imply that there is a negative relationship between earnings growth and initial wage levels, but this relationship occurs as a result of the correlation between u_{i0} and $u_{it} - u_{it-1}$ rather than the correlation between θ_i and β_i. Given that this estimate of $var(\nu_{it})$ differs wildly from the estimates of $var(\nu_{it})$ from other specifications of the error structure, and that the large estimate of $var(\nu_{it})$ combined with the high value of ρ is driving this result, we are skeptical of the ARMA(1,1) specification.

Second, when estimating and ARMA(1,2), the standard errors on the estimates of the initial condition and the MA parameters become very large. Not surprisingly, the point estimates of the ARMA parameters for this model are not robust to specification. Because of the problems with the ARMA estimates, we focus on AR(1) models in the Tables 11-13.

Many studies of wage growth find that the relationship between wages and experience is quadratic. Specifically, we follow Lillard and Reville (1999) by postulating the model

$$w_{it} = \theta_i + \beta_i(E_{it} + \gamma E_{it}^2) + u_{it}.$$

We can estimate γ separately using the moment condition:

$$E\left\{\frac{w_{it} - w_{it-1}}{(AE_{it} + \gamma AE_{it}^2) - \left(AE_{it-1} + \gamma AE_{it-1}^2\right)} - \frac{w_{i1} - w_{i0}}{(AE_{i1} + \gamma AE_{i1}^2)}\right\} = 0.$$

We can then set $\widehat{AE_{it}} = AE_{it} + \widehat{\gamma} AE_{it}^2$, and substitute $\widehat{AE_{it}}$ for AE_{it} in the moment equations. The moments above can then be used to obtain estimates of the parameters by the same method we used with the linear model. Similarly, we can estimate $\widehat{\gamma}$ for potential experience using the equation above, and construct $\widehat{PE_{it}} = PE_{it} + \widehat{\gamma} PE_{it}^2$

Estimates from this method are presented in Tables 11-13. We focus on the AR(1) model for the reasons stated above. In Table 11, results for the quadratic model are presented using the same specification of moments as in the previous two tables. Tables 12 and 13 use alternate specifications of the moments. Regardless of the specification of the moments, the variance of β_i is small and imprecisely estimated in both the linear and quadratic model, using both actual and potential experience. $Cov(\theta_i, \beta_i)$ is negative, although it varies in magnitude. The magnitude of cov(β_i, θ_i) is again more negative when actual, rather than potential, experience is used.

Tables 12-13 presents AR(1) results for both the linear and quadratic models using two alternate specifications: Table 12 uses only wages from period 8-12 in construction the moments, and Table 13 uses only wage changes over 2 or more years. As in the results above, the estimate of $cov(\theta_i, \beta_i)$ is negative. However, for actual experience the estimates of cov(β_i, θ_i) are larger in magnitude and more significant than the previous estimates. This occurs for two reasons. First the alternate specifications were chosen because of low standard errors. In many specifications we have found that constructing moments that only use wages from later years or that only use wage differences over 2 or more years consistently leads to estimates of $cov(\theta_i, \beta_i)$ that are larger in magnitude and that are more highly significant. Second, by further restricting which moments we use in the estimation, we lose about 200 observations. Most of these lost observations are women. Since the

$cov(\theta_i, \beta_i)$ tends to be smaller in magnitude and less significant for women as a group than for men, losing these observations could explain part of this increase in significance.

6 Conclusions

The primary goal of this paper is to estimate the relationship between wage growth and wage levels for low skill workers. Our results generally confirm our previous results that there is little relationship between skill levels and wage growth. These results differ to the extent that we find some evidence that the relationship may be negative, although the magnitude is small. Increased work experience should increase wages at about the same rate for low and medium skill workers.

There are a number of caveats to keep in mind. First, we are measuring the effects of experience on log wage increases, not level increases. If low wage workers have similar levels of log wage growth, then their gains in wage levels would be smaller than for higher wage workers. Second, the magnitude of these effects are not huge. A full year of labor force experience leads to wage gains of approximately 4%. This is nontrivial, but it would not have a huge effect on earnings inequality or poverty rates. Finally, the workers we study are not necessarily representative of the type of workers who would respond to particular policy changes. Sample size (and endogeneity) does not allow us to condition on welfare mothers as we would like.

While no particular specification that we use is perfect, our results are robust across a number of different underlying assumptions. Low skill workers experience at least as much wage growth as higher skill workers.

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Table 1

Regression of Wage Growth per Year of Potential Experience[†] on Initial Wages
Seven or More Years since Labor Force Entry
(Standard Errors in Parentheses*)

Variable	(1)	(2)	(3)	(4)
First Period Wage	-0.0082	-0.0106		
	(0.0067)	(0.0068)		
Second Period Wage			-0.0099	-0.0123
			(0.0052)	(0.0054)
White Male		0.0466		0.0487
		(0.0135)		(0.0113)
White Female		0.0425		0.0504
		(0.0132)		(0.0110)
Black Male		0.0402		0.0406
		(0.0133)		(0.0113)
Black Female		0.0228		0.0311
		(0.0132)		(0.0110)
Hispanic Male		0.0418		0.0542
		(0.0142)		(0.0119)
Hispanic Female		0.0351		0.0399
		(0.0151)		(0.0127)

† The dependent variable in these regressions is log wage differences, i.e. $w_{it} - w_{it-1}$.

* The standard errors are robust Huber/White standard errors for Panel Data.

Table 2

Regression of Wage Growth per Year of Actual Experience†
on Initial Wages
Seven or More Years since Labor Force Entry
(Standard Errors in Parentheses*)

Variable	(1)	(2)	(3)	(4)
First Period Wage	-0.0148	-0.0172		
	(0.0101)	(0.0101)		
Second Period Wage			-0.0202	-0.0212
			(0.0080)	(0.0081)
White Male		0.0639		0.0697
		(0.0198)		(0.0171)
White Female		0.0514		0.0658
		(0.0205)		(0.0168)
Black Male		0.0685		0.0673
		(0.0201)		(0.0172)
Black Female		0.0405		0.0571
		(0.0220)		(0.0188)
Hispanic Male		0.0458		0.0607
		(0.0215)		(0.0190)
Hispanic Female		0.0544		0.0771
		(0.0215)		(0.0203)

† The dependent variable in these regressions is log wage differences divided by experience differences, i.e. $\frac{(w_{it}-w_{it-1})}{(AE_{it}-AE_{it-1})}$.

$*$ The standard errors are robust Huber/White standard errors for Panel Data.

Table 3
Regression of Wage Growth per Year of
Predicted Experience†
on Initial Wages
Five or More Years since Labor Force Entry
(Standard Errors in Parentheses*)

Variable	(1)	(2)	(3)	(4)
First Period Wage	-0.0096	-0.0122		
	(0.0075)	(0.0077)		
Second Period Wage			-0.0120	-0.0147
			(0.0059)	(0.0060)
White Male		0.0526		0.0561
		(0.0153)		(0.0127)
White Female		0.0480		0.0581
		(0.0150)		(0.0125)
Black Male		0.0455		0.0473
		(0.0150)		(0.0128)
Black Female		0.0261		0.0364
		(0.0149)		(0.0124)
Hispanic Male		0.0474		0.0622
		(0.0160)		(0.0134)
Hispanic Female		0.0398		0.0462
		(0.0169)		(0.0143)

† The dependent variable in these regressions is log wage differences divided by predicted experience differences, i.e. $\frac{(w_{it}-w_{it-1})}{(\widehat{AE_{it}-AE_{it-1}})}$.

∗ The standard errors are robust Huber/White standard errors for Panel Data.

Table 4

Regression of Wage Growth per Year of Actual Experience[†] on Initial Wages

Seven or More Years since Labor Force Entry

By Gender

(Standard Errors in Parentheses*)

	Men		Women	
Variable	(1)	(2)	(1)	(2)
First Period Wage	-0.0188		-0.0144	
	(0.0111)		(0.0201)	
Second Period Wage		-0.0238		-0.0167
		(0.0101)		(0.0137)
White	0.0668	0.0748	0.0467	0.0578
	(0.0216)	(0.0208)	(0.0371)	(0.0262)
Black	0.0713	0.0720	0.0359	0.0497
	(0.0218)	(0.0203)	(0.0371)	(0.0276)
Hispanic	0.0487	0.0656	0.0495	0.0692
	(0.0231)	(0.0225)	(0.0367)	(0.0287)

[†] The dependent variable in these regressions is log wage differences divided by experience differences, i.e. $\frac{(w_{it}-w_{it-1})}{(AE_{it}-AE_{it-1})}$.

$*$ The standard errors are robust Huber/White standard errors for Panel Data.

Table 5

Regression of Wage Growth per Year of Potential Experience†

on Initial Wage Growth per Year of Potential Experience

Five or More Years since Labor Force Entry

(Standard Errors in Parentheses*)

Variable	(1)	(2)	(3)	(4)
First Period Growth‡	-0.0023	-0.0029		
	(0.0050)	(0.0051)		
Second Period Growth‡			0.0122	0.0124
			(0.0063)	(0.0063)
White Male		0.0255		0.0250
		(0.0042)		(0.0039)
White Female		0.0259		0.0276
		(0.0059)		(0.0054)
Black Male		0.0209		0.0159
		(0.0062)		(0.0057)
Black Female		0.0049		0.0115
		(0.0070)		(0.0064)
Hispanic Male		0.0205		0.0273
		(0.0063)		(0.0060)
Hispanic Female		0.0088		0.0093
		(0.0090)		(0.0086)

† The dependent variable in these regressions is log wage differences, i.e. $w_{it} - w_{it-1}$.

∗ The standard errors are robust Huber/White standard errors for Panel Data.

‡ First and second period wage growth represent log wage differences in the first and second periods, i.e. $w_{i1} - w_{i,0}$.

Table 6

Regression of Wage Growth per Year of
Actual Experience[†]
on Initial Wage Growth per Year of
Actual Experience
Seven or More Years since Labor Force Entry
(Standard Errors in Parentheses*)

Variable	(1)	(2)	(3)	(4)
First Period Growth[‡]	-0.0006	-0.0005		
	(0.0009)	(0.0009)		
Second Period Growth[‡]			-0.0016	-0.0015
			(0.0034)	(0.0034)
White Male		0.0292		0.0290
		(0.0055)		(0.0054)
White Female		0.0244		0.0278
		(0.0086)		(0.0079)
Black Male		0.0394		0.0272
		(0.0093)		(0.0092)
Black Female		0.0064		0.0183
		(0.0136)		(0.0103)
Hispanic Male		0.0095		0.0151
		(0.0108)		(0.0098)
Hispanic Female		0.0281		0.0300
		(0.0130)		(0.0132)

[†] The dependent variable in these regressions is log wage differences divided by experience differences, i.e. $\frac{(w_{it}-w_{it-1})}{(AE_{it}-AE_{it-1})}$.

[*] The standard errors are robust Huber/White standard errors for Panel Data.

[‡] First and second period wage growth represent log wage differences divided by experienced differences in the first and second periods, i.e. $\frac{(w_{i1}-w_{i0})}{(AE_{i1}-AE_{i0})}$.

Table 7
Covariance of Wage Growth per Year of
Potential Experience[†]
on Initial Wage
Using Alternative Moments
Five or More Years since Labor Force Entry
(Standard Errors in Parentheses)

	First Difference	Second Difference	Third Difference	Combined
First Period Wage	-0.0000	-0.0028	-0.0026	-0.0007
	(0.0018)	(0.0016)	(0.0013)	(0.0014)
Second Period Wage	-0.0027	-0.0019	-0.0021	-0.0027
	(0.0015)	(0.0014)	(0.0012)	(0.0014)
Third Period Wage	-0.0026	-0.0018	-0.0020	-0.0009
	(0.0015)	(0.0013)	(0.0013)	(0.0013)
Combined	-0.0002	-0.0021	-0.0022	-0.0009
	(0.0016)	(0.0012)	(0.0011)	(0.0013)

[†] These covariances represent the relationship between wage growth and initial wage levels i.e. $cov(w_{it} - w_{it-1}, w_{i0})$.

Table 8

Covariance of Wage Growth per Year of Actual Experience† on Initial Wage Using Alternative Moments Five or More Years since Labor Force Entry (Standard Errors in Parentheses)

	First Difference	Second Difference	Third Difference	Combined
First Period Wage	-0.0022	-0.0025	-0.0038	-0.0024
	(0.0032)	(0.0020)	(0.0016)	(0.0030)
Second Period Wage	-0.0012	-0.0031	-0.0040	-0.0026
	(0.0023)	(0.0020)	(0.0017)	(0.0023)
Third Period Wage	-0.0003	-0.0025	-0.0028	-0.0017
	(0.0026)	(0.0019)	(0.0015)	(0.0024)
Combined	-0.0023	-0.0024	-0.0036	-0.0031
	(0.0022)	(0.0016)	(0.0013)	(0.0021)

† These covariances represent the relationship between wage growth and initial wage levels i.e. $cov(\frac{(w_{it}-w_{it-1})}{(AE_{it}-AE_{it-1})}, w_{i0})$.

Table 9

GMM Parameter Estimates
NLSY 1979-1996,First 10 Years Out of School
Linear Model-Potential Experience
Specification I†
(standard errors in parenthesis)

parameter	(1)	(2)	(3)	(4)
var(β_i)	0.00042	0.0006	-0.0018	0.0002
	(0.00086)	(0.0026)	(0.0098)	(0.0181)
cov(β_i, θ_i)	-0.00083	-0.0016	0.0286	0.0070
	(0.00177)	(0.0023)	(0.0348)	(0.0324)
var(ε_{it})	0.09704	0.1097	0.1327	0.1241
	(0.00408)	(0.0111)	(0.0179)	(0.06852)
var(η_i)		0.0629	0.5476	0.2529
		(0.0330)	(0.5156)	(0.9285)
ρ		0.1673	0.7610	0.6507
		(0.0569)	(0.0974)	(4.26)
μ_1			-0.3646	-0.3581
			(0.0749)	(3.785)
μ_2				0.0083
				(0.9502)

† $Cov(\beta_i, \theta_i)$ is estimated using all covariances between ($w_{it} - w_{it-1}$) ($w_{it} - w_{it-2}$) and ($w_{it} - w_{it-3}$) t= 6-10, and w_{i1} w_{i2} and w_{i3}.

Table 10

GMM Parameter Estimates
NLSY 1979-1996, First 10 Years Out of School
Linear Model, Actual Experience
Specification I†
(standard errors in parenthesis)

parameter	(1)	(2)	(3)	(4)	(5)	(6)
var(β_i)	0.0010	0.0016	0.0010	0.0016	-0.0002	0.0031
	(0.0026)	(0.0025)	(0.0027)	(0.0025)	(0.0050)	(0.0080)
cov(β_i, θ_i)	-0.00172	-0.0007	0.0008	-0.0051	0.0239	-0.0028
	(0.0023)	(0.0024)	(0.0044)	(0.0050)	(0.0209)	(0.0544)
var(ε_{it})	0.11369	0.1333	0.1137	0.1333	0.1584	0.1424
	(0.0074)	(0.0107)	(0.0076)	(0.0109)	(0.0173)	(0.0511)
var(η_i)		0.0681		0.0681	0.4045	0.0933
		(0.0378)		(0.0379)	(0.3915)	(0.6788)
ρ		0.2414		0.2414	0.7556	0.3964
		(0.0452)		(0.0461)	(0.0957)	(3.1095)
cov($\beta_i, \beta_i E_{i1}$)			-0.0026	0.0043	0.0017	0.0047
			(0.0038)	(0.0044)	(0.0042)	(0.0341)
cov($\beta_i, \beta_i E_{i2}$)			-0.0039	0.0074	0.0031	0.0081
			(0.0060)	(0.0071)	(0.0066)	(0.0611)
μ_1					-0.3244	-0.0903
					(0.0482)	(2.777)
μ_2						0.0755
						(0.7161)

† $Cov(\beta_i, \theta_i)$ is estimated using all covariances between (w$_{it} - w_{it-1}$) (w$_{it} - w_{it-2}$) and (w$_{it} - w_{it-3}$) t= 6-10, and w$_{i1}$ w$_{i2}$ and w$_{i3}$.

Table 11

GMM Parameter Estimates
NLSY 1979-1996,First 10 Years Out of School
Quadradic Model
Specification I†
(standard errors in parenthesis)

parameter	Potential Experience		Actual Expenience	
	iid	AR(1)	iid	AR(1)
var(β_i)	0.0010	0.0012	-0.0019	-0.0001
	(0.0016)	(0.0016)	(0.0026)	(0.0038)
cov(β_i, θ_i)	-0.0022	-0.0021	-0.00653	-0.0211
	(0.0032)	(0.0032)	(0.0045)	(0.0114)
var(ε_{it})	0.0982	0.1110	0.0971	0.1131
	(0.0042)	(0.0051)	(0.0075)	(0.0089)
var(η_i)		0.0559		0.1224
		(0.0227)		(0.0387)
ρ		0.1607		0.2694
		(0.0399)		(0.4270)
cov($\beta_i, \beta_i E_{i1}$)			0.00385	0.02029
			(0.0038)	(0.0109)
cov($\beta_i, \beta_i E_{i2}$)			0.0026	0.0287
			(0.0060)	(0.0184)

† $Cov(\beta_i, \theta_i)$ is estimated using all covariances between (w$_{it} - w_{it-1}$) (w$_{it} - w_{it-2}$) and (w$_{it} - w_{it-3}$) t= 6-10, and w$_{i1}$ w$_{i2}$ and w$_{i3}$.

Table 12

GMM Parameter Estimates
NLSY 1979-1996,First 10 Years Out of School
AR(1) estimations
Alternate Specification I[†]
(standard errors in parenthesis)

	Potential Experience		Actual Expenience	
parameter	linear	quadratic	linear	quadratic
var(β_i)	0.0015	0.0012	0.0018	-0.0001
	(0.0025)	(0.0016)	(0.0025)	(0.0025)
$cov(\beta_i, \theta_i)$	-0.0041	0.0001	-0.0127	-0.0210
	(0.0029)	(0.0046)	(0.0053)	(0.0053)
var(ε_{it})	0.1333	0.1110	0.1118	0.1161
	(0.00113)	(0.0053)	(0.0110)	(0.0111)
var(η_i)	0.0681	0.0559	0.1117	0.1224
	(0.0395)	(0.0229)	(0.0466)	(0.0415)
ρ	0.2414	0.1607	0.3213	0.2694
	(0.0468)	(0.0411)	(0.0514)	(0.0524)
cov($\beta_i, \beta_i E_{i1}$)			0.0112	0.0203
			(0.0044)	(0.0044)
cov($\beta_i, \beta_i E_{i2}$)			0.0190	0.0287
			(0.0070)	(0.0071)

[†] $Cov(\beta_i, \theta_i)$ is estimated using all covariances between (w$_{it} - w_{it-1}$) (w$_{it} - w_{it-2}$) and (w$_{it} - w_{it-3}$) t= 8-10, and w$_{i1}$ w$_{i2}$ and w$_{i3}$.

Table 13

GMM Parameter Estimates
NLSY 1979-1996,First 10 Years Out of School
AR(1) estimations
Alternate Specification II[†]
(standard errors in parenthesis)

	Potential Experience		Actual Expenience	
parameter	linear	quadratic	linear	quadratic
var(β_i)	0.0015	0.0012	0.0018	-0.0001
	(0.0025)	(0.0015)	(0.0024)	(0.0038)
cov(β_i, θ_i)	-0.0023	-0.0020	-0.0131	-0.0223
	(0.0027)	(0.0031)	(0.0049)	(0.0119)
var(ε_{it})	0.1333	0.1110	0.1192	0.1161
	(0.0011)	(0.0045)	(0.0106)	(0.0089)
var(η_i)	0.0681	0.0559	0.1118	0.1224
	(0.0381)	(0.0220)	(0.0451)	(0.0389)
ρ	0.2414	0.1607	0.3213	0.2694
	(0.0462)	(0.0390)	(0.0510)	(0.0428)
cov($\beta_i, \beta_i E_{i1}$)			0.0112	0.0203
			(0.0043)	(0.0109)
cov($\beta_i, \beta_i E_{i2}$)			0.0190	0.0287
			(0.0069)	(0.0118)

[†] $Cov(\beta_i, \theta_i)$ is estimated using all covariances between (w$_{it} - w_{it-2}$) and (w$_{it} - w_{it-3}$) t= 6-10, and w$_{i1}$ w$_{i2}$ and w$_{i3}$.

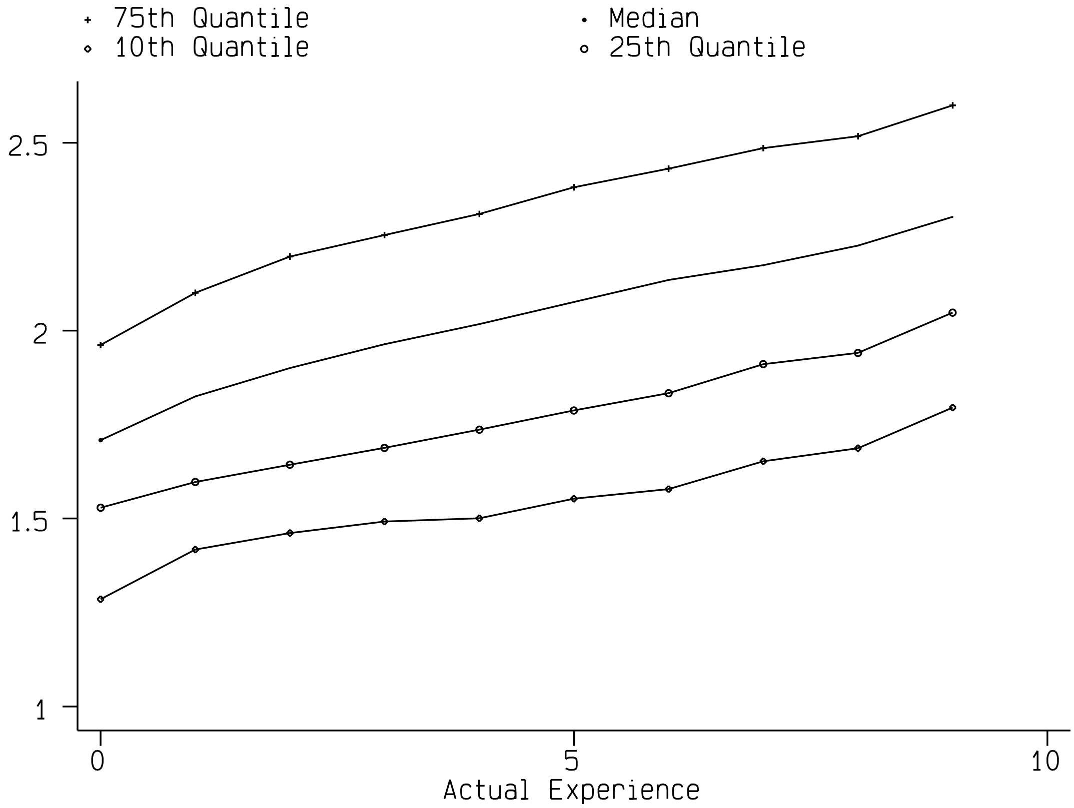

Figure 1a: Log Wages By Quantile

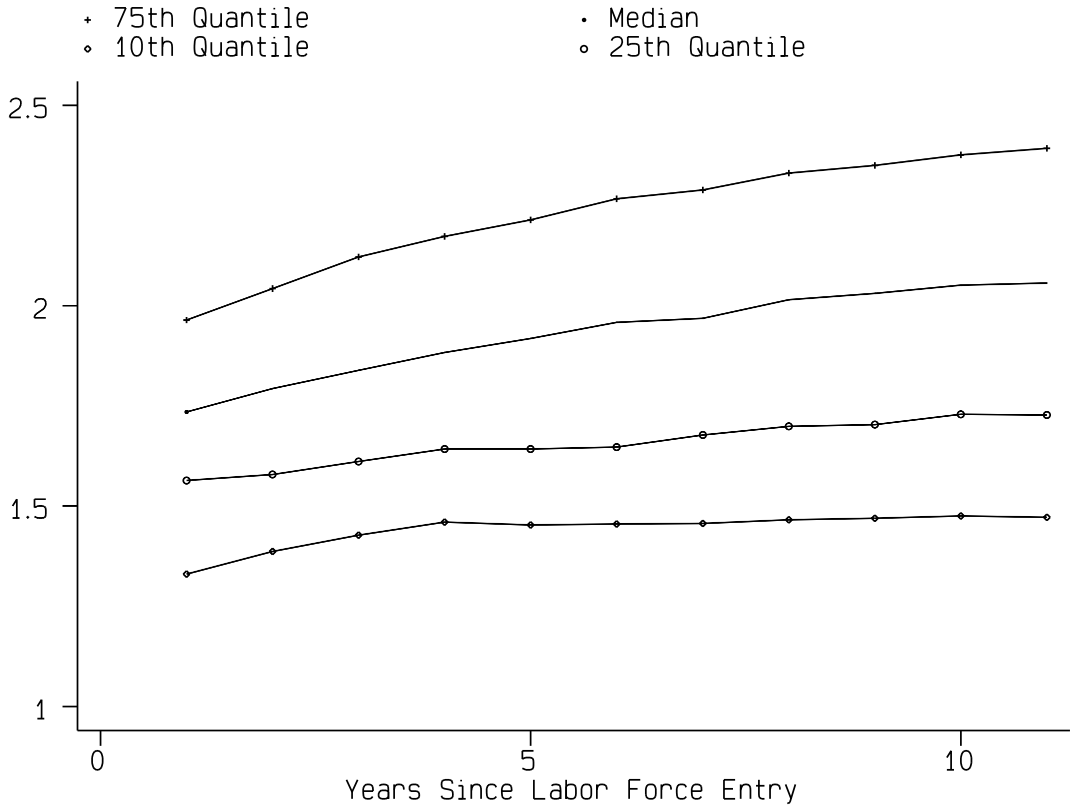

Figure 1b: Log Wages By Quantile

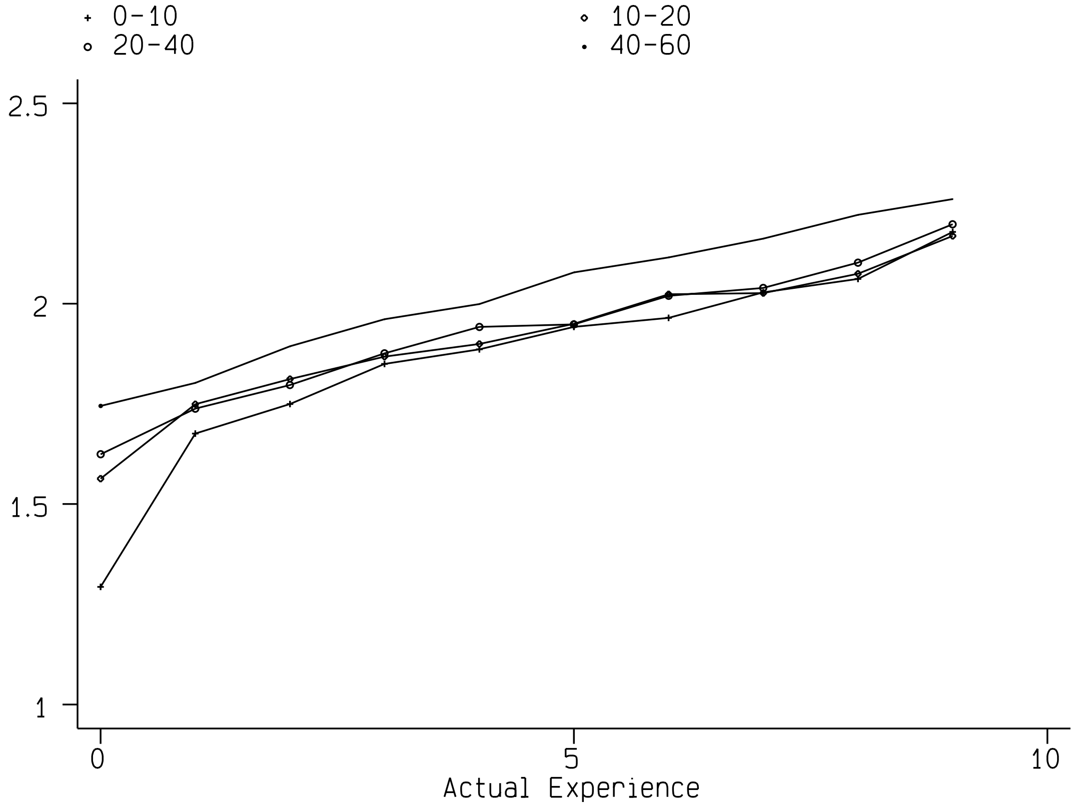

Figure 2a: Mean Log Wages by Initial Wage

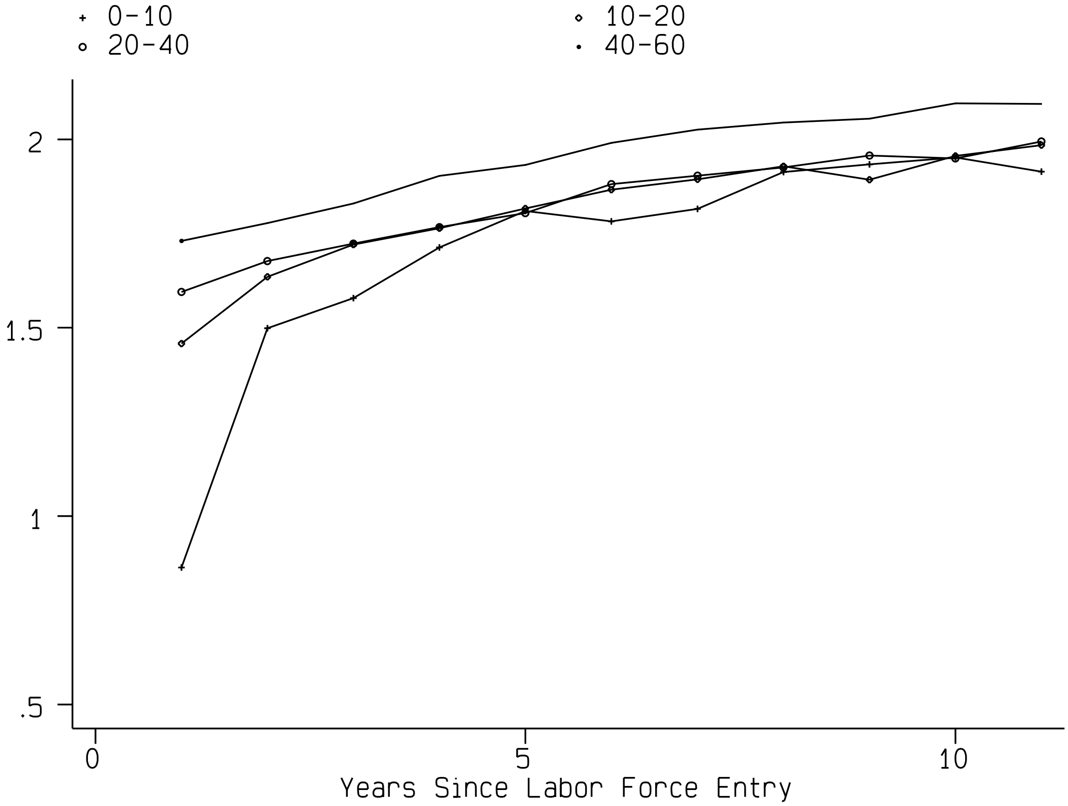

Figure 2b: Mean Log Wages by Initial Wage