Wages and Interrupted Careers

by

Manuelita Ureta
Department of Economics
Texas A&M University
College Station, TX 77843-4228

and

Finis Welch
Department of Economics
Texas A&M University
College Station, TX 77843-4228

January 2001

Comments welcome.

1 Introduction

We are all familiar with the Mincer-styled career wage progression models for which time worked and time out of school are the same, but there is no consensus regarding the modeling of wages with interrupted careers. As a point of departure consider the Mincer-Polachek (1974) model of women's wages where the career has three segments following completion of schooling. The first segment precedes child birth, the second is child rearing while out of the labor force, and the third is the return to full-time work. Imagine the complexity of this model of the stereotypical interrupted career. How do we model atrophy during the interruption? Does the rate of skill loss decline over time and how is it affected by the duration of the initial period of work? Do effects of the interruption diminish as the third segment unfolds? How do we mesh the three-part histories with continuous careers? Is a woman who until now has a continuous career in the first or third career phase? Would a man be treated differently? What about those who do not join the workforce soon after finishing school? What about multiple interruptions?

Although these questions are rightfully addressed in every wage study with longitudinal information of work histories, they have been largely ignored by resorting to the simplicity of the original National Longitudinal Surveys that described a woman's work career simply as the number of years she had worked at least half-time. The original Mincer-Polachek paper was the first to exploit the intermittent nature of careers using five variables: years worked before the first child, subsequent years worked, home time after first child, other home time, and current job tenure. Later, Mincer with

Ofek (1982) modified and simplified the earlier specification by aggregating work and non-work intervals into two spells: all work prior to the most recent spell, the most recent spell, all non-work intervals before the most recent, and the most recent non-work interval. Corcoran and Duncan (1979) adopted a similar approach when they addressed the wage rebound associated with entry into the wage labor market for women following interruptions for child care and work at home. It is important to note that these specifications are special. They may describe the wage profiles of groups of women with similar experiences that differ only in duration, but they cannot easily accommodate comparisons of those with and without interrupted careers. Note as well that in the revised Mincer approach, there is no sense of recency for previous work and non-work spells; only the most recent spells are identified.

Light and Ureta (1995) adopt a scheme that lacks parsimony, they use 31 variables to describe careers that are at most 13 years long, but permits comparisons across groups that are not possible using the more narrowly tailored specifications of the earlier literature.

Our purpose here is to suggest a specification that is more parsimonious than the earlier papers that address interrupted careers and also more general in the sense that the ideas naturally extend to types of activity that can be more specific than the generic work and non-work distinction. While our applications refer only to full- and part-time work along with spells of non-employment, they could easily include activities as specific as type-of-job, interruptions for school or other training, recuperation from injury, child birth and care, and so on. The essential idea is that an earlier activity affects current productivity, the effect is greater the longer is the duration of that activity, but the effect diminishes over time; both duration and recency are relevant.

To fix ideas consider three people who are currently employed full-time and have each worked for exactly ten years. They have equal schooling and work in the same occupation. Individual A finished school ten years ago and has worked continuously since that time. Individuals B and C finished school 15 years ago and had 5 years out of the workforce plus ten years of full-time work. B's interruption came five years into the career so that there is five years of work, five years out, which is then followed by five years of work. C's interruption followed the completion of school so that the ten years of job experience have been uninterrupted.

How would you expect the three wages to be ordered? While the ranking of A and C may be unclear, depending on the productive value of time not working, as long as time not working contributes less to individual productivity (skill) it should be clear that B earns less than C. Why? They have equal experience and time out, but they differ in the recency of time out. If experiences obsolesce or depreciate then the greater the time between the present and the occurrence of a less valuable event, the "age" of the event, the less harmful it will be as measured by current productivity. That is all there is to the model we propose.

We use the age of an event to measure recency and we aggregate events by duration while measuring their average age. The idea is not to explore the full complexity of widely diverse employment histories. Rather, it is to simplify job histories in a way that is less naive than simple aggregation without regard to timing.

Section 2 outlines our simple model. Section 3 describes the data and highlights the empirical diversity of careers measured by employment (full-time, part-time 20 to 34 hours per week, part-time less than 20 hours per week), unemployment and time out of the labor force. Section 4 describes our empirical strategy and provides estimates. Section 5 provides conclusions and suggestions for extensions.

2 The Statistical Model

In this section we describe a simple process governing the accumulation and depreciation of human capital through work experience that results in a specification of the wage regression that differs from the standard Mincer specification. One advantage of the specification we propose is that it distinguishes between workers who have identical amounts of work experience but whose work experience is of different "ages." Another nice property of the specification is that in the case of individuals who have worked full-time year-round since entering the labor force the specification yields the standard Mincer model.

Suppose a person works full-time between times t_1 and t_2. Let the instantaneous rate of human capital accumulation at time $t = \tau$ (while the person is working full-time) be equal to α. That is

$$\frac{d \ln K(\tau)}{d\tau} = \alpha \qquad\qquad \text{for } t_1 \leq \tau \leq t_2.$$

Assume the accumulated human capital depreciates at an instantaneous rate δ from the time it is acquired, τ, until the present time, T:

$$\begin{array}{l}\text{depreciation by time}\\ T \text{ of human capital}\\ \text{acquired at time } \tau\end{array} = \int_{\tau}^{T} \alpha\delta \, dt = \alpha\delta(T-\tau).$$

Then, the net accumulation of human capital, as of time T, for a person working full-time between times t_1 and t_2 is:

$$\begin{aligned}\int_{t_1}^{t_2} (\alpha - \alpha\delta(T-t)) \, dt &= \alpha(t_2 - t_1) - \alpha\delta\left(T(t_2-t_1) - \frac{t_2^2 - t_1^2}{2}\right)\\ &= \alpha D - \alpha\delta D\left(T - \frac{t_2+t_1}{2}\right)\\ &= \alpha D - \alpha\delta(DA),\end{aligned}$$

where

$$D = t_2 - t_1 = \text{duration of the spell, and}$$

$$A = T - \frac{t_2+t_1}{2} = \text{average “age” of the spell.}$$

Suppose the person has two such spells, so the net accumulation of human capital as of time T due to each spell is given by

$$\alpha D_1 - \alpha\delta(D_1 A_1) \qquad \text{and}$$

$$\alpha D_2 - \alpha\delta(D_2 A_2).$$

Aggregating the two spells we find

$$\alpha(D_1 + D_2) - \alpha\delta(D_1 + D_2)\left(\frac{D_1A_1 + D_2A_2}{D_1 + D_2}\right)$$

and if we have I spells

$$\alpha\left(\sum_{i=1}^{I} D_i\right) - \alpha\delta\left(\sum_{i=1}^{I} D_i \bar{A}\right)$$

where $\sum_i D_i$ is the aggregate spell duration and $\bar{A}$ is the duration-weighted average age of the I spells.

Note that for someone who works full-time year-round from 0 to T we have

$$\alpha T - \alpha\delta T(T/2) = \alpha T - (\alpha\delta/2)T^2$$

since $T/2$ is the midpoint of the spell and its average age. Of course, this corresponds to the Mincer "quadratic on experience" specification.

When individuals are not working they may be unemployed, out of the labor force or we have no information about their labor force status. In principle, unemployment spells may have a different impact on a worker's stock of human capital than does an out-of-the-labor-force spell, so we want to distinguish time spent on different labor force states. Also, the impact of an unemployment spell on the stock of human capital and wages may depend on how recently the unemployment spell occurred. Since the framework we develop for aggregating across employment spells readily applies to all types of spells we use it to summarize an individual's allocation of time across employment, unemployment, time out of the labor force and "no information."

3 The Data

We estimate the model using the National Longitudinal Survey of Youth (NLSY). The NLSY is a nationally representative sample of men and women. The first survey was conducted in 1979 and yearly thereafter. The sample of men and women was aged 14 to 22 in 1979, the year of the first survey. Our estimates cover the period 1979 to 1993, when the surveys were conducted annually, and are based on the "cross section" sample of the NLSY: we exclude the military samples and the oversample of blacks, Hispanics and low income whites. In each year of the survey, an individual contributes an observation to our "wage sample" if he or she reports a valid wage observation on a job that is current at the time of the interview. This criterion yields a wage sample of 54,770 observations on 5,899 individuals.

The NLSY survey instrument includes a "work history" covering the entire period since the previous year's survey. The work history records detailed weekly information on every job held during the week in question. Some of the measures are usual hours of work, occupation, industry, and wages. We use the measure of usual hours to distinguish full- and part-time work: we keep separate count of weeks worked when hours per week are greater or equal to 35, between 20 and 34, and less than 20.

The data contains detailed information about school attendance and degree recipiency. Because the individuals in the sample are relatively young, the vast majority at some point attends school part- or full-time and earns one or more degrees during the 1979-1993 period. They also work while they attend school, during summers, or after leaving school temporarily. Rather than follow an arbitrary rule for inclusion and omission of periods of work depending on their timing relative to the timing of schooling, we retain the information on every work spell observed in the data. The equation specification and construction of work-experience variables are easily modified to allow the returns to work experience to differ depending on the stage in an individual's career when the work took place. The measures of work-experience, time unemployed, time out of the labor force, etc., described in section 2, are divided into two components depending on the time when the most recent degree was earned. For example, at time t for individual i, full-time work is measured by 4 variables: (1) total number of weeks worked full-time *prior* to the date of the most recent degree, (2) the duration-weighted average age of the weeks aggregated in (1), (3) total number of weeks worked full-time *since* the recipiency of the most recent degree, and (4) the duration-weighted average age of those weeks aggregated in (3). Of course, over the duration of the panel "the date of the most recent degree" can change often, and a given week of work is often first included in the count of "post-degree full-time work experience" and subsequently it is counted as part of the "pre-degree work experience."

The construction of the experience variables demands knowledge of the date when each degree was received. While the education data in the NLSY is of very good quality, we had to do a fair amount of data cleaning to resolve inconsistencies. We also imputed degree dates when the data was missing but we had enough ancillary information to make educated guesses. In so doing we managed to retain a large number of observations that would have otherwise been left out of our wage sample.[1]

A primary concern in the analysis of panel data is the presence of attrition. The NLSY is particularly good at finding the individuals from the original sample. In Table 1 we report the percentage of respondents in the first survey who were contacted and interviewed in subsequent years, for the representative or "cross section" sample, separately for the men and the women. By 1993 about 10 percent of the initial sample is no longer present,

[1]The code that produces the working files with degrees data is available from the authors on request.

a small fraction considering that the survey was in its fourteenth year. The sample of women of the NLSY has experienced slightly less attrition than the sample of men. Our wage sample has every valid wage observation in the data regardless of the subsequent attrition status of the individual. Naturally, restricting the sample to the individuals who are still present in 1993 only exacerbates any biases due to attrition.

Table 2 presents the proportion, in each survey year, of respondents with a valid wage observation, i.e., the individual was holding a job at the time of the interview. Because the sample members are quite young in 1979 only 39 percent of the men and 34 percent of the women have a valid wage observation that year. The proportions rise steadily until the late 1980's when they appear to stabilize at around 81 percent for the men and 66 percent for the women. Note that the proportions in the years 1980 to 1993 refer to the percentage of those individuals who still are in the survey.

In addition to the very detailed information on labor market behavior, the NLSY has especially good data on school attendance and degree recipiency. We exploit this aspect of the data by using an extensive vector of variables that describe where an individual is on his or her path to the highest degree earned by 1993. This allows us to examine several interesting aspects of the returns to schooling that the usual "years of school completed" measure found in the Current Population Survey, for example, could not possibly address. Our findings on the returns to schooling are discussed later, when the wage regression estimates are presented. Summary statistics on the educational distribution of the sample members vary over the length of the panel. In Table 3 we present summary measures of the educational distribution of the members of the wage sample in the most recent year of data we use, 1993.

The youngest members of the panel are aged 28 in 1993 so it is likely that most of them are near or altogether finished with their formal education, especially regarding a high school degree or its equivalent. As of 1993, of the individuals in the wage sample, 11.1 percent of the men and 6.9 percent of the women report having no degree. Another 7.3 percent of the men and 7.7 percent of the women have a GED as their highest earned degree.

We classify the group of workers with a GED by their highest grade completed. Only 9.3 percent of these men quit high school before reaching the 10th grade. About 51 percent finished the tenth or the eleventh grade, and the remaining 40.1 percent actually finished the 12th grade. The comparable figures for women are 12.3 percent with a 9th grade education or less, 36.3 percent with a 10th or 11th grade education, and 51.4 percent with a 12th grade education.

A surprisingly small fraction of GED holders go on to earn an Associate's or Bachelor's degree—around 3 percent. While this suggests that, in practice, a GED has little option value, men who obtain at most a GED may have originally intended to continue their education for, on average, they attend college for .54 years. Women whose highest degree earned is a GED on average attend college for .67 years.[2]

The remaining educational distribution for men and women with a valid

[2]To be precise, the variable "additional years of schooling after receiving degree" is defined as "highest grade completed" minus the minimum years of schooling required for the degree. So in the case of, say, people with a Bachelor's degree, one additional year of schooling does not necessarily imply the person attended graduate school. Most likely it means that a person took 5 rather than 4 years of college attendance to graduate from college.

wage observation in 1993 is remarkably similar for men and women. By 1993, about 50 percent report that their highest degree is a high school diploma, and on average these men and women attend college for about one semester. Women are more likely to earn an Associate's degree: 10.5 percent of the women, versus 6.1 percent of the men. The women with Associate's degrees, on average, attend college for another .55 years after earning their degree. For men, the comparable figure is .36 years. Women are just as likely as men to end their formal education with a Bachelor's degree. A Bachelor's degree is the second most frequent highest degree in the wage sample, accounting for about 19 percent of the men and the women, and on average they went to school for .37 years beyond the minimum 16 years to complete the Bachelor's degree.

Graduate school attendance is quite low, partly perhaps because the younger members of the sample may still return to school in coming years. Combining Master's, Ph.D.'s and Professional degrees, we find that 5.7 percent of the men and 5.8 percent of the women have earned more than a college degree, with women earning almost exclusively Master's degrees.

Table 4 reports differences in full-time work among men and women for individuals who finished school at least 9 years prior to the 1993 survey. Only a very small fraction of the women in NLSY have not worked or work very little. For example, only 10 percent of the women have worked full-time for 6.0 percent of the time or less, while another 10 percent have worked full-time for at least 94.1 percent of their post-school career. The median woman has been employed full-time for slightly over half (51.9 percent) of the post-school career. Although men are more likely to have worked more, there is huge diversity among them—much more than one might expect from a review of the wage progression literature.

Bearing in mind that the observation period ranges between 9 and 15 years of potential career, fully 10 percent of the men were employed full-time for at most 29.1 percent of their post-school career and the median refers to only 78.7 percent full-time employment. Bluntly, fully half of the men in NLSY who have been out of school for at least 9 years have spent more than a fifth of their time (or the time for which NLSY accounts) either unemployed, employed part-time, or out of the labor force.

Table 5 presents summary statistics, for 1993, for the variables that describe a worker's career from the time he or she first joins the labor force. Initially we included pre- and post-highest degree measures for six labor force status: full-time work (35 or more hours of work per week), part-time work of 20 to 34 hours per week, part-time work of 10 to less than 20 hours per week, unemployment, out of the labor force, and, lastly, weeks for which the survey has no information on labor force behavior. In the preliminary rounds of estimation, three facts became obvious. First, the distinction between "time spent out of the labor force" and "time unaccounted for" carries no information, so the two measures were combined. Second, weeks of fewer than 20 hours of work per week proved to have no effect on wages, regardless of whether the work occurred before or after the date of the highest degree. As a result, we dropped this variable from the specification. Third, the only one of the "pre-degree" labor force activities that has an effect on wages is full-time work. Thus, all other pre-degree measures were dropped.

There are some important differences in the amount and the timing of work between men and women. We focus first on the individuals in the 1993 survey wage sample, that is, workers who report a valid wage observation on a job that is current at the time of the 1993 interview. In the 1993 survey wage sample, the 2215 men have 9.27 years of post-highest degree full-time work, versus 7.28 years for the 1902 women in the sample—a gap of almost 2 years by the time these workers have held their highest degree, on average, for about 12 years. The women make up part of this gap by working part-time (10 to 34 hours per week): they average 1.82 years of part-time work compared to 1.06 years for the men. The men have experienced more weeks of unemployment, 0.74 years compared with 0.52 years for the women. There are no gender differences in the amount of pre-degree full-time work. The men and the women have averaged 0.94 years of full-time work prior to the date when they earned their highest degree. Note that men have, on average, spent 0.98 years (12.05 – 9.27 – 1.06 – 0.74) out of the labor force (or time unaccounted for) since receiving their highest degree. The comparable figure for women is 2.23 years (11.85 – 7.28 – 1.82 – 0.52).

The gender differences in the timing of these activities is even more striking. To gauge how "recent" or how "old" is a given activity, we present the mean age of an activity (in years) relative to the minimum possible mean age—the age that results if all the time spent on the activity occupied the period of time immediately prior to the survey week. The (relative) mean age of full-time work is 1.16 for the men and 1.49 for the women in the 1993 survey wage sample. That is, the men's full-time work is 16 percent "older" than it would be if all their work had been concentrated in the period just prior to the 1993 survey. In contrast, women's full-time work is 49 percent older than its minimum possible age.

Both men and women are likely to work part-time shortly after receiving their highest degree, as evidenced by the relative mean age of part-time work: 16.09 for the men and 7.72 for the women. Thus, the women both rely more on part-time work and have done so more recently than the men. Unemployment, on the other hand, is a more recent activity for the men than for the women. The relative age of weeks spent unemployed is 16.28 for the men and 23.25 for the women.

Turning now to the figures for everyone else, *i.e.,* individuals not in the 1993 survey wage sample, we find that the men and the women, on average, have considerably fewer years of full-time work experience, and have spent more time unemployed. Also, their full-time work experience is considerably "older" than is the case for those in the 1993 survey wage sample, while their part-time work and their unemployment is much more recent.

This completes our discussion of the data and description of the wage sample. In the following section we report the findings from estimation of the wage regressions.

4 Empirical Findings

The wage data (converted to weekly wages) contain some implausibly high and low values so we top- and bottom-code the data. The high end of the wage distribution in each year of the survey is top-coded at 3.5 times the median weekly wage for that year. The low end of the wage distribution is bottom coded at 0.1 of the median weekly wage. The resulting distribution is deflated by the Price of Consumer Expenditures index, with 1994 as the base year.

Table 7 reports our estimates of the log-weekly wage regression based on the cross-section or representative sample of men and women for the years 1979 through 1993. We report the estimated coefficients and t-statistics (or z-statistics where appropriate) from 5 estimators: ordinary least squares (OLS), generalized estimating equations (GEE), [3] random effects (or variance-components), and the within and between estimators of a fixed-effects regression equation. There are 54,770 observations on 5,899 individuals.

To the extent that past labor force behavior has an effect on current wages and, thus, on current labor force behavior the OLS estimates of the wage regression equation are probably biased and inconsistent. We present them because they provide conditional means of the log weekly wages for various classifications of the workers in the sample.

The equations include calendar-year indicator variables, and the standard deviation of the log-weekly wage about calendar year means is .663. It drops to .529 when we add indicators for part-time work. The root mean square error for the OLS estimated equation is .455.

The estimates are organized into 4 categories: coefficients pertaining to demographic characteristics, returns to schooling, current employment and the individual's work history. We describe the specific variables and their construction in each group and discuss the findings before moving on to the

[3]For a terse discussion of the estimator see STATA, *Reference Manual* (1997). The GEE estimator has an important advantage over more traditional methods of panel data estimation. Rather than impose a (perhaps erroneous) covariance structure, the GEE estimator allows us to estimate the covariance structure along with the rest of the parameters in the wage equation, and it readily produces robust standard errors for the estimates. This feature of the GEE estimator gives us a rare insight into the dynamic aspects of earnings over a worker's career.

following group.

The regression equation has indicator variables for sex (female = 1), Hispanic, black, and interactions of the race/ethnicity and sex indicators. We also control for the worker's age in 1978. This is a crude attempt to correct for the fact that we do not have the full work history for everyone in the sample. The oldest workers are 22 years in 1979, and depending on how much formal schooling they acquired, we may be missing as many as five or six years of their work experience. To examine the sensitivity of the estimates to this potential initial conditions problem we estimate the regression equation limiting the sample to those who were 16 or younger in 1979. The main results are essentially unchanged though the precision of the estimates is quite a lot worse.

The OLS estimates indicate that, controlling for all the other demographic, schooling and work experience factors, the women on average earn wages that are 23.9 percent lower than the wages of the men. Black men earn wages that are 12.4 percent lower than those of white men. And black and Hispanic women earn higher wages than their white counterparts.

Focusing now on average log wages by schooling categories, the OLS estimates reveal that workers without a school degree earn lower wages than high school graduates, and the penalty increases with an early departure from school, especially before the 10th grade. Workers holding a GED have, in this sample, higher average log wages than high school graduates *if they completed the 12th grade.* This result is robust across all specifications we estimate. Perhaps it reflects the self-selection of those who decide to work toward a GED after failing to graduate from high school.

Some of the high school graduates go to college for a few years but never get a degree. The next set of coefficients give the mean difference in the log wages for workers with some college education.[4] Interestingly, a degree isn't everything. Worker's with a year of college beyond high school have wages that are on average 7.5 percent higher. Two or three years of college increase average wages by about 11 percent, and 4 years of college by a much as 26.9 percent.

On average, workers with an Associate's degree earn wages that are 27.6 percent higher than the wages of high school graduates. A Bachelor's degree is associated with 49.2 percent higher wages than the reference group, high school graduates with no college education. Average wages very clearly do not increase linearly with years of schooling beyond high school. Workers with Master's degrees on average earn wages that are 72.6 percent higher than the wages of the reference group. A Ph.D. is associated with 89.5 percent higher wages, and a Professional degree with 101 percent higher wages.

The variable indicating that a worker is currently enrolled in school has an estimated coefficient equal to -.131, that is, all else constant, workers who are going to school while working have average wages that are about 13 percent lower than those of workers not in school. And the wages of part-time workers are significantly lower than those of full-time workers, especially so if the work involves fewer than 20 hours per week. This is to be expected since the left-hand-side variable is the log of the weekly, not the hourly, wage.

The last variable in this group measures the number of years since the

[4]We cap the post-degree schooling of high school graduates at 4 years.

worker received the current highest degree. In the OLS specification and all others the coefficient estimate is about 1 percent. Because we control for years of full- and part-time work and unemployment, this coefficient captures the effect of time spent doing everything else: working less than 20 hours per week, staying out of the labor force, and having time unaccounted for. An estimate of 1 percent suggests that, at least for relatively young workers, there is no penalty for these activities above and beyond the lower accumulation of work experience they necessarily entail.

The last group of variables listed in Table 7 describes a worker's allocation of time since he or she first joins the labor force. On average, every year of full-time employment (35 or more hours per week) is associated with 12.5 percent higher wages, while a year of part-time work (20 to 34 hours per week) is associated with 7.8 percent higher wages. A year of unemployment is associated with 5.7 percent lower wages. The only activity prior to receiving the current highest degree that matters for current wages is full-time work, which is associated with 7.9 percent higher wages for every year of work.

The estimated coefficients on the interactions of years of a given activity and its "average age" are also reported in Table 7. The coefficients estimate the product of the parameters α and δ so we cannot read the estimate of the rate of depreciation or decay directly. We do this in Table 9. Before moving on to Table 8, a few comments about the set of estimates that the various estimators produce are warranted.

The estimates are remarkably similar across specifications. With few exceptions, noted below, coefficients that are significantly different from zero show no sign reversals across specifications, and their magnitudes are very close as well. For instance, the coefficient on the indicator variable for females ranges from a low (in absolute value) of -.230 (between estimator) to a high of -.252 (random effects). The only departure from this pattern is the set of estimates of the parameters on the schooling variables that obtain from the within estimator. For an Associates or higher degree, the estimated returns to schooling are quite higher for the within estimator of the fixed effects model. If any of the other estimators is deemed consistent (the GEE estimator perhaps), at first blush the direction of the difference in the estimates lends support to the argument offered by Willis and Rosen (1979). They argue that individuals pursuing their comparative advantage choose to remain high school graduates or become college graduates based on their comparative advantage. Thus, a high school graduate would not see her wages increase, upon earning a Bachelor's degree, by as much as someone with a comparative advantage in becoming a college graduate. This implies that (1) we cannot interpret the estimated returns to schooling (from cross sectional data) as the wage rate increase that a high school graduate would have earned had she gone to college. And (2), that the estimated returns to schooling underestimate the true return for those individuals who have a comparative advantage in becoming college graduates.

This is precisely what the estimates in Table 7 suggest. The GEE estimates, for instance, of the returns to a given degree are a based on a weighted average of the within-person difference in earnings upon earning the degree, and the between-person difference in earnings between those with and without the given degree. The within-person estimate, instead, is based solely on earnings growth for individuals who do eventually earn the given degree.

This finding is made possible because of the nature of the NLSY: the fact that we observe a great many individuals in the sample working prior to and after they attain given degree levels.

Table 8 reports the GEE estimated correlation matrix of residuals of the log weekly wage equation. The GEE estimator imposes no structure on the correlation matrix. The results are quite striking. First, it is immediately apparent that the often specified covariance structure of the random-effects model is entirely at odds with these data. The off-diagonal terms show a pronounced decline as they get farther away from the main diagonal. Nor is a simple serial correlation process like AR(1) a good fit—the correlations do not get steadily smaller as the residuals move farther apart in time. In fact they rather level off quite above zero. Lastly, the correlations between residuals that are one and two and three years apart grow larger as the workers accumulate more wage observations. This is a correlation structure that no combination of random effects and serial correlation can generate.

Lillard and Willis (1978), in their study of dynamic aspects of earning mobility, estimate a random-effects, serially correlated covariance structure using a sample of men aged 18 to 58 (at the start of the panel) from the Panel Study of Income Dynamics (PSID). Their estimate of the correlation in adjacent years is 0.840, and it is 0.775 for observations two years apart, and declines asymptotically to 0.731. Our estimates of the one-year apart correlations range from 0.16 to 0.64, and the majority are of the order of 0.40, about half the Lillard and Willis estimate. One likely, partial, explanation for this difference lies in the age composition of the two samples. The NLSY is a much younger sample than the PSID sample they use. Our estimates strongly suggest that the adjacent year correlations increase steadily with time in the labor force. Another possible source for this difference may be our inclusion of women in the sample.

Our estimates of the correlations for observations farther apart than one year decline far more quickly than do theirs. If our estimates are not driven exclusively by the relative "youth" of our sample (the oldest sample members are 36 years old in 1993) they cast doubt on Lillard and Willis's conclusion that "the majority of cross-section earnings variation is due to permanent rather than transitory factors ... there is a considerable tendency for individuals to retain their position in the earnings distribution over time ...."

In Table 9 we present the GEE estimates of the rates of depreciation or decay of the human capital acquired through full- and part-time work and through unemployment. We also report z-statistics and the 95 percent confidence intervals. The top panel in Table 9 reports the coefficients that result from the set of estimates presented in Table 7. The middle panel reports the estimates from estimating the log wage regression equation with a sample of men only. The full set of estimates for the sample of men is reported in Appendix Table A1. The bottom panel of Table 9 presents GEE estimates of the rates of decay from a sample of women only, and the full set of regression coefficient estimates for the women appear in Appendix Table A2.

The estimates are surprisingly different for the men and the women. The estimated rates of decay for the men for post-highest degree activities are 9.1 percent (full-time work), 14.6 percent (part-time work), and –4.0 percent (unemployment). A negative rate of decay implies appreciation, but in this case the estimate is not significantly different from zero. For pre-degree full-time work the estimated rate of decay for the men is 5.9 percent. The estimates suggest that the negative impact on wages of a spell of unemployment does not go away over time. And the human capital that accumulates through work experience (full- and part-time) depreciates at a brisk pace, especially in the case of part-time work.

The estimates for the women, instead, are clustered around 7 percent: for post-degree activities they are 7.5 percent (full-time work), 8.0 percent (part-time work), and 6.4 percent (unemployment). The estimated rates of decay for pre-degree full-time work is only 3.8 percent with a z-statistic of 2.0. So while we must reject the notion that there exist "a" rate of depreciation for the activities of men, the estimates for the women suggest otherwise.

Table 10 presents the estimates of rates of depreciation that obtain from the other 4 estimators. The pattern they present is similar to the results from the GEE estimator. As we mentioned earlier, the full set of estimates for the separate samples of men and women are reported in Appendix Tables A1 and A2.

When we test the hypothesis that the four rates of decay (full- and part-time work, unemployment, and pre-highest degree full-time work) are equal, we fail to reject the hypothesis for the sample of women, across all specifications. For the men, we reject the hypothesis, and subsets of it, in all specifications.

5 Overview and Concluding Remarks

In this paper we present and estimate a wage regression specification that differs from the Mincer specification in its handling of work experience and other labor force activities. We form counts of time spent on various activities and compute a duration-weighted average age for each activity, therefore allowing for differences in the *timing* of work and unemployment across workers. In addition to the usual estimators typically used for panel data we use the Generalized Estimating Equations (GEE) estimator in the empirical implementation of the specification.

Both the amount and the timing of work-related behavior matters. The estimates suggest that, on average, every year of full-time employment (35 or more hours per week) is associated with 12.5 percent higher wages, while a year of part-time work (20 to 34 hours per week) is associated with 7.8 percent higher wages. A year of unemployment is associated with 5.7 percent lower wages. The only activity prior to receiving the current highest degree that matters for current wages is full-time work, which is associated with 7.9 percent higher wages for every year of work.

We find significant differences between the set of estimates that obtain from OLS, GEE, random-effects, and the between estimator versus the estimates from the within estimator of a fixed-effects model. At first blush the direction of the difference in the estimates lends support to the argument offered by Willis and Rosen (1979) that individuals pursuing their comparative advantage choose to remain high school graduates or become college graduates based on their comparative advantage.

Our GEE estimates of the correlation matrix of residuals of the log wage regression cast doubt on Lillard and Willis's conclusion that "the majority of cross-section earnings variation is due to permanent rather than transitory factors." Our estimates, which may only be valid for young workers, suggest otherwise.

The estimates of rates of decay are surprisingly different for the men and the women. The estimates for the men suggest that the negative impact on wages of a spell of unemployment does not go away over time. And the human capital that accumulates through work experience (full- and part-time) depreciates at a brisk pace, especially in the case of part-time work. The estimates for the women, instead, are clustered around 7 percent.

Regarding extensions to this work, three obvious ones come to mind. The first one is to treat schooling as just another activity, perhaps with negative obsolescence. That is, the human capital that accumulates through schooling improves with use so recency is costly. This treatment of schooling permits a natural incorporation of work while enrolled in school and interruptions to schooling, for marriage and childbirth or for "real world" work experience. An additional refinement is to measure activities more finely, e.g., experience in the current job versus "other" work experience. Lastly, one can address the question of whether interruptions are foreseen. Polachek, in a series of articles, suggests that women select occupations with low atrophy rates.

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