Returns to Tenure and Experience Revisited--Do Less Educated Workers Gain Less from Work Experience?

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Abstract

This paper explores whether within job and between job wage growth is lower for less-educated workers. While a simple model of heterogeneous learning ability predicts that individuals with low learning ability will have flatter wage profiles, this prediction has been largely ignored in the recent welfare reform debates. The key econometric problem in estimating returns to tenure and experience is that wages depend on the unobservable job match component, which is endogenous. We depart from the standard method for dealing with this problem in one important way. We show that this alternative implies that wages grow with the number of previous successful job matches. In our empirical work we show that this source of between job wage growth is large. Furthermore, we show that this source of wage growth, as well as the standard returns to tenure and experience, are substantially smaller for the least educated.

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I. Introduction

This paper explores whether wage growth differs by educational level. Specifically it asks whether returns to tenure and experience are lower for less-educated workers. While a simple model of heterogeneous learning ability predicts that individuals with low learning ability will have flatter wage profiles, this prediction has been largely ignored in the recent welfare reform debates. Advocates for a work-based welfare system have either implicitly or explicitly assumed that welfare recipients would gain as much from work experience as a randomly chosen employed worker. Since welfare recipients have less education than the average worker, this implicitly assumes that wage growth is independent of educational attainment.

While the focus of the paper is on the substantive question of whether returns to experience and tenure differ by educational level, we also contribute to the methodological literature on estimating returns to tenure and experience. We argue that job match quality improves with the number of previous successful matches rather than the number of previous draws from the job offer distribution, as has been implicitly assumed in the previous literature. This simple insight, coupled with our use of changes in wages between and within jobs leads to an alternative source of identification and a new specification for the estimating equations.

The remainder of our paper is divided into five sections. Section II reviews the methodological literature on estimating returns to experience and tenure, as well as the substantive literature on estimated returns for less-skilled workers. Section III presents the econometric framework that we use. Section IV presents our data and Section V presents results. The final section summarizes our findings.

II. Literature Review

Our study contributes to two bodies of literature. The first is the influential literature on identification and estimation of returns to tenure and returns to experience. In a lively debate, Altonji and Shakotko (1987) and Topel (1991) developed two different methodologies to deal with the inherent problem that the job match component in a standard log wage equation is not exogenous to tenure and experience. Agents with longer tenure have more to give up when moving to a new job since they will lose the rewards to job-specific tenure obtained on the current job. Therefore, these agents require a higher job match component in order to switch jobs. Likewise, match quality improves as agents move to better jobs. Altonji and Shakotko (1987) and Topel (1991) both argue that this matching process leads to a positive correlation between the job match component and labor market experience.

Based on these observations, the literature in this area has largely used the following standard log wage model with person- and match-specific error components:

(1) $Y_{ijt} = \beta_x X_{ijt} + \beta_T T_{ijt} + \varepsilon_{ijt}$ and

(2) $\varepsilon_{ijt} = \phi_{ijt} + \mu_i + \upsilon_{ijt}$,

where X_{ijt} is accumulated labor market experience and T_{ijt} is tenure for person *i* in job *j* in period *t*. μ_i is a person-specific error component and ϕ_{ijt} is a job match-specific component given by:

(3) $\phi_{ijt} = \alpha_0 + \alpha_x X_{ijt} + \alpha_T T_{ijt} + \eta_{ijt}$,

where v_{ijt} and η_{ijt} are assumed to be serially independent. Equation (3) is motivated as a linear approximation to the matching process.[2]

Altonji and Shakotko (1987) use an IV strategy to deal with this endogeneity, while Topel (1991) uses a two-stage estimator in which ϕ_{ijt} is first differenced out by estimating within-job wage growth. This identifies $\beta_x + \beta_T$. Topel s second stage is to estimate equation (1) using observations for the first period of each job.[3] Since tenure is zero at the start of each job, tenure does not appear in the second stage estimator. This procedure yields an estimate of $\beta_x + \alpha_x$, which can be subtracted from the first stage estimate of $\beta_x + \beta_T$ to recover $\beta_T - \alpha_x$. Thus, returns to experience and tenure are identified up to an additive parameter that captures the effect of experience on job match.

We modify this procedure in two ways. First, we argue that a simple on-the-job search model implies that the job match component, ϕ_{ij}, depends on *j* not X_{ijt}. This modifies equation (3) in an important way. While the number of previous jobs, *j*, and experience are correlated, they have substantially different implications for identification and estimation. Second, Topel s second stage estimator is based on levels, which includes the person-specific match component, μ_i. We use another set of differences (differences in starting wages between jobs *j* and *j+1* and differences between the ending wage in job *j* and the starting wage in job *j+1)* to eliminate μ_i.[4]

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[2] Note that while the match component is conceptually time invariant, the inclusion of T_{ijt} implies that the expected value of the job match component increases the longer the individual stays in the job. We will return to this later.

[3] Topel s estimator actually uses all observations, but each observation is used to obtain an estimate of starting wages. That is, $Y_{ij0} = Y_{ijt} - \hat{\beta} T_{ijt}$, where $\hat{\beta}$ is the sum of returns to tenure and experience obtained from the first stage estimator.

[4] Altonji and Williams (1997) also use changes in their second stage estimator.

The second body of literature relevant to our study is the small but important literature on the value of work in raising future wages of less-skilled workers. While this literature is crucial in accessing the likelihood that a work-based welfare system will lead to upward mobility, the evidence is at best mixed.[5] The experimental evidence on work-based programs indicates that there are modest increases in earnings from job placements, with most of the gains coming from increases in hours worked, not higher wage rates.[6] This experimental evidence suggests that wage profiles for less-educated workers are very flat, even if earnings (i.e., wages times hours) profiles slope upward. The non-experimental evidence points in the same direction, though there are exceptions. For example, Moffitt and Rangarajan (1989) estimate that the wages of female heads with children under 18 increase by two percent per year. Similarly, Burtless (1994) finds that former welfare recipients experience less than a one percent per year growth in wages over a ten-year period; Card, Michalopolous and Robbins (1999) estimate an annual real wage growth of anywhere from 1.6 to 2.6 percent per year for long-term Canadian welfare recipients. In contrast, Gladden and Taber (1998) estimate that the wages of persons with a high school degree or less grow considerably faster. Their estimates (based on the NLSY) show wages growing by 7.7 percent per year, which is even higher than estimates for the mean wage growth across all education levels found in other studies.[7]

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[5] The conjecture that wage profiles are flatter for workers with less education was supported by early estimates presented in Mincer (1974), who included an interaction of schooling and tenure. See Gottschalk (2000) for a review of the recent literature.

[6] See Gueron and Pauly (1991, Table 1.1) for a summary of these results.

[7] See Loprest (1992) for estimates across all education levels. Gladden and Taber s (1998) results are their IV estimates in Table 1. While their sample is clearly less disadvantaged than the samples in the other studies, it is difficult to reconcile their estimates, which are nearly three times as high as these other studies.

These studies have two major drawbacks for determining how the returns to experience and tenure vary across educational groups. First, while these studies focus on less-advantaged groups, they do not offer an explicit comparison group. At best they offer estimates that can be compared to estimates for other groups based on different definitions and data sets.[8] The second, and more important, drawback of these studies is that they do not differentiate between returns to tenure and returns to experience. This distinction, which lies at the heart of human capital theory, plays a crucial role in understanding the options faced by less-skilled workers.

III. Identification and Estimation

In this section we present the econometric framework we use to estimate returns to experience, tenure, and job switching. A simple model of on-the-job search predicts that a person with $T_{i,j-1,t}$ periods of tenure in job *j* will accept a job offer if the match component in the new job exceeds the sum of the match component in the current job plus the foregone returns to tenure in the current job.[9] Let ϕ_{ij}^{*} be the resulting reservation value for job *j*:

$$(4) \qquad \phi_{ij}^{*} = \phi_{ij-1} + \beta_T T_{i,j-1,t} .$$

The expected value of accepted offers is, therefore, given by $E(\phi_{ij} | \phi_{ij} > \phi_{ij}^{*})$, which increases with tenure at the end of job *j*-1 and with each successive job match. The relationship between completed tenure in the previous job and the conditional mean of

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[8] Gladden and Taber (1998) compare high school graduates with high school dropouts, but do not compare either of these groups to more-educated workers.

[9] This assumes there are no costs to moving to a new job and that offers are received at zero costs. Jobs differ in intercept but not slope (conditional on education).

ϕ_{ij} reflects the well-known prediction that the returns to job-specific tenure is lost when moving to a new job. The new job must, therefore, compensate for this loss in job-specific human capital, which grows with the length of time the agent has been on the previous job.

The relationship between *j* and the conditional mean of ϕ_{ij} is equally straightforward, but has been ignored in this branch of the literature that has, in place, focused on the relationship between experience and the conditional mean of ϕ_{ij} (see equation (3)). The argument in the previous literature for allowing the conditional mean of ϕ_{ij} to vary with X_{ijt} is that persons with more experience have received more draws from the match component distribution. As a result, more experienced workers are more likely to have obtained an acceptable draw. Hence, the conditional mean of ϕ_{ij} is higher. But, as we have argued, it is not the number of draws that raises the conditional mean at the start of job *j* but rather the number of previously accepted draws that raises the reservation value for ϕ_{ij} and, hence, the conditional mean. Thus, one should condition on the number of previous accepted offers, *j*-1, rather than the number of previous draws to obtain the expectation of the match component at the start of job *j*.

We again take a linear approximation to conditional expectations of ϕ_{ij}, but condition on *j*-1 rather than X_{ijt}:

(3') $$\phi_{ijt} = \alpha_0 + \alpha_1 (j-1) + \alpha_T T_{ijt} + \eta_{ij}$$

Substituting equation (3) into equation (2) and substituting the results into equation (1) yields:

(5) $$Y_{ijt} = (\alpha_0 - \alpha_1) + \beta_x X_{ijt} + \tilde{\beta}_T T_{ijt} + \alpha_1 j + \varepsilon_{ijt}$$ and

(6) $\varepsilon_{ijt} = \eta_{ij} + \mu_i + \nu_{ijt}$,

where $\tilde{\beta}_T = \beta_T + \alpha_T$. The estimated returns to tenure, $\tilde{\beta}_T$, will, therefore, include both the direct effect of tenure on wage growth within the job (β_T) plus the indirect effect through the improvement in job match (α_T). Since β_T cannot be identified separately from α_T, we follow the previous literature in noting that when we refer to returns to tenure we are implicitly including both the direct impact and the impact through improved job match (i.e., $\beta_T + \alpha_T$). Note, however, that in our framework, β_x is identified, while it is not identified separately from α_x in the framework that uses equation (3) rather than equation (3). The second, and more important, implication of using (3) instead of (3) is that the job number, *j*, now appears explicitly in equation (4).

We follow Topel (1991) in estimating the combined impact of experience and tenure ($\beta_x + \beta_T$) by taking first differences of equation (1) for periods in which the respondent is in the same job. The within-job estimator is given by:

(7) $\Delta_w = Y_{ijt+1} - Y_{ijt} = (\beta_x + \beta_T) + \Delta\upsilon_{ij}$.

Therefore, estimating equation (7) by least squares yields consistent estimates of $\beta \equiv \beta_x + \beta_T$. While not separately identifying returns to experience from returns to tenure, β does yield an unbiased estimate of on-the-job wage growth.

Topel s second stage estimator is based on estimating equation (1) in levels. We propose an alternative estimator that uses changes in wages, rather than wage levels to obtain estimates of β_x, β_T, and α_1. Our alternative has two advantages. First, since it is based on *changes* in wages rather than on wage levels, μ_i cancels. This eliminates a potentially important source of endogeneity. Second, our method allows us to estimate

α_1, without having to measure the previous number of job matches. Estimating equation (5) in levels requires knowledge of the total number of job matches over the respondents total career. When equation (5) is written in terms of changes in wages between successive jobs, the change in (*j*-1) is equal to one by definition. Thus, we do not need a direct measure of the number of previous jobs.

We use two different versions of changes in wages across jobs to identify the parameters. The first uses the wage change from the last period in job *j* to the first period in job *j*+1:

(8) $$\Delta_b = Y_{i,j+1,0} - Y_{ijs} = [\beta_x + \alpha_1] - \tilde{\beta}_T \tilde{T}_{ij} + \Delta\eta_{ij} + \Delta\varepsilon_{ij},$$

where $\tilde{T}_{ij}$ is total tenure at the end of job *j* and Y_{ijs} is the wage in the last period of job j. The intercept captures the returns to experience from the additional period of work, β_x, plus the improved job match associated with having made one more transition, α_1.

We also use changes in starting wages to estimate the parameters. Taking the difference in wages at the beginning of jobs j and $j+1$ yields:

(9) $$\Delta_s \equiv Y_{i,j+1,0} - Y_{ij0} = \alpha_1 + \beta_x\left(X_{i,j+1,0} - X_{j0}\right) + \Delta\eta.$$

Since $X_{i,j+1,0} - X_{j0} = \tilde{T}_{ij} + 1$, this can be rewritten as:

(9) $$\Delta_s = \alpha_1 + \beta_x(\tilde{T}_{ij} + 1) + \Delta\eta.$$

We, therefore, only need a measure of completed tenure in the previous job, rather than a direct measure of lifetime labor market experience to estimate equation (9).[10] Since tenure is zero at the start of each job, the change in starting wages is not affected by $\tilde{\beta}_T$. This allows us to identify β_x and α_1 from equation (9).

The implications of allowing ϕ_{ij} to vary with *j* instead of X_{ijt} should now be clear. This modification allows us to estimate the pure effect of experience, β_x, rather than the combined impact, $\beta_x + \alpha_x$, as in the previous literature. Second, allowing ϕ_{ij} to vary with *j* implies that wages will increase with each new job match, even after conditioning on experience and tenure in the current job. This testable implication of our model is strongly supported in our empirical work.

Since β_x, $\tilde{\beta}_T$, and α_1 appear more than once in equations (7), (8), and (9) we impose the implied constraints across equations. Rewriting the equations compactly shows the constraints clearly:

$$(10) \qquad \begin{bmatrix} \Delta_w \\ \Delta_b \\ \Delta_s \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & -\tilde{T}_{ij} & 1 \\ \tilde{T}_{ij}+1 & 0 & 1 \end{bmatrix} \begin{bmatrix} \beta_x \\ \tilde{\beta}_T \\ \alpha_1 \end{bmatrix} + \begin{bmatrix} \Delta\nu_{ij} \\ \Delta\eta_{ij} + \Delta\nu_{ij} \\ \Delta\eta_{ij} \end{bmatrix}$$

This constrained structure can be estimated using a minimum distance estimator, which yields consistent estimates of β_x, $\tilde{\beta}_T$, and α_1 under the identifying assumptions that change in the match-specific component, $\Delta\eta_{ij}$, and the change in the idiosyncratic component, $\Delta\nu_{ij}$, are independent of completed tenure in the prior job, $\tilde{T}_{ij}$.[11]

We initially estimate equation (10) assuming that the parameters are constant across education groups. We then allow these parameters to vary with educational attainment and test whether the constraint can be rejected.

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[10] In the application of this model, however, we also include the change in experience squared.

[11] This requires either that v_{ijt} and η_{ijt} are serially independent or that decisions to change jobs are not influenced by autocorrelated shocks after controlling for person- and job-specific fixed effects, μ_i and ϕ_{ij}.

IV. Data

We use the 1986-1993 panels of the Survey of Income and Program Participation (SIPP) to measure wage growth while working for the same employer and the wage gains associated with changes in employers. Each SIPP panel consists of a series of nationally representative longitudinal surveys of nearly 30,000 individuals who are followed for 24 to 40 months, depending on the panel. A new panel was started in every year (other than 1989) starting in 1984.[12]

This data set has substantial advantages over the Panel Study of Income Dynamics (PSID), the primary data source used in previous studies. While the PSID offers a long time span, it only offers limited information on tenure and wage rates while working for the same employer.[13] The wage data in the PSID is the most problematic. Annual earnings last year is a mixture of earnings on the new and the old job when a job change occurs. The alternative is to use the wage rate at the time of the interview. With annual interviews, however, it is not possible to obtain wage changes for jobs that last less than a year. Measures of tenure in the PSID are also problematic since the questions have changed over time, though recent questions have consistently asked tenure with current employer .[14]

The SIPP overcomes these problems by including the key variables necessary to

[12] We do not use the 1984 and 1985 panels because the monthly school enrollment questions were not asked before the 1986 panel. The 1984 panel was also not used because the employer identification number was not coded consistently in that panel.

[13] Both Altonji and Shakotko (1987) and Topel (1991) were limited to annual data with which to measure wages and tenure.

[14] See Brown and Light (1992) for a discussion of the weakness of the tenure questions in the PSID. The PSID started collecting retrospective monthly information on changes in employers in 1988. Altonji and Williams (1997) use these to determine tenure at each interview. They, however, only have wage information at each yearly interview.

identify when respondents change jobs and the wage changes both while working for the same employer and when moving to a new employer.[15] Individuals within each panel are interviewed every four months. During these interviews, respondents are asked detailed questions on job and earnings histories that cover the previous four months. Unique codes are assigned to each employer allowing us to identify when respondents change employers.

Respondents are asked both their wage rate and their earnings. For those who do not report hourly wages, we impute their wage rates by dividing monthly earnings by hours worked per week and weeks worked in each month.[16] These wages are then deflated using the Total Personal Consumption Expenditures deflator to obtain real hourly wage rates in each month.[17]

While the linear specification described in the previous section does not require a direct measure of experience, the inclusion of experience squared in the log wage equation requires that we calculate the change in experience squared. This can be calculated from a series of questions that allow us to calculate labor market experience directly rather than having to rely on potential experience (age minus education minus six).

Our sample includes all males and females with positive weights who were 18 to

[15] The SIPP also allows us to include all males and females rather than having to limit our study to heads and wives, as is necessitated by the PSID.

[16] We also construct this measure for persons reporting an hourly wage rate and find the correspondence between the reported and calculated wage rate is high.

[17] Since the number of weeks in a month varies between 4 and 5 this will introduce spurious fluctuations in imputed wage rates. Therefore, if a respondent reports the same earnings and same hours worked in each month covered by the interview, we assume that they also worked the same number of weeks in each month. We, therefore, divide their monthly wages by 4.33 in each of the four months covered by the interview.

55 at some point during the panel. For each person we include all months of employment while not in school.[18] Months when the respondent is in school are dropped in order not to confound the low wages of students with those of other low-wage respondents.

Summary Statistics

The top section of Table 1 shows the sample size of our data set, which includes a little more than 60,000 males and over 59,000 females. Each respondent is observed, on average, for a little less than two years resulting in over 2.4 million person months. The descriptive statistics on race, ethnicity, and education confirm that our sample is largely representative of the national population on these observed characteristics. White non-Hispanics make up roughly 77 percent of the sample. Females with a high school degree or less make up 55.1 percent of the sample while 24.5 percent have some college but not a bachelor's degree. Among males, 55.3 percent have a high school degree or less and 21.8 percent have attended college without receiving a degree.

We start by presenting descriptive statistics on wage growth within and between jobs for persons classified by educational attainment. We then turn to educational differences in returns to experience, tenure, and job switching, which are the fundamentals that lie behind differences in wage growth.

Wage Growth Within and Between Jobs

Table 2 presents the mean monthly within-job wage growth across all person months. These tabulations show a clear positive relationship between within-job wage

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[18] In a separate analysis we also exclude left-censored jobs since these oversample long jobs which may, in turn, oversample jobs with high returns to tenure. This smaller sample gives results very similar to those reported here.

growth and educational attainment for both females and males. Female high school dropouts experience a .0006 monthly growth rate (.7 percent per year) while females with a high school degree or some college experience within-job wage growth of roughly .0012 per month (or 1.4 percent per year). In contrast, female college graduates experience a growth rate of .0030 per month (or 3.6 percent per year). Thus, the within-job wage growth of female college graduates is five times as large as the growth rate for female high school dropouts.

The educational differential is even larger for males. Males with a high school degree or less, experience a wage growth of .0007 per month. Males who have completed college experience a monthly growth rate of .0021 per month. Thus, on average, growth rates in wages while working for the same employer are three times as large for males with a college degree than for males with a high school degree or less.

Columns 1 and 3 of Table 3 show the average wage growth that job changers experience when moving directly from one job to another.[19] These wage increases are large and increase with educational attainment. Females with a high school degree who change employers experience a 2.9 percent increase in real wages. In contrast, females with some college who change employers experience a 4.5 percent increase in wages. While the pattern is not monotonic, females with more than a high school degree experience substantially larger wage increases than do females with a high school degree or less. For males the patterns are monotonic in education. Males with less than a high

[19] It is well known that the selected sample of job changers is not representative of all workers. The means in Table 3, therefore, do not represent the mean wage change that a random worker would experience if she changed employer, but rather the expected wage growth conditional on having changed employers.

school degree experience a 2.8 percent increase in wages while college graduates experience a 5.1 percent increase.

Columns 2 and 4 of Table 3 show wage changes between the last month of one job and the first month of the following job when the transition was accompanied by an intervening spell of non-employment. While the SIPP does not provide sufficient information to distinguish between voluntary and involuntary separations, the negative wage changes for jobs with an intervening spell of non-employment indicate that these transitions lead to very different outcomes.[20] On average, females with an intervening spell of non-employment experienced a 2.6 percent decline in wages. For males the mean decline is 2.9 percent. For females there is no clear pattern across education groups ,while for males the largest losses are experienced by the most educated.

These differences in wage changes between job-to-job transitions and transitions with an intervening spell of non-employment can be incorporated into the conceptual framework developed earlier. Once a person leaves a job, the reservation value for the match component in the new job no longer reflects the match component in the previous job since the option of staying in that job has been eliminated. As a result, the reservation value for the match component is lower. In our empirical work, therefore, we allow the between-job wage changes to reflect whether the transition was directly to a new job or whether there was an intervening spell of non-employment. Consistent with the descriptive statistics in Table 3, we find that the wage gains are significantly smaller when there is an intervening spell of non-employment.

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[20] A topical module administered early in the panel asks the reason for leaving the last job. Since this question covers only one job that often occurred before the start of the panel there is insufficient information to use this question in the estimation.

Figure 1 plots the kernel-smoothed within-job wage changes by single year of education for males and females to see whether wage growth increases within educational categories as well as between the broad educational categories shown in Table 2. These plots indicate a positive relationship between educational attainment and within-job wage growth, even within the broad educational categories. Between-employer wage changes, shown in Figure 2, also increase with educational attainment but there are considerably greater fluctuations around the kernel-smoothed values, especially for females.

Thus far, we have shown that more-educated workers experience faster wage growth than less-educated workers. This educational differential holds both for wage growth while working for the same employer and wage gains when moving directly to a new employer. While these purely descriptive statistics show that there is positive correlation between wage growth and educational attainment, the source of this wage growth is not identified. We now turn to the statistical model developed in the previous section to obtain estimates of the underlying parameters.

V. Returns to Experience, Tenure, and Improved Job Match

Obtaining estimates of the returns to experience, tenure, and job match is important in accessing the cause of the wage growth. Do the flatter profiles of less-educated workers reflect smaller investments in firm-specific relationships or do they reflect smaller wage gains independent of whether the person stays with the same employer? A direct consequence of lower returns to firm-specific investments would be that less-educated workers would have less to lose from leaving a job either voluntarily or involuntarily. Alternatively, if the flatter profiles reflect lower returns to general experience, then this implies that less-educated workers receive fewer transferable skills.

We use the methodology developed earlier to estimate the key underlying parameters.[21] For expositional clarity we focused on returns to experience and tenure in our discussion of the estimation strategy. In our empirical work we include other factors that affect wages. Our omission of time-invariant covariates in equation (1) is innocuous since these variables cancel when taking differences in wages both within and between jobs. Time varying covariates, however, do not difference out. We, therefore, include part-time status, as well as tenure and a quadratic in experience, as time-varying covariates in the levels equation. Taking differences implies that wage changes reflect changes in part-time status. We allow this variable to have a different impact on within- and between-job wage changes since changing to part-time status while staying with the same employer may have a different effect on wages than moving to a part-time job with a new employer.

Tables 4 and 5 present the estimated parameters for females and males, respectively. Robust standard errors are used to take account of the nonspherical nature of the error terms. Coefficients are shown for all persons (column 1 and 2), white non-Hispanics (columns 3 and 4) and non-whites and Hispanics (columns 5 and 6). For expositional purposes we refer to the former as whites and the latter as non-whites. Columns 1, 3, and 5 show estimates without education interactions while columns 2, 4, and 6 allow the coefficients to differ by educational attainment.

As a point of comparison, column 1 of each table constrains returns to tenure, experience, and job match to be the same for all persons, regardless of their educational

[21] Throughout this section we follow the previous literature in referring to $\tilde{\beta}_T$ as returns tenure. We, however, remind the reader that this term differs from β_T if α_T is non-zero.

attainment. Based on these estimates we would falsely conclude that the within-job wage growth of females reflects returns to tenure, not experience. While the coefficient on tenure of .0029 is statistically significant at the .01 level, the coefficients on experience and experience squared are not significantly different from zero, as indicated by the F statistic of 1.24. Therefore, these estimates, that constrain returns to experience and tenure to be the same for females of all educational levels, imply that that wage growth within jobs reflects returns to tenure, not experience.

Column 2 shows the importance of allowing the parameters to vary by educational attainment. The null hypothesis that all the education interactions are zero is strongly rejected by the F statistic of 12.92. Furthermore, almost all the interactions are individually significant at the .01 level. Having relaxed the constraint that returns to tenure and experience are the same across educational attainment also alters the conclusion that wages of females increase only with tenure, not experience. The joint test that all coefficients on experience are zero is strongly rejected by the F statistics of 3.24.

The educational interactions indicate that returns to tenure increase with education, but that returns to experience decrease with educational attainment.[22] The positive coefficient of .003 on the tenure interaction indicates that the monthly returns to tenure increase by .125 percent for each additional year of educational attainment. On the other hand, the negative coefficient of .001 on the experience interaction indicates that it is the least-educated females who have the highest return to experience. Since the positive coefficient on the tenure interaction is larger than the negative coefficient on the experience interaction, the net impact of these two offsetting factors is that within-job wage growth increases with education. This is consistent with the plots in Figure 1. We now, however, see that this is the result of returns to tenure increasing with education while returns to experience decline, but not by as much.

If more highly educated females gain more from job-specific tenure, then they have more to lose when moving to a new job. This would imply that they would experience smaller between-job wage growth than less-educated females unless gains in the job match component increase with educational attainment. Column 2 indicates that this is indeed the case. More-educated females who move from one employer to another gain substantially larger wage increases than do less-educated females. The positive coefficient of .010 on the interaction of the job match component and education indicates that each additional year of education increases α_1 by 1.0 percent. A female with nine years of education who changes jobs has an expected increase in the job match component of 2.8 percent.[23] In contrast, a job changer with a high school degree has an expected increase in the job match component of 5.8 percent. This indicates that improvements in job match are an important component of wage growth for more-educated females.

As a side note, it is important to recognize the potential bias that will result in estimating wage functions for more-educated females with data sets that do not distinguish between wage growth while working for the same employer and wage changes that occur when changing employers. For example, a college graduate would experience a 9.8 percent increase in the job-specific match component when she changes

[22] The coefficient on the interaction of education and experience squared is positive, but not large enough to offset the negative coefficient on the interaction of experience and education.

jobs, which is roughly equivalent to the wage growth she would experience over a 48-month period working for the same employer. Estimates of earnings functions which fail to distinguish between within- and between-job wage growth will falsely attribute this wage growth to returns to experience instead of attributing the wage growth to improved job match, conditional on experience.

We now turn to estimates of returns to tenure, experience, and change in job match for females disaggregated by race. Estimates for non-whites are of particular interest given the racial composition of the population expected to work under the recent welfare reforms. Columns 3 and 4 provide estimates for whites and columns 5 and 6 provide results for non-whites. These estimates indicate that the qualitative results are similar for both groups. The experience and tenure interactions with education are statistically significant and of the same sign for the two groups. More-educated white and non-white females have higher returns to tenure than less-educated females of the same race. This is offset by lower returns to experience, but the positive impact of education on returns to tenure dominates the negative impact on returns to experience. As a result, the within-job wage growth increases with education for both white and non-white females.

In summary, there is strong evidence that returns to experience and tenure vary with educational attainment for females. More highly educated females of both races experience greater within-job wage growth and larger wage increases when they change employers.

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[23] 9 x .010 - .062 = .028

Table 5 presents the corresponding estimates of returns to tenure, experience, and improved job match for males. In many ways the results for males are similar to those for females. Improvement in job match is an importance source of wage growth, as indicated by the large and statistically significant estimates of α_1. On average, white males who go directly from one job to another experience a 5.9 percent increase in the job match component. Non-whites experience an increase of 6.2 percent. Both are statistically significant at the .01 level. Having an intervening spell of non-employment, however, almost totally offsets these gains.

Results for males also resemble those for females in the sense that the hypothesis that all educational interactions are zero is rejected by the F statistics of 9.28 and 1.95 for whites and non-whites, respectively. While the null hypothesis that returns to tenure, experience, and job match do not vary by education is rejected, individual coefficients on these interactions are not statistically different from zero. It is, therefore, not possible to determine whether the positive relationship between within-job wage growth and education (shown in Figure 1) reflects higher returns to tenure or higher returns to experience for more-educated males.

VI. Conclusions

We started this paper by asking whether returns to experience, returns to tenure, and returns to improved job match differ by educational attainment. The answer to this question is of particular interest given the recent emphasis on work as an alternative to welfare. While much of the welfare reform debate has implicitly assumed that less-educated females will experience substantial growth in wages as they obtain valuable labor market experience, the existing literature does not provide estimates of returns to experience, tenure, and job match by skill level. At best, such claims implicitly assume that less-educated females will obtain the average returns to tenure, experience, and job match

We have shown that this implicit assumption is strongly rejected by the data. For females, all three components of wage growth increase with educational attainment. As a result, the less-educated workers experience little wage growth while working for the same employer and only limited gains when moving to a new employer. The general patterns are similar for males, but our estimates are considerably less precise.

In the process of answering the substantive question of whether wage growth differs by educational level we reconsidered the standard methodology for taking account of the endogeneity of the job match component. In the process, we identified a source of wage growth previously ignored in this literature. Specifically, we argued that the job match component should increase with the number of previously accepted jobs, even after conditioning on experience and tenure. Intuitively, if each successive job-to-job transition has to dominate the previous job, then the threshold for acceptable offers increases with the number of previously accepted jobs. This testable implication is strongly confirmed by our estimates that show large and significant increases in the job match component, especially for more-educated workers. This additional source of between-job wage growth implies that studies that do not distinguish between within- and between-job wage growth overestimate the returns to experience. This is a direct result of omitting the number of previous transitions, which will be correlated with experience.

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Table 1

Summary Statistics by Gender

	Females	*Males*
Sample size		
Persons	59,457	60,137
Person Months	1,166,948	1,273,784
Characteristics		
Race/Ethnicity		
White non-Hispanic	.771	.773
Non-white/non-Hispanic	.149	.131
Hispanic	.079	.095
Education		
Less Than High School	.146	.177
High School Graduate	.405	.376
Some College	.245	.218
College Plus	.208	.229

Table 2

Mean Monthly Within Job Growth in Log Wages by Gender and Education

	Females	***Males***
Less Than High School	.0006	.0007
High School Graduate	.0012	.0007
Some College	.0013	.0009
College Plus	.0030	.0021
All	.0016	.0011

Table 3

Mean Change in log Wages between Employees by Gender and Education

	Females		*Males*	
	(1)	(2)	(3)	(4)
	Job to Job	Intervening Non-employment	Job to Job	Intervening Non-employment
Less Than High School	.039	-.011	.028	-.014
High School	.029	-.044	.041	-.033
Some College	.045	-.006	.041	-.033
College Plus	.041	-.024	.051	-.042
All	.037	-.026	.040	-.029

Table 4

Estimates of Returns to Tenure, Experience, and Job Match White and Non-White (Females)

	(1) All	(2) All	(3) white	(4) white	(5) non-white	(6) non-white
Δ Tenure $(\tilde{\beta}_T 10^2)$	.291	-1.330	.321	-1.369	.172	-1.206
	(.062)***	(.355)***	(.072)***	(.464)***	(.114)	(.458)***
Δ Experience $(\beta_X 10^2)$	-.062	1.219	-.080	1.261	.013	1.047
	(.068)	(.384)***	(.079)	(.506)**	(.125)	(.511)**
Δ Exp^2 $(\beta_{X^2} 10^4)$	-.009	-.049	-.005	-.060	-.032	.033
	(.011)	(.060)	(.012)	(.076)	(.020)	(.092)
Δ Part-time (within job)	.036	-.062	.037	-.073	.032	-.044
	(.003)***	(.017)***	(.003)***	(.021)***	(.006)***	(.027)
Δ Part-time (between job)	-.053	.084	-.062	.068	-.019	.076
	(.006)***	(.032)***	(.006)***	(.044)	(.010)*	(.045)*
Δ Match intervening non-employ	-.047	-.044	-.048	-.111	-.044	.049
	(.005)***	(.031)	(.006)***	(.043)**	(.010)***	(.039)
Δ Match All transitions (α_1)	.066	-.062	.066	-.073	.064	-.040
	(.005)***	(.027)**	(.005)***	(.035)**	(.009)***	(.037)
<u>Education Interaction with:</u>						
Δ Tenure $(\tilde{\beta}_T 10^2)$		.125		.129		.112
		(.028)***		(.036)***		(.038)***
Δ Experience $(\beta_X 10^2)$		-.099		-.103		-.084
		(.031)***		(.040)***		(.043)**
Δ Exp^2 $(\beta_{X^2} 10^4)$		.003		.004		-.005
		(.005)		(.006)		(.007)
Δ Part-time (within job)		.008		.008		.006
		(.001)***		(.002)***		(.002)***
Δ Part-time (between job)		-.011		-.010		-.008
		(.003)***		(.004)***		(.004)**
Δ Match intervening non-employ		.000		.005		-.008
		(.003)		(.003)		(.003)**
Δ Match All transitions $(\alpha_{1\cdot Ed} 10^2)$		.010		.011		.008
		(.002)***		(.003)***		(.003)***
Observations	1,201,220	1,201,220	959,450	959,450	241,770	241,770
R-squared	.003	.003	.003	.004	.003	.003
F $(\beta_X = \beta_{X^2} = \beta_{X\cdot Ed} = \beta_{X^2\cdot Ed} = 0)$	1.24	3.24	.89	2.09	1.41	2.70
Prob	.29	.012	.41	.079	.24	.029
F $(\tilde{\beta}_T = \beta_{T\cdot Ed} = 0)$		16.950		13.893		4.946
Prob		.000		.000		.007
F (all Ed interactions=0)		12.92		10.45		3.59
Prob		0.00		0.00		0.00

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5

Estimates of Returns to Tenure, Experience, and Job Match White and Non-White (Males)

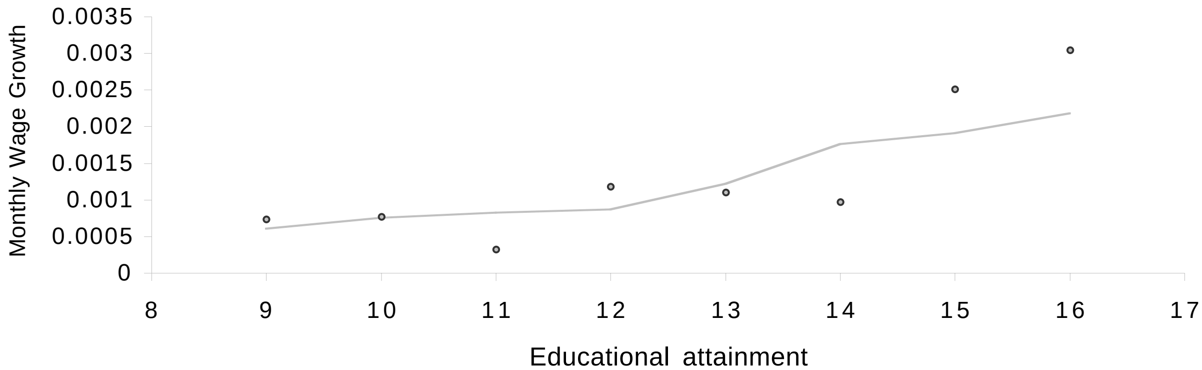
	(1) All	(2) All	(3) white	(4) white	(5) non-white	(6) non-white
Δ Tenure $(\tilde{\beta}_T 10^2)$	.085	-.199	.076	-.309	.122	-.006
	(.063)	(.388)	(.072)	(.516)	(.122)	(.470)
Δ Experience $(\beta_X 10^2)$	.121	.291	.150	.412	.002	.152
	(.065)*	(.386)	(.074)**	(.502)	(.132)	(.521)
Δ Exp ^{2} $(\beta_{X^2} 10^4)$	-.019	-.052	-.021	-.054	-.012	-.053
	(.010)*	(.048)	(.011)*	(.060)	(.023)	(.082)
Δ Part-time (within job)	.043	-.107	.047	-.170	.030	-.015
	(.004)***	(.022)***	(.005)***	(.032)***	(.007)***	(.028)
Δ Part-time (between job)	-.055	.059	-.055	.080	-.053	.031
	(.006)***	(.035)*	(.007)***	(.048)*	(.012)***	(.050)
Δ Match intervening non-employ	-.053	-.027	-.053	-.021	-.050	-.038
	(.005)***	(.028)	(.006)***	(.037)	(.011)***	(.041)
Δ Match All transitions (α_1)	.060	-.005	.059	-.012	.062	.002
	(.004)***	(.023)	(.005)***	(.032)	(.009)***	(.031)
<u>Education Interaction with:</u>						
Δ Tenure $(\tilde{\beta}_{T \cdot Ed} 10^2)$	.023		.031		.013	
	(.032)		(.042)		(.040)	
Δ Experience $(\beta_{X \cdot Ed} 10^2)$	-.015		-.021		-.015	
	(.031)		(.040)		(.044)	
Δ Exp ^{2} $(\beta_{X^2 \cdot Ed} 10^4)$	.002		.002		.004	
	(.004)		(.005)		(.007)	
Δ Part-time (within job)	.012		.017		.004	
	(.002)***		(.003)***		(.003)	
Δ Part-time (between job)	-.009		-.011		-.007	
	(.003)***		(.004)***		(.004)*	
Δ Match intervening non-employ	-.002		-.002		-.001	
	(.002)		(.003)		(.004)	
Δ Match All transitions $(\alpha_{1 \cdot Ed} 10^2)$	.005		.006		.005	
	(.002)***		(.003)**		(.003)*	
Observations	1,310,510	1,310,510	1,071,760	1,071,760	238,750	238,750
R-squared	0.003	0.003	0.003	0.003	0.003	0.003
F $(\beta_X = \beta_{X^2} = \beta_{X \cdot Ed} = \beta_{X^2 \cdot Ed} = 0)$	2.57	1.48	2.77	1.66	0.16	0.18
Prob	0.08	0.204	0.06	0.156	0.85	0.948
F $(\tilde{\beta}_T = \beta_{T \cdot Ed} = 0)$		1.237		0.758		0.709
Prob		0.290		0.469		0.492
F (all Ed interactions=0)		10.76		9.28		1.95
Prob		.00		.00		.058

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Figure 1

Kernel-Smoothed Within-Job Wage Growth by Education

Females



Males

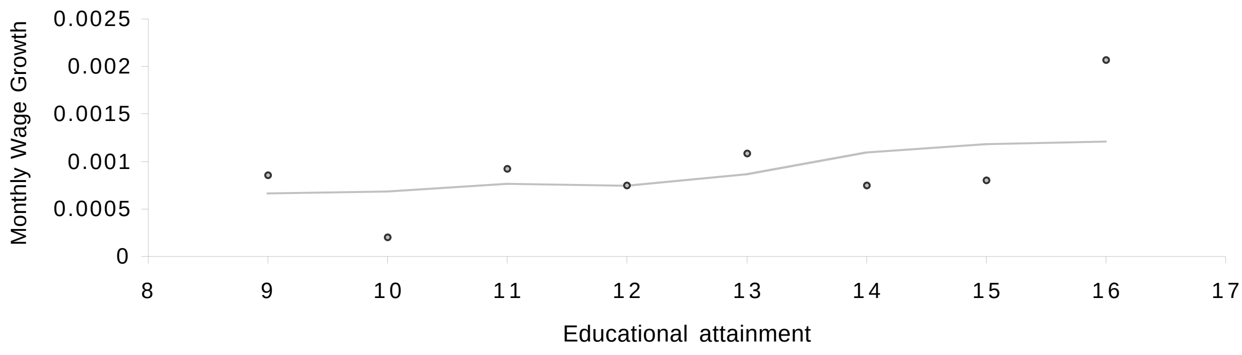
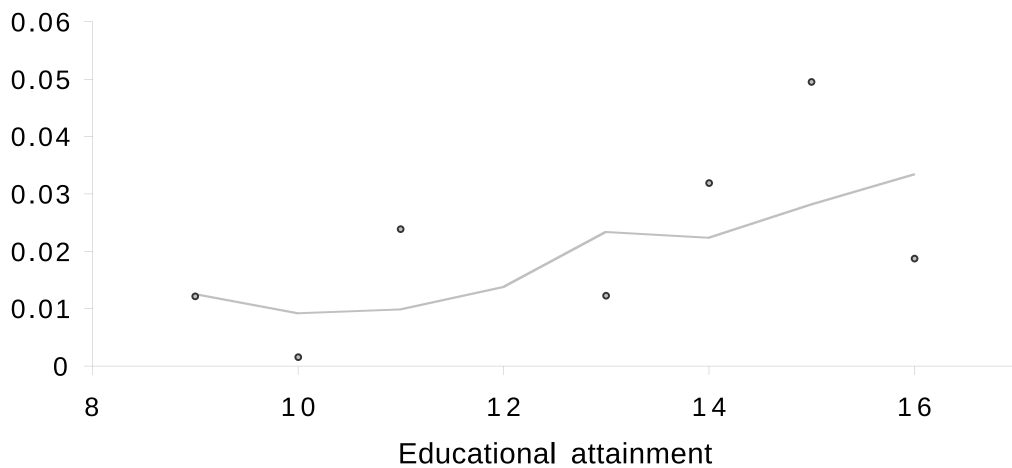


Figure 2

Kernel-Smoothed Between-Job Wage Growth by Education

Females



Males