Changes across Cohorts in Wage Returns to Schooling and Early Work Experiences*

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Abstract

This paper investigates the wage returns to schooling and actual early work experiences, and how these returns have changed over the past twenty years. Using the NLSY surveys, we develop and estimate a dynamic model of the joint schooling and work decisions that young men make in early adulthood, and quantify how they affect wages using a generalized Mincerian specification. Our results highlight the need to account for dynamic selection and changes in composition when analyzing changes in wage returns. In particular, we find that ignoring the selectivity of accumulated work experiences results in overstatement of the returns to education.

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1 Introduction

Since the 1970s, there have been dramatic changes in the structure of the U.S. labor market. Foremost among these is a steep increase in the college wage premium during the 1980s, followed by a slower increase thereafter (see, e.g., Katz and Murphy, 1992; Card and Lemieux, 2001; Carneiro and Lee, 2011; Valletta, 2019). The characteristics and skill accumulation of American youth also have changed over this same time period. For example, using data from the 1979 and 1997 panels of the National Longitudinal Survey of Youth, Altonji et al. (2012) note an increase in skills over time, along with an overall widening of the skill distribution which appears to be driven by trends in parental education. College attendance has drastically increased, college graduation has been delayed, and the average amount of in-college accumulated work experience has gone up (see, e.g., Bacolod and Hotz, 2006; Scott-Clayton, 2012; Bound et al., 2012). Accounting for these changes in composition is important to understand how the premium for skill investment has evolved over time.

Our paper addresses three related research questions. First, what are the cross-cohort changes in the wage returns to schooling and early career work experiences? Second, how much of the cross-cohort change in the college wage premium actually reflects an increase of in-school, and, more generally, early work experience? Third, how did the returns to cognitive ability and other non-cognitive skills change across cohorts of young men? Answering these questions requires controlling for selection into schooling and work experiences. We do this by specifying and estimating, for two different cohorts, a dynamic model of schooling and work decisions. We estimate this model with data on two longitudinal data sets, the 1979 and 1997 panels of the National Longitudinal Surveys of Youth (NLSY), with our 1979 panel containing data on young men born in 1959–1964 and our 1997 panel on those born in 1980–1984.

Our use of longitudinal, rather than repeated cross-sectional, data allows us to more accurately measure early-career schooling and actual accumulated work experiences and to account for their endogeneity.[1] From each of the NLSY surveys, we construct comparable

[1] See also Bacolod and Hotz (2006); Altonji et al. (2012); Castex and Dechter (2014); Lee et al. (2015); Böhm (forthcoming); Deming (2017), who also have used NLSY data to make cross-cohort comparisons about the labor market.

measures of schooling, employment, and military histories from ages 16 through 35, along with comparable measures of earnings, educational attainment, cognitive skill, local labor market and higher-education conditions, and personal and family background characteristics. From these histories, we are able to construct measures of multiple dimensions of human capital investment, including whether or not work experience occurred simultaneously with schooling. Of particular relevance for us is the important work of Altonji et al. (2012), who also use the NLSY 1979 and 1997 surveys to document the cross-cohort changes in the unobserved distribution of cognitive ability. We follow Altonji et al. (2012) to construct comparable measures of correlates of unobserved cognitive ability from the Armed Services Vocational Aptitude Battery (ASVAB) administered to respondents in each panel of the NLSY.[2] However, while their analysis highlights the implications of the changes in skill distribution in terms of wages and employment, in this paper we focus instead on the endogeneity of skill accumulation—i.e., schooling and work experiences—and document how the returns to these skills, as well as to cognitive ability, have changed across these cohorts.

Our analysis builds on the extensive literature that estimates the returns to schooling, beginning with the seminal work of Mincer (1974), who introduced what has become known as the Mincer model. This model interprets the coefficient on schooling in a log wage equation that controls for a quadratic in potential experience as a rate of return. Heckman et al. (2006a) show that using flexible polynomials of schooling and potential work experience in the wage equation, as well as allowing for non-linearities associated with degree completion (also known as "sheepskin effects"), is essential to accurately estimate the returns to schooling. Extending the insights of Heckman et al. (2006a), an important contribution of our paper is to show that it also is crucial to use *actual*, rather than *potential*, work experience when estimating the returns to the latter and that accounting for actual work experiences also affects estimated returns to schooling.

We deal with selection into schooling and work experiences by specifying and estimating a dynamic model of schooling and work decisions that controls for person-specific unobserved heterogeneity.[3] We follow Cameron and Heckman (1998, 2001) and Heckman et al. (2006b),

[2] A subset of the measures in the ASVAB are used to construct the Armed Forces Qualifying Test (AFQT) score, which is used by the U.S. Military in determining qualifications of young adults for military enlistment.

[3] See also recent work by Belzil and Hansen (2019) who estimate, using data from the NLSY79 and

among others, and use a factor model to reduce the dimensionality of the unobserved state space.[4] We use initial background conditions, local college conditions, cognitive test scores and the panel structure of the data to identify the heterogeneity factors. Noteworthy, unlike most of the literature on the wage returns to schooling and work experience, we separately account for work experience that is accumulated before or after graduation. Distinguishing between these two forms of work experience is important since they may be rewarded differently upon post-schooling labor market entry. Furthermore, failure to account for pre-graduation work experience may bias estimates of the returns to schooling by incorrectly attributing to schooling the portion of the wage that in fact corresponds to in-school work experience.[5]

Our paper also contributes to the literature on understanding the effect of in-school work on future educational and labor market outcomes (Hotz et al., 2002; Bacolod and Hotz, 2006; Scott-Clayton, 2012; Baum and Ruhm, 2016). Working while in school may cause students to take longer to complete schooling, or drop out altogether. However, accumulating work experience during school also may have long-term benefits in the form of higher wages. Key to distinguishing between the costs and benefits of in-school work is accounting for the selection decisions of the individuals who participate. If, for example, high-ability students disproportionately obtain in-school work experience and are much more likely to graduate from high school and/or college, then failure to account for this type of selection will produce misleading policy conclusions about the labor market benefits of in-school work experience. We attempt to account for such selection in our econometric analyses.[6]

NLSY97, a dynamic model of schooling choices in which they control for dynamic selection on unobservables. Unlike Belzil and Hansen (2019), we account in our paper for dynamic selection into schooling as well as work experiences. Furthermore, while their paper focuses on the determinants of schooling outcomes, our main focus is on the wage returns to schooling and work experiences. Related research by Kejriwal et al. (forthcoming) also examines changes over time in the return to schooling. Using data from the Survey of Income and Program Participation (SIPP) linked with administrative earnings data, they account for multi-dimensional unobserved heterogeneity using an interactive fixed effects framework. Their approach does not account for actual work experience.

[4]For other examples of factor models that have been used in the context of the returns to schooling, see, among others, Taber (2001); Hotz et al. (2002); Cunha et al. (2011); Heckman et al. (2018).

[5]For example, Arcidiacono et al. (2016) find that pre- and post-graduation work experience is rewarded differently for college graduate workers.

[6]Hotz et al. (2002) also control for dynamic selection into in-school work when estimating the returns to in-school work experience. Unlike Hotz et al. (2002), our paper explicitly accounts for the fact that unobserved skills are multidimensional in nature.

Using estimates of our dynamic model, we examine the selection-corrected returns to schooling and work experiences, as well as to unobservable cognitive and other, non-cognitive skills, and how they changed across the cohorts we study. Our findings contribute to a small but growing empirical literature that has focused on decomposing the trends in the returns to education (Taber, 2001; Fang, 2006; Fortin, 2006; Lee and Wolpin, 2010; Cunha et al., 2011; Carneiro and Lee, 2011).[7]

We find that failure to account for selection into various types of schooling and work experience results in sizable overstatements of the wage returns to degree attainment, and a slight understatement of the wage returns to completed years of schooling. In addition, our selection-corrected estimates indicate that the return to an additional year of schooling is 3 percentage points higher among recent cohorts. With respect to degrees, we find that the return to a high school degree was slightly higher for the NLSY97, but find no meaningful difference across cohorts in the returns to a bachelor's degree.

At the same time, controlling for selection has less of an effect on the returns to actual in-school and post-schooling work experiences than on the returns to schooling. The selection-corrected estimated returns to working while in high school are negative for both cohorts, more so for more recent ones, while early cohorts had a 6% return to working while in college, but none for more recent ones. With respect to post-schooling work experiences, selection-corrected return to part-time work is negative for both cohorts, more so for the earlier cohorts, while return to full-time work ranges from 2% to 4%, with more recent cohorts having a higher one.

Finally, based on our selection-correction factor model, we find sizable returns to both cognitive and other, non-cognitive skills, with the returns to cognitive skills being lower for more recent cohorts relative to earlier ones, while returns to other non-cognitive skills are considerably higher for the more recent cohorts compared to the earlier ones.

The remainder of the paper is organized as follows. Section 2 details the data we use and its construction; Section 3 presents descriptive statistics for the two cohorts we examine. In Sections 4 and 5, we lay out the specification and estimation of our econometric model. In

[7]While they focus on a different set of questions, Lee and Wolpin (2010) is particularly relevant for us as, to do so, they estimate a dynamic structural (equilibrium) model of schooling and work decisions in which they distinguish between six different types of sector-occupation-specific skills.

Section 6, we present the results for our various models and their implied returns to schooling and work experiences, along with those for unobserved skills. Finally, Section 7 summarizes the paper and discusses some implications of our findings. All tables are collected at the end of the paper.

2 The Data

The data we use to determine the wages, education and types of work experience across cohorts are derived from two panels of the National Longitudinal Survey of Youth (NLSY), the NLSY79 and NLSY97. These surveys interview American youth beginning in their adolescent years and follow them through adulthood. They contain information on education, employment, background variables and location (county), among many others. The NLSY79 began in 1979 with a sample of respondents born in 1957–1964, when they were aged 14–22. The respondents in the NLSY97 were born in 1980–1984, and were first interviewed in 1997 when they were aged 12–17.

From these data, we make several sample selections. First, we restrict our analysis to male respondents.[8] Second, we restrict ourselves to the male respondents in the NLYS79 who were no more than age 20 in 1979 (i.e., were born in 1959–1964), in order to minimize recall error at the first interview about their work and schooling experiences during adolescence (no such restrictions were imposed on the NLSY97, given that the oldest respondents were only age 17 at the start of the latter survey). Third, we drop respondents in the military and in the economically disadvantaged white NLSY79 oversamples, since the former oversample was not followed after 1984 and the latter oversample was not followed after 1990. Finally, we drop respondents who were screened as "mixed race" in the NLSY97, since this was not an option in the NLSY79. After these restrictions, which are documented in detail in Appendix Tables A.1 and A.2, we end up with 3,862 male respondents from the NLSY79 and 4,559 from the NLSY97. In all of the analysis presented below, we split our data by these two NLSY surveys. One set of birth cohorts consists of NLSY79 respondents born in

[8]We focus on men for two main reasons: (*i*) including women during early adulthood would require us to model their fertility decisions, which is outside of the scope of the present analysis; and (*ii*) much of the literature that has studied human capital formation to which our analysis is comparable has focused on men.

years 1959–1964 (henceforth referred to as "NLSY79"), while the other set of birth cohorts consists of NLSY97 respondents (henceforth referred to as "NLSY97").

In both of the NLSY surveys, individuals are interviewed annually for the first 15 survey rounds and biennially thereafter. At each interview, respondents provide a history of what has transpired in their lives since the previous interview.[9] For example, the survey collects information on all jobs held between the current and previous interview, the wage and hours worked at each of those jobs, and the industry and occupation code of each job. Data related to educational attainment and schooling enrollment/attendance are similarly rich. Linking the survey reports together, it is possible to get measures of employment, schooling enrollment, military service, and hourly wages for those employed on a month-by-month basis. We track activities on a monthly basis so as to be able to distinguish between work experience that occurred during school as opposed to over the summer or between semesters, as well as work experience that occurred before graduation as opposed to after graduation. In the analysis below, we focus on the activities of respondents in our two cohorts over the ages 16 through 35, covering the years 1975 through 1999 for the NLSY79 and 1996 through 2016 for the NLSY97.[10]

With respect to initial conditions, young men in both cohorts are asked detailed questions in their first interview about their family situations. These family background characteristics (parental education, family income and household structure) are assumed to affect labor market outcomes only through activity choices, and, as such, serve as exclusion restrictions in our econometric model. In addition, the NLSY tracks the location of each individual in the surveys. Using the restricted-access Geocode supplement of the NLSY data, we are able to match individuals in the NLSY with county-level data from the Census Bureau, Bureau of Labor Statistics (BLS), and Bureau of Economic Analysis (BEA). This allows us to analyze the local labor market conditions that each individual faces over time. With additional data from the Integrated Postsecondary Education Data System (IPEDS), we

[9]At the first interview, the survey asked extensive questions related to working and schooling history before the survey. Thereafter, for respondents who missed an interview, interviewers attempted to contact the individual during the following cycle and collect data on experiences between the current interview and the most recently completed interview.

[10]See Appendix Tables A.1 and A.2 for the number of person-months observations for each of our birth cohorts and Appendix Table A.3 for the ages and years covered for each.

create variables representing the higher-education landscape that these young men faced as teenagers (presence and number of four-year colleges in the age-16 county of residence and tuition at state flagship university), which serve as further exclusion restrictions (see Section 5.3).

Our analysis is conducted on the following two samples: 3,852 men in the NLSY79 (854,179 person-month observations) and 4,443 men in the NLSY97 (792,652 person-month observations).[11] The additional sample cuts are due to attrition from the survey or missing interview spells of three or more years. A complete summary of sample selection criteria is included in Appendix Tables A.1 and A.2. In Appendix A, we also describe the construction of the variables used in our analysis from the NLSY79 and NLSY97 data, as well as the other data sources.

3 Cohort Differences in Background Characteristics, Skill Attainment and Skill Wage Premia

In this section, we present some stylized facts across our two cohorts about differences in backgrounds, skill attainment, and wage premia to skills. We present these numbers at age 29—an age by which almost all individuals have completed their educational attainment.[12]

3.1 Personal and family background

We start by describing the differences across our two cohorts in personal and family background characteristics.

In the first panel of Table 1, we show differences in race/ethnicity and nativity. There is no change in the percentage of African Americans, but we do see a very significant increase in the percentage of Hispanics across cohorts (from 7% to 14%). Interestingly, there is no significant change in the percentage of those who were born outside of the United States.

In the next panel of Table 1, we display differences in mothers' and fathers' education, family income, and status of who is the head of the household.[13] Between the NLSY79 and

[11] Our wage analysis comprises 464,330 person-month observations in the NLSY79 and 422,114 person-month observations in the NLSY97.

[12] Keeping in mind that we are using monthly data, the numbers are calculated in the month before the respondents turn 29.

[13] These are the family background variables that make up some of our model's exclusion restrictions.

the NLSY97 cohorts, parental education increased by more than one grade level for mothers and more than four-fifths of a grade level for fathers. With respect to the more recent cohorts, they grew up in households with higher family income ($33.58K vs. $32.86K), although this difference is not statistically significant. Finally, the share of young men in our samples that grew up in female-headed households increased by 11 percentage points between the NLSY79 and NLSY97.[14]

There also are differences across the two cohorts in measures of cognitive skills. We focus here on differences in scores on the Armed Forces Qualification Test (AFQT).[15] The third panel of Table 1 displays the median and standard deviation of AFQT scores for the two cohorts, as well as cross-cohort differences. AFQT scores for the NLSY97 are, in general, higher and more dispersed than those for the NLSY79, with an overall large (but not statistically significant) increase of 0.07 standard deviations in the *median score* as well as a small (but statistically significant) increase in the standard deviation itself. These results are consistent with the findings of Altonji et al. (2012), who document a widening of the AFQT distribution between the NLSY79 and NLSY97 cohorts.

3.2 Educational attainment and work experiences

We now consider differences across the two cohorts in months of accumulated schooling and work experiences, and educational degree attainment.

Table 2 describes schooling attainment and college completion at age 29 for both cohorts. In the first panel, there is a clear increase over time in educational attainment. While there is little change in the high school dropout rate over time, there is a 3 percentage point increase in those that complete some college and a 4 percentage point increase in those that receive a

[14] In Appendix Table B.2, we show cross-cohort differences in local labor markets and local college characteristics. The local college characteristics account for the remainder of our exclusion restrictions.

[15] The AFQT is a subset of the ASVAB (Armed Services Vocational Aptitude Battery). Specifically, AFQT scores are a weighted average of four ASVAB sub-tests: Arithmetic Reasoning (AR), Mathematics Knowledge (MK), Paragraph Comprehension (PC), and Word Knowledge (WK). In our model, we make use of six ASVAB sub-tests, the four in the AFQT as well as Coding Speed (CS) and Numerical Operations (NO).

To make both the AFQT and ASVAB scores comparable across cohorts, we follow Altonji et al. (2009) and Altonji et al. (2012) by making use of an equipercentile mapping in ASVAB test scores that corrects for both testing medium (i.e. pencil and paper vs. computer assisted) and age at test (NLSY97 respondents were much younger than NLSY79 respondents when they took the ASVAB).

bachelor's degree. For comparison purposes, in Appendix Table B.1, we report educational attainment from identically-aged men in the Current Population Survey (CPS); the CPS shows cross-cohort changes similar to those in the NLSY.[16]

In the second panel of Table 2, we find an increase in the number of young men starting college, although there is not a significant change in the college graduation rate among those who start (though there is a nominal increase). Further, we see a significant increase of two-fifths of a year in the time to a college degree, which finding is consistent with Bound et al. (2012).

We also examine differences across the two cohorts in months of accumulated schooling and work experience. Table 3 reports average levels of schooling and work experience (in months) by age 29 (beginning at age 16). Consistent with Table 2 and Bound et al. (2012), we find that students in the NLSY97 spent longer in school by almost a full year. Despite this, those in the NLSY97 also accumulated slightly *more* total work experience by age 29 as the NLSY79 (almost 2 months more). That said, there were differences in the types of work experience the two cohorts accumulated by this age. In particular, there was an increase across cohorts in the accumulated level of in-high-school work experience (about 2.5 months), and a much larger increase in in-college work experience (over 8 months). Furthermore, while the overall level of out-of-school part-time work was basically the same, the overall level of out-of-school full-time work sharply declined (by over 9 months).

These differences across cohorts in the types of accumulated work experiences that young men experienced motivate our differential treatment of in-school and out-of-school work experience.

3.3 Wage premia

Finally, we examine how wage premia have varied across our two cohorts by documenting how the association between wages at age 29 and amounts of schooling or work experience has changed across cohorts. Herein, we refer to differences in wages across school and work experience levels as "wage premia," although we hasten to add that these measures are not to

[16] For a more complete comparison of educational wage premia in the NLSY, CPS, and other major US household surveys, see Ashworth and Ransom (2019).

be interpreted as causal effects. Below, in Sections 4 and 5, we develop a model to estimate the causal effects of schooling and work experience on wages.

The first panel of Table 4 reports the wage premia associated with various experiences for those working full-time at age 29. Each row shows the mean change in the full-time log wage with an additional year of each type of experience. The wage premia are highest for working in college, in the range of 7% to 9%.[17] On the other hand, out-of-school part-time work experience is associated with lower wages, in the range of -9 to -13% for an additional year of experience.[18] For full-time work experience, the wage premia are small and not statistically different from zero. For each of the work experience wage premia, we see a decrease over time. The model we present in the next section will shed light on whether these patterns in wage premia similarly hold for wage returns.

The other panels of Table 4 allow us to assess how the observed wage premia associated with educational attainment have changed across these cohorts. The second panel shows average log wages associated with the four different educational attainments described in Table 2, and reveals a decrease in inflation-adjusted wage levels over time of between 3 and 10 log points for each education level. The third panel shows the wage premia for each degree. Most notable is the significant decrease in the college wage premium, which is 3 log points lower in the more recent cohort.[19]

As noted above, our discussion thus far has ignored the possibility that selective differences in educational attainment and accumulated work experiences may affect the suggested impacts of the latter on wages among young men and how they changed across cohorts. In the next section, we introduce the model that we use to account for selection into the various

[17] To further investigate whether the timing of in-college work experience matters, we separate in-college work experience into two types: experience attained in the freshman and sophomore year, and experience attained in later years of college. Table 4 shows that earlier in-college work experience has a larger premium in the NLSY79, but that the two have similar premia in the NLSY97.

[18] As we will show later in the paper, this negative association partly reflects negative selection into part-time work.

[19] While our finding of a decreasing college wage premium between the NLSY79 and the NLSY97 is at odds with some previous research (Castex and Dechter, 2014; Böhm, forthcoming; Deming, 2017), it is consistent with some recent studies of changes in wages over time and is robust to a number of different specifications. Ashworth and Ransom (2019) perform a full comparison of the college wage premium using five different U.S. surveys and find that, compared to other U.S. surveys, the NLSY shows a much lower college wage premium for the NLSY97 cohorts and a much lower advanced degree premium for the NLSY79 cohorts born in 1960–1964.

types of experience, and, in our final results, present and discuss selection-corrected wage returns. The differences we have documented in schooling and work experiences, as well as in personal and family background characteristics, are the prime motivation for our model in which we estimate the evolution of wage returns to skills by accounting for these changes in composition.

4 The Model

In this section, we develop a dynamic model of schooling and work decisions. We use it to form an econometric model that accounts for the endogeneity of accumulated schooling and work experiences in the estimation of wage returns across our two cohorts.

4.1 Activity choices

We assume that, at each age a—which is measured in months in our case—individual i, who is a member of birth cohort c, chooses *activity* j from a set of possible activities, which may vary with age and/or the occurrence(s) of one or more previous events. For simplicity, we suppress notation indexing the individual's cohort. We estimate the model separately for both the NLSY79 and NLSY97 cohorts, so all the parameters should be understood as cohort-specific. Let R_{ia} denote the choice set for individual i at age a, where we assume that there are K possible choice sets, i.e., $R_{ia} = r \in 1, \ldots, K$. Then, conditional on facing choice set $R_{ia} = r$, individual i chooses from among J^r activities, where we define

$$d_{iaj}^r = \begin{cases} 1 & \text{if } i \text{ chooses activity } j \text{ from choice set } r \text{ at age } a \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

and $\sum_{j=1}^{J^r} d_{iaj}^r = 1$, for all i, a and r. In practice, we consider $K = 3$ choice sets, which are composed of the potential activities for those who: (i) have not graduated from high school ($R_{ia} = 1$); (ii) have graduated from high school but have not graduated from college ($R_{ia} = 2$); and (iii) have graduated from college ($R_{ia} = 3$). The three choice sets and the activities associated with each are given in Table 5.

4.2 School and work experiences

We are interested in estimating the effects of accumulated experiences on various outcomes. In particular, we are interested in accumulated years of school attendance, as well as years of work experiences. We also use our model to estimate the effect of educational attainment, such as high school and college graduation, on these outcomes. In the following, we will refer to these work experiences, schooling activities and graduation outcomes collectively as "experiences." The vector of types of experience is given by:

$$\mathbf{x}_{ia}^r \equiv \Big(x_{1ia},\quad \mathbf{x}_{2ia}^r,\quad x_{3ia},\quad x_{4ia},\quad x_{5ia},\quad x_{6ia},\quad I_{ia}(R_{ia} > 1),\quad I_{ia}(R_{ia} = 3)\Big)' \tag{2}$$

where the experience variables are: x_{1ia}, the number of years of schooling attendance as of age a; $\mathbf{x}_{2ia}^r$, the number of years of in-school work experience (given the relevant choice set r); x_{3ia}, the total number of years of part-time (non-school) work as of age a; x_{4ia}, the total number of years of full-time (non-school) work as of age a; x_{5ia}, the number of years in the military as of age a; x_{6ia}, the number of years spent in other activities as of age a;[20] $I_{ia}(R_{ia} > 1)$, an indicator equal to 1 if individual i has received a high school degree as of age a; and $I_{ia}(R_{ia} = 3)$, an indicator equal to 1 if individual i has received a bachelor's degree as of age a.[21] For $j = 1, 3, \ldots, 6$, the experience variables are accumulated from a starting age, $a_0 = 192$ (16 years old):[22]

$$x_{jia} = \frac{1}{12} \sum_{\ell=a_0}^{a-1} d_{i\ell j}. \tag{3}$$

For $j = 2$ and before high school graduation, the vector $\mathbf{x}_{2ia}^r$ is a scalar for the number of years spent working in high school since a_0, $x_{2,HS,ia}$. If the individual has graduated from high school, then the vector contains two elements: the number of years already accumulated from working while in high school and the number of years spent working while in college or

[20]This residual category includes home production as well as unemployment.

[21]Note that schooling experience x_{1ia} is the sum of school-only and work-in-school experience so as to be comparable to the literature originating with Mincer (1974).

[22]Since there is no ambiguity here, we suppress the r superscript from the activity indicators d_{ilj}^r.

graduate school, $x_{2,COL,ia}$. Thus,

$$\mathbf{x}^r_{2ia} \equiv \begin{cases} x_{2,HS,ia} & \text{if } R_{ia} = 1 \\ (x_{2,HS,ia}, x_{2,COL,ia}) & \text{if } R_{ia} > 1, \end{cases} \tag{4}$$

where

$$x_{2,HS,ia} = \frac{1}{12} \sum_{\ell=a_0}^{a-1} d_{i\ell 2}$$
$$x_{2,COL,ia} = \frac{1}{12} \sum_{\ell=a_{HS_i}}^{a-1} d_{i\ell 2} \text{ if } R_{ia} > 1,$$

and where a_{HS_i} is the age of graduation from high school.

4.3 Wages

Let W_{iaj} denote the potential hourly wage rate that individual i would realize at age a if he were to choose activity j, $j = 2, 3, 4$. We assume that W_{iaj} is determined by the individual's accumulated human capital, or skills, H_{ia}, as of the beginning of age a, measured in efficiency units; the occupation-specific skill price P_{iaj} per efficiency unit that varies across the local labor market in which i resides at age a;[23] and idiosyncratic shocks, denoted by $e^{\varepsilon_{iaj}}$, that are unanticipated by the individual:

$$W_{iaj} = P_{iaj} H_{ia} e^{\varepsilon_{iaj}}, \tag{5}$$

so that the log of wages, denoted by w_{iaj}, is given by the following linear function:

$$\begin{aligned} w_{iaj} &= p_{iaj} + h_{ia} + \varepsilon_{iaj} \\ &= w^e_{iaj} + \varepsilon_{iaj}, \end{aligned} \tag{6}$$

where $p_{iaj} \equiv \ln P_{iaj}$, $h_{ia} \equiv \ln H_{ia}$, and $w^e_{iaj} \equiv p_{iaj} + h_{ia}$ is i's expected log wage at age a, i.e., the wage that i expects to get if he chooses activity j. We assume that p_{iaj} is the following

[23] See Moretti (2011) for a survey of models of local labor markets.

function of the conditions of the local labor market in which i resides at age a, $\mathbf{m}_{ia}$:

$$p_{iaj} = \beta_{0j} + \boldsymbol{\beta}_{\mathbf{m}}\mathbf{m}_{ia}. \tag{7}$$

We further assume that the (log of the) individual's stock of human capital, h_{ia}, is determined by some observed personal characteristics, e.g., one's birth year, race, etc., denoted by the vector $\mathbf{z}_i$, the individual's accumulated schooling and work experience and degree completion, $\mathbf{x}_{ia}^r$, and the individual's unobserved characteristics, $\boldsymbol{\xi}_i$, which are broken out into elements pertaining to the individual's cognitive (ξ_{1i}) and other (non-cognitive) abilities (ξ_{2i}):

$$h_{ia} = \boldsymbol{\beta}_{\mathbf{z}}\mathbf{z}_i + \boldsymbol{\beta}_{\mathbf{x}}g\left(\mathbf{x}_{ia}^r\right) + \beta_{\xi 1j}\xi_{1i} + \beta_{\xi 2j}\xi_{2i}. \tag{8}$$

It follows that

$$\begin{aligned} w_{iaj} &= w_{iaj}^e + \varepsilon_{iaj}, \\ &= \beta_{0j} + \boldsymbol{\beta}_{\mathbf{m}}\mathbf{m}_{ia} + \boldsymbol{\beta}_{\mathbf{z}}\mathbf{z}_i + \boldsymbol{\beta}_{\mathbf{x}}g\left(\mathbf{x}_{ia}^r\right) + \beta_{\xi 1j}\xi_{1i} + \beta_{\xi 2j}\xi_{2i} + \varepsilon_{iaj}, \end{aligned} \tag{9}$$

where $g(\cdot)$ contains: (i) a cubic polynomial in all types of accumulated experience;[24] (ii) pairwise interactions between school experience and each of the work experience variables (work in school, part-time work and full-time work); and (iii) indicators for having graduated high school and for having graduated college (see also Heckman et al., 2006).

One of our primary interests is in obtaining consistent estimates of the parameters in (9). As we make clear below, the central obstacle is that the elements of $\mathbf{x}_{ia}^r$ are endogenous unless one conditions on the unobserved factors, $\boldsymbol{\xi}_i$. We now develop the nature of that linkage through the sequences of activity choices individual i makes over his life cycle.

4.4 Activity-specific value functions

Let the value function for individual i who is of age a and who engages in activity j (from choice set r) be denoted by V_{iaj}^r. These value functions depend on the elements of the in-

[24] See also Belzil and Hansen (2002) who estimate the returns to schooling using an extended Mincerian specification in which they relax the assumption that wages are linear in the number of years of schooling.

dividual's information set at age a, namely, personal characteristics, $\mathbf{z}_i$, family background characteristics, $\mathbf{f}_i$, local college characteristics at age 16, $\mathbf{c}_i$, local labor market characteristics, $\mathbf{m}_{ia}$, accumulated school and work experiences $\mathbf{x}^r_{ia}$, and the individual's unobserved characteristics, $\boldsymbol{\xi}_i$.[25] For computational simplicity, we approximate the V^r_{iaj}'s as a sum of a linear function of these characteristics and interactions between $\mathbf{x}^r_{ia}$ and $\mathbf{z}_i$:

$$\begin{aligned} V^r_{iaj} &= \boldsymbol{\alpha}^r_{\mathbf{z}j}\mathbf{z}_i + \boldsymbol{\alpha}^r_{\mathbf{f}j}\mathbf{f}_i + \boldsymbol{\alpha}^r_{\mathbf{c}j}\mathbf{c}_i + \boldsymbol{\alpha}^r_{\mathbf{m}j}\mathbf{m}_{ia} + \boldsymbol{\alpha}^r_{\mathbf{x}j} b\left(\mathbf{x}^r_{ia}, \mathbf{z}_i\right) + \alpha^r_{\xi 1j}\xi_{1i} + \alpha^r_{\xi 2j}\xi_{2i} + \omega_{iaj} \\ &= v^r_{iaj} + \omega_{iaj}, \end{aligned} \tag{10}$$

where $b\left(\cdot\right)$ contains: (i) a set of up to nine bin indicators for each type of accumulated experience; and (ii) linear interactions between race/ethnicity and each type of accumulated experience.[26] Finally, ω_{iaj} captures the idiosyncratic factors that affect the individual's value from choosing activity j at age a.

It follows that at each age a, individual i chooses the activity j^{r*}_{ia} from among the activities in the current choice set that yields the highest value:

$$j^{r*}_{ia} = \underset{j}{\operatorname{argmax}}\, V^r_{iaj}. \tag{11}$$

4.5 Unobserved skills

Our model incorporates two unobserved random factors representing the unobserved cognitive and other, non-cognitive abilities of individuals. To measure unobserved cognitive ability (ξ_{1i}), we use six subject tests from the ASVAB.[27] We chose to include these subjects

[25] See Appendix Table A.4 for a detailed description of these elements.

[26] As an example of the bin indicators, we include a set of nine bins for the number of months of full-time work experience outside of school. The cut points for each of the bins occur at the following values: 12 months, 24 months, 36 months, 48 months, 60 months, 72 months, 84 months, and 96 months. While the choice of cut points for each experience is different, the cut points are constant across NLSY cohorts. Allowing the different types of experience to vary in this way allows us to estimate highly non-linear effects of experience on the decision to invest in different types of human capital. This non-linear relationship is necessary in order to match the observed data. All experience terms have nine bins except for military, which has five.

[27] The six subject tests we use are: Arithmetic Reasoning, Coding Speed, Mathematics Knowledge, Numerical Operations, Paragraph Comprehension, and Word Knowledge. The frequently used AFQT score is a composite of all of these subjects except for Coding Speed and Mathematics Knowledge. Our six subject tests are the same as used by Heckman et al. (2018).

because (i) each appears in both the NLSY79 and the NLSY97; and (ii) they are measure constructs typically thought to be associated with individuals' cognitive ability or skills. For each subject test s, the z-scored test score y for individual i is expressed as a linear function of personal characteristics $\mathbf{z}_i$ and the cognitive ability ξ_{1i}, namely

$$y_{is} = \gamma_{0s} + \boldsymbol{\gamma}_{\mathbf{z}s}\mathbf{z}_i + \gamma_{\xi 1s}\xi_{1i} + \eta_{is}, \tag{12}$$

where η_{is} captures idiosyncratic variation in test scores not related to the cognitive ability or other test score determinants.[28]

There is little overlap in the measures of non-cognitive traits across the two NLSY surveys.[29] Due to this data limitation, we are unable to include comparable measures of non-cognitive ability for both of our NLSY cohorts. For this reason, we rely on the panel nature of the data—along with exclusion restrictions to be discussed in the next section—to identify the residual ability factor ξ_{2i}. Thus, this second ability factor can be interpreted as non-cognitive in the sense that it captures all unobserved permanent person-specific determinants of the agent's wage and decision process that are orthogonal to the cognitive factor.

5 Inference

In this section, we further characterize our econometric model and the strategy for estimating its parameters. In particular, we summarize the specification of the error structure of our model and the estimation procedure we employ. For now, we continue to not notationally distinguish between the NLSY79 and NLSY97, although we allow all of the parameters of our model to be cohort-specific and we explicitly examine the cross-cohort differences in the estimated marginal returns to schooling and work experiences. Finally, we also discuss the identification of the model.

[28] The mean and standard deviation used to compute the z-scores are taken across both cohorts.

[29] The NLSY79 contains the Rotter locus of control score and Rosenberg self-esteem scale for all individuals. These have been used in other studies as non-cognitive measures (Heckman et al., 2006b; Cunha et al., 2011). The NLSY97 does not collect information on any of these tests, but instead collects information on risky behavior such as school suspensions, sexual promiscuity and substance abuse. See, e.g., Aucejo and James (2019) who use school suspensions, fights, precocious sex, grade retention, substance abuse, and 8th grade GPA as non-cognitive measures.

5.1 Error structure

We assume that $\boldsymbol{\xi}_i$ is a person-specific vector of factors that is stochastically independent of the distributions of the observables, $\mathbf{z}_i$, $\mathbf{f}_i$, $\mathbf{c}_i$, $\mathbf{m}_{ia}$, and of the unobservables, $\boldsymbol{\omega}_{ia}$, $\boldsymbol{\varepsilon}_{ia}$, and $\boldsymbol{\eta}_i$, for all a and i.[30] At the same time, because the choice of past activities determines the accumulated experience in $\mathbf{x}^r_{ia}$ it is not the case that the elements of this vector are independent of $\boldsymbol{\xi}_i$.

We further normalize, for both cohorts, the distribution of the unobserved factors $\boldsymbol{\xi}_i$ to be mean zero with an identity covariance matrix. With respect to $\boldsymbol{\omega}_{ia}$, $\boldsymbol{\varepsilon}_{ia}$, and $\boldsymbol{\eta}_i$, respectively, we assume that they are mutually independent, are independently distributed both across ages and at each age a, and have mean zero and constant variances. That the vector of activity shocks $\boldsymbol{\omega}_{ia}$ is uncorrelated with $\boldsymbol{\varepsilon}_{ia}$ is the result of assuming that decisions about activities are made at each age a before the actual realizations of wages are known by individual i.

5.2 Likelihood function and estimation method

We assume that the idiosyncratic errors in the activity payoff functions, ω_{iaj}, have a Type I extreme value distribution so that the choice probability for any individual i at age a to choose activity j in choice set r, conditional on the unobserved factors $\boldsymbol{\xi}_i$, has the logistic form:

$$P^r_{iaj} = \frac{\exp\left(v^r_{iaj}\right)}{\sum_{k=1,\ldots,J^r} \exp\left(v^r_{iak}\right)}, \tag{13}$$

where, as defined in the first line of (10), v^r_{iak} is the component of the value function associated with activity k that is deterministic from individual i's viewpoint. Recall that v^r_{iak} depends on the unobserved factors $\boldsymbol{\xi}_i$, and on personal characteristics $\mathbf{z}_i$, family background characteristics $\mathbf{f}_i$, local college characteristics at age 16 $\mathbf{c}_i$, local labor market characteristics

[30] The assumption that individual effects $\boldsymbol{\xi}_i$ are independent of the observable characteristics and of the idiosyncratic shocks is very common in dynamic discrete choice models. See, among others, Taber (2001); Belzil and Hansen (2002); Hotz et al. (2002); Heckman et al. (2006b).

$\mathbf{m}_{ia}$, as well as accumulated school and work experiences $\mathbf{x}_{ia}^r$:

$$v_{iak}^r = \boldsymbol{\alpha}_{\mathbf{z}j}^r \mathbf{z}_i + \boldsymbol{\alpha}_{\mathbf{f}j}^r \mathbf{f}_i + \boldsymbol{\alpha}_{\mathbf{c}j}^r \mathbf{c}_i + \boldsymbol{\alpha}_{\mathbf{m}j}^r \mathbf{m}_{ia} + \boldsymbol{\alpha}_{\mathbf{x}j}^r b\left(\mathbf{x}_{ia}^r, \mathbf{z}_i\right) + \alpha_{\xi 1j}^r \xi_{1i} + \alpha_{\xi 2j}^r \xi_{2i} \tag{14}$$

Additionally, we assume that the idiosyncratic errors entering the wage function in (9) are normally distributed with zero mean and variance $\sigma_{w_j}^2$. Thus, the corresponding contribution to the likelihood, conditional on $\boldsymbol{\xi}_i = \boldsymbol{\xi}$, is given by:

$$\ell_{w_{iaj}} = \frac{1}{\sigma_{w_j}} \phi\left(\frac{w_{iaj} - \beta_{0j} - \boldsymbol{\beta}_{\mathbf{m}} \mathbf{m}_{ia} - \boldsymbol{\beta}_{\mathbf{z}} \mathbf{z}_i - \boldsymbol{\beta}_{\mathbf{x}} g\left(\mathbf{x}_{ia}^r\right) - \beta_{\xi j1}\xi_1 - \beta_{\xi j2}\xi_2}{\sigma_{w_j}}\right), \; j = 2, 3, 4,$$

where $\phi(\cdot)$ is the standard normal pdf.[31]

We also assume that the idiosyncratic errors entering the ASVAB test score function in (12) are normally distributed with zero mean and variance $\sigma_{y_s}^2$. Thus the likelihood contribution, conditional on $\xi_{i1} = \xi_1$, is given by:

$$\ell_{y_{is}} = \frac{1}{\sigma_{y_s}} \phi\left(\frac{y_{is} - \gamma_{0s} - \boldsymbol{\gamma}_{\mathbf{z}s} \mathbf{z}_i - \gamma_{\xi s1}\xi_1}{\sigma_{y_s}}\right). \tag{15}$$

It follows that the (unconditional) log likelihood function is given by:

$$\log \mathcal{L}\left(\boldsymbol{\theta}\right) = \sum_i \log \int \mathcal{L}_i\left(\theta \,|\, \boldsymbol{\xi}\right) f_{\boldsymbol{\xi}}(\boldsymbol{\xi}) d\boldsymbol{\xi}, \tag{16}$$

where, conditional on $\boldsymbol{\xi}_i = \boldsymbol{\xi}$, the individual contribution to the likelihood is given by:

$$\mathcal{L}_i\left(\theta \,|\, \boldsymbol{\xi}\right) = \prod_s \ell_{y_{is}} \prod_a \prod_r \left[\prod_{j=1,5,6,7} \left(P_{iaj}^r\right)^{d_{iaj}^r} \prod_{k=2,3,4} \left[P_{iak}^r \ell_{w_{iak}}\right]^{d_{iak}^r}\right]^{I(R_{ia}=r)}, \tag{17}$$

with $\boldsymbol{\theta} \equiv \begin{pmatrix} \boldsymbol{\alpha}', & \boldsymbol{\beta}', & \boldsymbol{\gamma}' \end{pmatrix}'$, $I(A)$ is the indicator function that is equal to one if A is true and zero otherwise, and $f_{\boldsymbol{\xi}}(\cdot)$ is the pdf of $\boldsymbol{\xi}$. In the analysis that follows, we assume that $\boldsymbol{\xi}$ has a standard multivariate normal distribution, and estimate the model via maximum likelihood.[32]

[31] Recall that choice-set-specific intercepts are included in $\mathbf{x}_{ia}^r$ through degree attainment dummies.

[32] In practice, we use quadrature to approximate the integral of the likelihood function. Specifically, we use Gaussian quadrature with seven points of support for each dimension of the integral. As starting values

5.3 Identification

In this section, we discuss the identification of key features of the model. Note that we cannot readily identify the effects of endogenously-determined schooling and work experiences on wages or subsequent school and work decisions by relying on standard instrumental variables techniques, as finding valid instruments for these sequences of past choices over individuals' careers is very challenging, if not impossible.[33] Herein, we deal with dynamic selection into schooling and work experiences by explicitly modeling the underlying choice process, controlling for person-specific unobserved factors as in Cameron and Heckman (1998, 2001) and Heckman et al. (2006b). In what follows, we discuss how identification is achieved within this econometric framework.

First, one can use the results of Hu and Shum (2012) to show nonparametric identification of the conditional choice probabilities, P^r_{iaj}. This identification result relies on the first-order Markov structure, and the resulting dynamic exclusion restrictions implied by our dynamic discrete choice model.[34] Under the assumption that the idiosyncratic preference shocks are distributed following a Type 1 extreme value assumption, the conditional value functions are then identified (up to a reference alternative) by inverting the conditional choice probabilities, P^r_{iaj}.

We now turn to the unobserved individual factors, (ξ_1, ξ_2), and the outcome equations. Aside from the aforementioned dynamic exclusion restrictions, we also impose two types of exclusion restrictions which play an important role in identifying the covariate effects in the outcome equations, as well as the distribution and the returns to these unobserved factors (i.e. the factor loading parameters). First, we impose the restriction that the non-cognitive factor,

for the parameters, we use perturbed point estimates from the specification of the model without unobserved heterogeneity. Finally, standard errors are computed using the estimated cluster-robust asymptotic covariance matrix, which accounts for within-person serial correlation of the error terms.

[33] A number of papers in the returns to schooling literature follow Card (1995) and use presence of a college (or geographical distance to college) in the local labor market at age 14 as an instrument for college attendance (see, among others, Kane and Rouse, 1995; Kling, 2001; Currie and Moretti, 2003). Kane and Rouse (1995) also use tuition at local public four-year colleges at age 17. See Card (2001) for a survey. Unlike these papers, our goal is to estimate the wage returns to schooling, along with the different types of work experiences. As such, our approach does not lend itself to a standard instrumental variables strategy. Importantly though, we build on this literature and use density of local colleges as well as flagship tuition as exclusion restrictions in our model.

[34] In our model, choices and outcomes today only depend on the past sequence of choices through the accumulated experiences at the beginning of the period, once we condition on unobserved heterogeneity.

ξ_2, does not enter the ASVAB test score equations. This results in a system of six continuous and selection-free measurements that are dedicated to the first factor ξ_1. From this set of measurements, the factor loadings associated with ξ_1 are identified from the covariances of the ASVAB test scores. Having identified the factor loadings, the distributions of ξ_1 and of the idiosyncratic performance shocks are identified in a second step using deconvolution arguments (Kotlarski, 1967).

Note, however, that we cannot directly use the same arguments for the second unobserved factor ξ_2, as we do not have access to a set of selection-free continuous measurements dedicated to that factor. In our model, the continuous outcomes (wages) along with the discrete choices of activities play the role of noisy measurements of the underlying factors. Two main aspects of the data and the model are then central to the identification argument. First, the panel dimension of the data—in particular, the autocorrelation of wages and choices (conditional on observed covariates)—along with the correlation between these two sets of variables and the ASVAB measurements play an important role in identifying the returns to unobserved factors (ξ_1, ξ_2) in the outcome and choice equations. Second, as we discuss below, exclusion restrictions in the form of variables affecting individual decisions but excluded from the potential wages are key to addressing the underlying selection issue. Having identified the distribution of ξ_1 in the previous step, these exclusion restrictions make it possible in turn to identify the distribution of the unobserved factor ξ_2 using standard deconvolution arguments applied to the distribution of potential wages.

In practice, we exclude the vector of family background characteristics $\mathbf{f}_i$ and local college characteristics at age 16, $\mathbf{c}_i$, from the wage equations (see, for similar restrictions regarding family background characteristics, Willis and Rosen, 1979, Taber, 2001, Hotz et al., 2002, Heckman et al., 2006b, and Card, 1995, and Kane and Rouse, 1995, who use exclusion restrictions based on the existence of a local college and local tuitions, respectively). The assumption that these characteristics affect wages only indirectly through activity choices is central in identifying the distribution of potential wages and the wage equation parameters from the realized wages of the selected group of labor market participants.

6 Results

In this section, we present the results of our estimation. We first focus on how the specification of the log wage function impacts the measured returns to schooling and work experiences. In particular, we highlight the importance of generalizing the classic Mincer model by controlling for observed and unobserved selection. Second, we discuss how the returns to schooling and work experiences, as well as the returns to unobserved ability as measured by our factor loading estimates, have changed across cohorts.

6.1 Specifications of wage equations

Our empirical framework allows us to estimate wage returns to various types of school and work experiences by accounting for the endogeneity of schooling and work choices. As described above, our most comprehensive (and preferred) specification of the wage equation includes non-linear functions of school and work experience variables, indicators for graduation attainment and type of work, personal background characteristics, local labor market conditions, and measures for unobserved cognitive and non-cognitive abilities. We compare this specification with other models, specifically an extension of the classic Mincerian (1974) model where we control for high school and college graduation dummies and potential work experience, and a model along the lines of the flexible specification introduced in Heckman et al. (2006a). While our version of the latter specification (referred to as HLT hereafter) is parametric, it remains very flexible and includes controls for race, ethnicity, high school and college graduation, cubic polynomials in school and potential work experience, as well an interaction between schooling and potential experience.

The classic Mincerian model restricts log wages to be a linear function of the number of years of schooling and a quadratic function of the number of years of potential experience (defined as age − years of schooling − 6). Heckman et al. (2006a) relax these assumptions by using indicators for each year of schooling and each year of potential experience and allow returns to potential experience to vary by levels of schooling: high school dropout, high school graduate, some college, and college graduate. They find that the returns to schooling change drastically with the introduction of non-linearities in schooling as well as non-separability between schooling and work experiences.

Our preferred specification differs from Heckman et al. (2006a) in three notable ways. First, we include controls for personal background characteristics, in particular nativity (native-born or foreign-born), birth year, and local labor market conditions (employment rate and income per capita).[35] The second difference relates to work experience. This is one of our main contributions, as we use *actual* work experience accumulated at each age a instead of *potential* work experience, distinguishing between in-high-school, in-college, part-time, full-time, and military work experiences. Third, and importantly, we control for selection into schooling and work experience levels based on unobservable characteristics. We do so by allowing the cognitive-skill factor, ξ_1, and the other non-cognitive skill factor, ξ_2, to enter the wage equation.

We estimate the model for all individuals i in our dataset at each age a for which we observe them, up to and including age 35. We report the marginal effects associated with these different specifications and different variables of interest in Tables 6 and 7.[36] For the accumulated experience variables, $\mathbf{x}^r_{ia}$, i.e., schooling, work, military, etc., that enter the model in a nonlinear fashion, we evaluate the marginal effects using the average experience vector at age 29 ($\overline{\mathbf{x}}^r_{29}$),[37] but using parameters that are estimated from the entire age range. We also report marginal effects at age 32 in Appendix Tables B.3 and B.4.[38] Finally, our Mincerian specification allows the marginal effects to vary over the life cycle through changes in the amount of accumulated experiences.

6.2 Returns to schooling

Table 6 presents estimates of the returns to schooling for our various specifications. Panel (a) displays the return to an additional year of schooling, while Panels (b) and (c) present estimates of "sheepskin effects" for graduating from high school and college, respectively. We

[35] Note that we do not directly control for the ASVAB test scores as these are used as noisy measurements for the cognitive factor, ξ_1, which also enters the wage equation.

[36] The full estimation results are available from the authors upon request.

[37] We use this age because (*i*) it is an age by which most people have completed schooling, and (*ii*) it is the last age for which we have a full-sized cross section in our panel.

[38] Consistent with Section 3, when we say age 29 (32), we are actually referring to the month before their 29th (32nd) birthday.

report six different specifications on separate rows within each panel, beginning with raw premia and ending with our preferred specification which accounts for selection on observable and unobservable characteristics.

We start by comparing results for the Mincerian and HLT specifications, which are reported in rows (ii) and (iii), respectively. There is virtually no difference in the estimated returns to high school graduation [Panel (b)] across these two specifications, while the estimated returns to college graduation [Panel (c)] for the HLT specification are about 2–3 percentage points lower than for the Mincer specification. In contrast, the estimated returns to an additional year of schooling [Panel (a)] are slightly larger in the HLT specification compared to the Mincer, with the return to an extra year of schooling based on the former specification being about 2 points higher in the NLSY79 but nearly identical for the NLSY97.

In row (iv) of the panels in Table 6, we extend the above specification to include controls for local labor market conditions (displayed in Table B.2), birth year and nativity. Adding these variables slightly reduces the estimated returns to a year of schooling by 1.1 points for the NLSY79 cohort, and 0.4 points for the NLSY97. This specification also results in smaller returns to college degrees, by about 2 points each. And while there is no impact on the high school sheepskin effect for the NLSY79, adding these controls does reduce it further for the NLSY97.

In row (v) of the panels in Table 6, we present estimates for the wage equation specification in which we replace potential work experience with actual work experience. Note that these estimates do not account for the potential endogeneity of work experience. Relative to the estimates in the preceding rows of the Panels, the estimates of returns to an extra year of schooling, high school and college graduation are all substantially lower. Taken together, these findings suggest that a sizable part of the estimated returns to schooling and sheepskin effects in the previous rows actually may be attributable to returns to the work experiences individuals acquire during their transition from school to work. We examine the role of school-related work experiences in Section 6.3 below.

The estimated returns to schooling and degrees for the last and preferred specification we consider, which accounts for selection on unobservable characteristics, are found in row (vi) of the panels in Table 6. This specification accounts for selection by jointly estimating the wage equation with our choice model and ability measurement equations, as described in Section 5.2. Compared to the estimates of our model that do not control for unobserved selection in row (v), accounting for selection reduces the returns to college degrees for both cohorts [Panel (c)], reduces the returns to high school for NLSY79 only [Panel (b)] but increases the returns to each additional year of schooling [Panel (a)]. Importantly, the returns to schooling and degrees in row (vi) are much lower than the unadjusted ones in row (i) of each Panel.

Finally, we compare how our estimates of the returns to schooling when one controls for selection in row (vi) have changed across these two cohorts. These changes are recorded in the last column of Table 6 for each panel. We find that the estimated returns to an additional year of schooling [Panel (a)] and the return to a high school degree [Panel (b)] have both increased across the two NLSY cohorts, though the latter is not statistically significant at standard levels. Our estimation results also indicate that the return to college degree [Panel (c)] has been essentially stable across these two cohorts. Finally, an important takeaway from this table is that the cross-cohort changes in the returns to education in row (vi) are quite different than the corresponding changes for the estimated returns produced by the other specifications, suggesting that the selection processes that govern educational and early work experiences have changed over the past 20 years.

Overall, we find that accounting for the accumulated actual work experiences of young men and their endogeneity not only affects one's conclusions about the magnitudes of returns to years of schooling and to degrees, but also alters the conclusions one draws about how these returns have changed over time.

6.3 Returns to work experiences

We next consider the returns to various types of work experiences and how they have changed across cohorts. Estimates for the returns to work experiences are presented in Table 7. Panel (a) displays results for the wage equation specification that corresponds to controlling for actual work experience and was used to produce row (v) in Table 6, while Panel (b) is based on the selection-corrected wage equation used to produce the returns to education estimates in rows (vi) of Table 6. The first marginal effect of both Panel (a) and Panel (b) of Table 7 (*Year of School*) is the same as rows (v) and (vi) of Panel (a) of Table 6, respectively. The second and third marginal effects of both Panels display the additional returns to working while in high school and college, respectively. The next two display the estimated returns to part- and full-time out-of-school work experience. Finally, the remaining two rows report the total return to college graduation (assuming four years to degree) under two scenarios. The first one is the pure return to college, which is equal to the sum of the return to four additional years of schooling, and the college sheepskin effect. The second one accounts for the additional wage return to in-college work, and is computed by adding to the previous return the product of the average number of years worked while in college and the return to an additional year of working while in college. As before, the estimated returns to the various types of work experiences are measured at age 29, with additional results at age 32 included in Appendix Table B.4.

We begin with the returns to working while in school. Consider, first, the returns to working while in college. For this type of work experience, we find sizable returns, with 6% for the NLSY79 and 4 for the NLSY97. Both are higher than those to any other form of work experience we consider or, for that matter, the return to an extra year of pure schooling. However, when adding in unobserved heterogeneity, the return vanishes in the NLSY97 but stays the same in the NLSY79. This is notable considering the findings of the previous table: controlling for unobservable heterogeneity resulted in a substantial *increase* in the return to a year of school in the NLSY97. Thus, for the NLSY97, much of the perceived return to in-college work experience is actually based on selection into those work experiences. Regardless, with and without controls for unobserved heterogeneity, we see a decrease over time in the return to working in college.

With respect to the returns to working while in high school, Table 7 shows that they are lower in every instance than the corresponding returns to working while in college. The estimated returns to working while in high school initially are 3% in the NLSY79 and negligibly small in the NLSY97. After controlling for unobserved heterogeneity, these returns become negligibly small and negative (-2.4%), respectively. Our finding of a negligible or negative return to working while in high-school is consistent with the findings of Hotz et al. (2002), who also estimate the wage returns to early work experiences using data from the NLSY79. Also, we once again see a decrease over time in the returns to in-school work, this time for work in high school.

With respect to non-school-related work experiences, we estimate an increase in the return to an additional year of full-time experience, from 2% in the NLSY79 to 4% in the NLSY97. This return is robust to the inclusion of unobserved heterogeneity. In contrast, the estimated return to part-time, non-school-related experience is quite sensitive to controls for unobserved heterogeneity. The returns are about -5% without considering unobserved heterogeneity, but become -2% in the NLSY79 and -1% in the NLSY97 thereafter. In short, it appears that those individuals who tend to accumulate part-time, non-school work experience are negatively selected on unobservables and their wage losses greatly exaggerate the detrimental consequences of early part-time work for the subsequent wages of young men.

Finally, as mentioned above, the last two rows of each panel report the total return to four-year college, with and without accounting for in-college work experience. In both cases, the estimated returns only show a modest and non-significant increase across cohorts when ignoring unobservable selection. However, results from our preferred specification point to significant and quantitatively sizable increases across cohorts in the returns to four-year college. Namely, we find that this return is 13 (7) percentage points higher in the NLSY97 when one ignores (accounts for) in-college work experience.

Taken together, our results indicate that the returns to work experiences, especially those for in-school and part-time out-of-school work experiences, differ substantially depending on whether one controls for unobserved heterogeneity, which has significant impacts on the implied cross-cohort changes in the returns to work experiences.

6.4 Returns to unobserved skills

Finally, we examine the contribution of the unobserved factors to the wages of young men. Table 8 contains estimates of the cognitive and non-cognitive factor loadings for the full-time wage equation for each of the three cohorts. Recall that the distribution of the factors is multivariate normal with mean zero and identity covariance matrix. It follows that these estimates can be interpreted as the change in log wages due to a one standard deviation increase in the corresponding unobserved factor, holding fixed all observable characteristics and the other dimension of unobserved ability.

We find that the wage return to cognitive ability (or cognitive skills) of young men decreased over time from 15% to 11% for a one-standard-deviation increase in cognitive skills. On the other hand, the return to non-cognitive skills increased from 9 to 16% for a one-standard-deviation increase. Interestingly, our results are consistent with Castex and Dechter (2014) and Deming (2017), who also examine the wage returns to skills between the NLSY79 and NLSY97 cohorts and find that the returns to cognitive skills (as measured by AFQT) have diminished across the two. Additionally, Deming (2017) also finds an increasing return to non-cognitive skills across both cohorts.

7 Conclusion

This paper examines the returns to both schooling and various forms of work experience for men from two birth cohorts, using longitudinal data from the 1979 and 1997 panels of the National Longitudinal Survey of Youth. To deal with the endogenous nature of accumulated work experience and schooling and its potential impact on estimating the wage returns to these different types of experience, we develop and estimate a dynamic model of the schooling and work decisions that individuals make in their early adulthood and how they affect subsequent wages for each of these cohorts. Building on previous work by Heckman et al. (2006a), our empirical framework generalizes the classic Mincerian model of returns to human capital in four main ways: (*i*) it allows for a more flexible function of schooling and work experiences, rather than the original linear-quadratic specification; (*ii*) it incorporates additional controls for an individual's background as well as degree sheepskin effects; (*iii*) it accounts for individual-specific multi-dimensional unobservable heterogeneity to correct for the endogeneity of past human capital investment decisions; and, importantly, (*iv*) it moves away from the concept of potential experience by differentiating among and controlling for various forms of work experience that were actually attained by the individual.

Based on the estimates from this model, we produce several key findings. First, the failure of previous estimates to account for the influences of accumulated actual work experience and its endogenous determination results in sizable overstatements of the wage returns to degree attainment, and, for the 79 cohort, of the wage returns to schooling. Second, we find that the returns to various types of school and work experiences significantly differ between cohorts. For example, we find that the returns to an extra year of schooling have increased, while the returns to an additional year of in-school work have decreased. Although the return to a college degree has remained stable, the overall return to four years of college has increased. Third, consistent with Deming (2017), we find that the return to unobservable cognitive skills has declined, while the return to other non-cognitive skills has increased.

Overall, our analysis highlights the need to account for dynamic selection and changes in composition of skills when analyzing secular changes in the wage returns to skills. An interesting future research avenue would be to build on our analysis and estimate a dynamic generalized Roy model to quantify the relative importance of cross-cohort changes in wage returns to skills and non-wage components—in particular, increasing costs of college education—in explaining changes in the acquisition of schooling and early work experiences.

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Tables

Table 1: Demographic, Family and AFQT characteristics

Variable	NLSY79	NLSY97	97–79
Demographics:			
White:	0.79	0.71	-0.08***
Black:	0.15	0.16	0.01
Hispanic:	0.07	0.14	0.07***
Foreign Born:	0.04	0.05	0.01
Family Characteristics:			
Mother's education:	11.76	12.91	1.14***
Father's education:	12.17	12.98	0.81***
Family Income:	32.86	33.58	0.71
Share lived in female-headed HH:	0.12	0.23	0.11***
AFQT:			
Median of AFQT score	0.37	0.44	0.07
Standard Deviation of AFQT score:	0.96	0.97	0.01***
N at age 29	3,464	3,569	

Notes: Education is highest grade completed by the respondent's biological parents. Family income is in 1,000's of 1982-84$. All demographic and family variables are measured as of the first survey round in both cohorts except female-headed household, which is from age 14 in NLSY97. The AFQT distribution is normalized so that the distribution including all cohorts is mean-zero, variance one. For median AFQT score, the significance comes from bootstrapped standard errors of the median (500 replications). For standard deviations of AFQT score, the significance comes from two-tailed F-tests of the ratio of the variances. Statistics weighted by NLSY sampling weights. Significance reported at the 1% (***), 5% (**), and 10% (*) levels. Sample size for statistical analysis varied for some variables due to missing values (see Appendix Table A.1 for more on sample creation.)

Table 2: Schooling attainment and graduation probabilities at age 29

Variable	NLSY79	NLSY97	97–79
Schooling Attainment:			
% HS Dropouts	0.11	0.09	-0.01**
% HS Graduates	0.29	0.25	-0.05***
% Some College	0.38	0.40	0.03**
% College Graduates	0.22	0.26	0.04***
Graduation Probabilities and Time to Degree:			
Pr(Start College)	0.60	0.66	0.06***
Pr(Grad College | Start Col)	0.37	0.39	0.02
Time to College Degree (years)	5.08	5.49	0.41***

Notes: *HS Graduates* included in this table are those who have either a GED or a diploma but who never attended college. *Some College* are those who attended college but did not graduate with a 4-year degree. *College Graduates* are those who graduated with a 4-year degree. As in Bound et al. (2012), time to college degree is defined as the number of calendar months between high school graduation and 4-year college graduation. Statistics utilize NLSY sampling weights. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

Table 3: Changes in school and work experience

Variable	NLSY79	NLSY97	97–79
Overall:			
Total months of schooling	40.53	52.24	11.71***
Total months of work experience	116.85	118.61	1.76**
By Type:			
Months of school only	19.52	20.64	1.12**
Months of work in high school	9.41	11.84	2.43***
Months of work in college	11.60	19.76	8.16***
Months of part-time work	13.39	14.30	0.91***
Months of full-time work	82.45	72.71	-9.74***

Notes: All counts begin at age 16, thus the average individual in the NLSY79 had a total of 40.5 months of school after turning 16. Statistics weighted by NLSY sampling weights. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

Table 4: Changes in wage premia for experience and educational attainment at age 29 for full-time workers

Variable	NLSY79	NLSY97	97–79
Average log wage premia for one more year of experience:			
Year of School	0.066	0.056	-0.010*
Work in HS	0.055	0.031	-0.024
Work in college	0.089	0.067	-0.022***
Early college work	0.137	0.065	-0.072**
Late college work	0.073	0.068	-0.005
Work part time	-0.091	-0.128	-0.037***
Work full time	0.005	0.002	-0.003
Average log wages by highest educational attainment:			
HS Dropouts	1.81	1.75	-0.05
HS Graduates	1.95	1.92	-0.03
Some College	2.09	1.99	-0.10***
College Graduates	2.35	2.30	-0.05*
Average log wage premia for highest educational attainment:			
High School Wage Premium	0.14	0.16	0.02
Some College Wage Premium	0.14	0.07	-0.07***
College Wage Premium	0.41	0.38	-0.03***

Notes: The sample is conditional on working full-time. Estimates for work experience are coefficients from separate bivariate regressions of log wage on each cumulative experience term. The exception is for the breakout of Work in college. *Early college work* refers to work done as a Freshman or Sophomore (no more than 16 months of college, ie 4 semesters), while *Late college work* refers to work done as a Junior or Senior (more than 16 months of college). The premia for these two experiences are from a joint regression. *HS Graduates* included in this table are those who never attended college. *Some College* are those who attended college but did not graduate with a 4-year degree. *College Graduates* are those who graduated with a 4-year degree. *High School Wage Premium* refers to the log wage difference between *HS Graduates* and *HS Dropouts*. *Some College Wage Premium* refers to the log wage difference between *Some College* and *HS Graduates*. *College Wage Premium* refers to the log wage difference between *College Graduates* and *HS Graduates*. Statistics weighted by NLSY sampling weights. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

Table 5: Definitions of Activities by Educational Choice Sets

Activity (j^r)	Description
$R_{ia} = 1$ (Pre-High School Graduate):	
1	School only, no HS diploma or GED
2	Work in school, no HS diploma or GED
3	Work PT (no school), no HS diploma or GED
4	Work FT (no school), no HS diploma or GED
5	Military, no HS diploma or GED
6	Other, no HS diploma or GED
7	Graduate from HS at age a (Attainment Activity)
$R_{ia} = 2$ (High School Graduate):	
1	School only, has HS diploma or GED
2	Work in school, has HS diploma or GED
3	Work PT (no school), has HS diploma or GED
4	Work FT (no school), has HS diploma or GED
5	Military, has HS diploma or GED
6	Other, has HS diploma or GED
7	Graduate with bachelor's degree at age a (Attainment Activity)
$R_{ia} = 3$ (College Graduate):	
1	School only, has bachelor's degree
2	Work in school, has bachelor's degree
3	Work PT (no school), has bachelor's degree
4	Work FT (no school), has bachelor's degree
5	Military, has bachelor's degree
6	Other, has bachelor's degree

Table 6: Measures of wage returns to schooling across specifications, at age 29

Specification	NLSY79	NLSY97	97–79
Panel (a): Return to Year of Schooling			
(i) Raw	0.077***	0.072***	-0.005
(ii) Mincer	0.036***	0.043***	0.006
(iii) HLT (2006)	0.054***	0.047***	-0.006
(iv) + Background	0.043***	0.043***	0.000
(v) + Actual Exper	0.006	0.006	-0.001
(vi) + Unobserved	0.014**	0.046***	0.032***
Panel (b) : Return to Graduation from HS (Sheepskin)			
(i) Raw	0.191***	0.197***	0.007
(ii) Mincer	0.101***	0.074***	-0.027
(iii) HLT (2006)	0.102***	0.073***	-0.029
(iv) + Background	0.104***	0.067***	-0.037**
(v) + Actual Exper	0.073***	0.049***	-0.023
(vi) + Unobserved	0.033**	0.049***	0.016
Panel (c) : Return to Graduation from College (Sheepskin)			
(i) Raw	0.401***	0.417***	0.016
(ii) Mincer	0.299***	0.294***	-0.005
(iii) HLT (2006)	0.261***	0.274***	0.013
(iv) + Background	0.238***	0.257***	0.019
(v) + Actual Exper	0.204***	0.227***	0.023
(vi) + Unobserved	0.187***	0.187***	0.001

Panel (a) is the wage return at age 29 of one extra year of schooling.
Panel (b) is the wage premium (sheepskin effect) of earning a high school diploma relative to not earning a diploma.
Panel (c) is the wage premium (sheepskin effect) of earning a bachelor's degree relative to a high school diploma.
(i) Indicates raw premium, controlling only for type-of-work dummies (in-school, part-time, full-time).
(ii) Adds to (i) a quadratic in potential experience (= age − years of schooling − 6), a linear term for years of schooling, and degree dummies.
(iii) Increases flexibility similar to Heckman et al. (2006a). Adds a cubic in schooling, a linear interaction between schooling experience and potential experience, and adds race/ethnicity indicators. Additionally, idiosyncratic error variance is allowed to be heteroskedastic by type of work.
(iv) Adds personal background characteristics and local labor market conditions.
(v) Replaces potential experience in (iv) with actual work experience type (in-school, part-time, full-time), military experience, and other experience. Also includes linear interaction between schooling and actual work experiences, except for military and other.
(vi) Adds person-specific random factors to account for dynamic selection. See Eq. (9)
All standard errors are clustered at the individual level and are on the order of 0.005–0.020. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

Table 7: Measures of wage returns of work experiences at age 29 for selection- & non-selection-correction specifications

Variable	NLSY79	NLSY97	97–79
Panel (a): Full model without controlling for selection			
Years of School	0.006	0.006	-0.001
	(0.008)	(0.007)	(0.011)
Work in HS	0.029***	-0.005	-0.034***
	(0.010)	(0.008)	(0.013)
Work in College	0.065***	0.044***	-0.021
	(0.012)	(0.008)	(0.014)
Work PT Only	-0.052***	-0.049***	0.003
	(0.007)	(0.006)	(0.009)
Work FT Only	0.023***	0.041***	0.018***
	(0.001)	(0.002)	(0.002)
4-year college (no work)	0.229***	0.249***	0.020
	(0.022)	(0.020)	(0.029)
4-year college (+ work)	0.292***	0.317***	0.025
	(0.025)	(0.021)	(0.033)
Panel (b): Full model controlling for selection			
Years of School	0.014***	0.046***	0.032***
	(0.005)	(0.004)	(0.007)
Work in HS	-0.001	-0.024***	-0.024**
	(0.008)	(0.005)	(0.010)
Work in College	0.066***	0.000	-0.066***
	(0.010)	(0.004)	(0.011)
Work PT Only	-0.020***	-0.008**	0.012**
	(0.005)	(0.003)	(0.006)
Work FT Only	0.022***	0.039***	0.017***
	(0.001)	(0.001)	(0.002)
4-year college (no work)	0.242***	0.372***	0.129***
	(0.015)	(0.010)	(0.018)
4-year college (+ work)	0.306***	0.372***	0.066***
	(0.018)	(0.011)	(0.021)

Panel (a) refers to wage equation marginal effects without correcting for selection on unobservables. This is specification (v) ("+Actual Exper") in Table 6.

Panel (b) refers to wage equation marginal effects correcting for selection on unobservables. This is specification (vi) ("+Unobserved") in Table 6.

Marginal effects are evaluated at the cohort-specific sample averages at age 29 for 1 additional year of each component of experience. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

"4-year College (no work)" is calculated as the sum of the marginal effect of "Years of School" (times 4), plus the "Return to Graduation from College (Sheepskin)" (from the relevant specification in Table 6).

"4-year College (+ work)" is calculated as the sum of 4-year college (no work) plus the marginal effect of "Work in College" (times the average years spent working in college from Table 3).

Table 8: Full-time wage factor loading estimates

Variable	NLSY79	NLSY97	97–79
Cognitive	0.148***	0.111***	-0.037***
	(0.003)	(0.002)	(0.003)
Non-Cognitive	0.091***	0.161***	0.070***
	(0.003)	(0.002)	(0.004)

Factor loading estimates are from the specification found in the "+ Unobserved" row in Table 6. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

Appendices

A Data Creation and Sampling

This section details our method for constructing comparable variables across both NLSY surveys, as well as how each variable was created. We divide our discussion into the following groups: personal and family background characteristics and cognitive ability; local labor and education market conditions; earnings and educational degrees; school and work activity variables; and efforts undertaken to maximize comparability across surveys.

A.1 Personal and family characteristics and cognitive ability

Personal characteristics observed in the data include the individual's Armed Services Vocational Aptitude Battery (ASVAB) subject test scores, race, nativity, and birth year. Family background characteristics in the data are not time-varying and are measured at the first interview. They include the education level of each of the individual's biological parents, family income at the start of the survey, maternal co-residence status and whether or not the household had a female head when the respondent was of a certain age (age at first interview for the NLSY79 and age 14 for the NLSY97). For the parental education and family income variables, we also include a dummy indicating if the value was missing, as a way to maximize our sample size.

A.2 Local labor market and higher education conditions

We observe local labor and education market conditions at the county level. These include the percentage of all residents who are employed in the individual's county of residence (which we call the "employment rate"),[39] the income per worker in the county, the existence and number of bachelor's-degree-granting institutions in the county (per 100,000 people), and the tuition of the flagship university in the individual's state.[40] As mentioned, we create these

[39] "Employment rate" is the number of employees reported by employers divided by population. Because individuals can hold more than one job, the numbers are much higher than the corresponding national employment-population ratio, which has ranged between 57% and 64% over the time period we consider.

[40] Tuition for all cohorts is in constant 2010 dollars.

labor market and higher-education variables using the restricted-access Geocode supplement of each of the NLSY surveys, combined with data from the Census Bureau, Bureau of Labor Statistics (BLS), Bureau of Economic Analysis (BEA), and Integrated Postsecondary Education Data System (IPEDS).

A.3 Wages and educational degrees

The wage in our analysis is defined as the average hourly wage across all jobs worked in the month, weighted by the hours worked at each job. Wages are deflated using the CPI-U with a base year of 1982-84. We only include wages observed during employment spells (i.e. we discard wages reported when the individual was in the military or did not report working). We trim outliers by dropping wages outside of the range $2-$50 in 1982-84 dollars.

Educational attainment has three values, based on whether or not an individual holds a high school diploma or bachelor's degree. Individuals with neither are classified as high school dropouts. Those who hold a GED or a high school diploma are considered high school graduates. Those who hold a bachelor's degree are considered college graduates.

A.4 School and work activity variables

In the analysis, we make use of a monthly activity variable, which takes on six possible values in each of three different educational attainment sets (discussed previously, and hereafter referred to as choice sets). The activity set contains the following choice alternatives: not working while in school; working while in school; working part-time (not in school); working full-time (not in school); military service; and all other activities (a residual category that includes home production and unemployment). The activity variable thus takes on 18 possible primary values. For example, work in school in the first choice set would be work during high school. Similarly, work in school in the second choice set would be work during college. In addition to these activities, the individual can transition to another choice set by graduating either high school or college. This results in two transition values that the activity variable can take on, one for each of the first two choice sets. The full set of possibilities is displayed in Table 5.

The primary monthly activity variable within each choice set is constructed as follows:

- Military if the person spent at least as many weeks in the military as working, and was not enrolled in school.
- Full-time working if the person was not in school, reported working all weeks of the month, and worked 35 or more hours per week.
- Part-time working if the person was not in school, and either reported positive weeks worked or more than 42 total hours worked in the month.
- Working while in school if the person was in school and worked at least one week in the month or at least 8 hours in the month.
- School only if the person was in school but did not report any weeks worked and reported less than 8 total hours worked in the month.
- "Other activities" if the person did not fall into any of the above categories.

A.5 Comparability across surveys and cohorts

As discussed previously, the two NLSY surveys are quite comparable in their methodology and the types of information they collect. However, there are some key differences between them, which we discuss here.

Foremost among the differences is the age of respondents at the first interview. In the first wave of the NLSY79, respondents are aged 14–21 (aged 14–19 for the birth cohorts we use), in contrast to the NLSY97 where respondents are aged 12–16 at the first interview. This difference in starting ages makes it more difficult to create comparable pre-interview work and schooling histories, and ASVAB test scores.[41] As much as possible, we attempt to construct comparable measures of each variable of interest. As a compromise, we start measuring work history at age 16 and discard the oldest group of individuals in the NLSY79 (i.e. those who were 20 or older at the time of the first interview).

[41] We follow the procedure outlined in Altonji et al. (2012) to equate the ASVAB scores for both test-taking age and medium. This procedure is outlined at length in Altonji et al. (2009).

A.6 Sample selection

The details of our sample selection can be found in Tables A.1 and A.2

Table A.1: Choice Sample Selection

Category	NLSY79	NLSY97
Starting persons	12,686	8,984
Drop females	6,283	4,385
Drop older birth cohorts[a]	1,698	0
Drop non-race oversamples[b]	843	0
Drop other race	0	40
Resulting No. of persons (males)	3,862	4,559
Survey Waves	18	17
Survey person-years[c]	73,645	81,955
Add retrospective data years[d]	3,595	843
Potential person-years	77,240	82,798
Potential person-months	926,880	983,460
Drop missing interview months[e]	72,701	200,916
Resulting person-months	854,179	792,660
Final No. of persons[f]	3,852	4,443
Final No. of person-months	854,179	792,652
Ave. No. of months per person	221.7	178.4
Max. No. of months per person	240	240
No. of persons in age 16 cross-section	3,852	4,443
No. of persons in age 29 cross-section	3,485	3,596
No. of persons in age 32 cross-section	3,324	2,754
No. of persons in age 35 cross-section	3,265	501

[a] Birth years 1957 and 1958.
[b] Oversamples of military personnel and disadvantaged white individuals are both excluded from the analysis.
[c] This refers to the number of calendar years available before an individual turns 36. For some survey waves, the reference period is two years, rather than one year.
[d] This refers to adding retrospective data for years 1974-1978 or 1993-1996 (if applicable).
[e] This refers to dropping any right-censored missing interview spells or any observations during or after a spell of 3+ missed interviews.
[f] This refers to anyone appearing at least once between ages 16 and 36.

Table A.2: Wage Sample Selection

Category	NLSY79	NLSY97
Potential wage observations[a]	651,281	538,648
Drop self-employed wages	31,246	32,252
Drop outlying wages[b]	8,563	33,780
Drop non-reported wages	134,681	50,480
Final wage observations	476,791	422,136

[a] Potential wage observations refers to the the number of person-months choosing a work alternative.
[b] We drop wages below $2 and above $50 (in 1982-84$).

A.7 Cohort year-age and variable mappings

Table A.3 maps age and calendar year for each birth year in both the NLSY79 and NLSY97 cohort. Our panel stops when the individual turns 36 years old, or at their last seen observation. Further, there are a small number of individuals in the NLSY97 who complete their Round 17 interview in 2016. In these cases, we include their data in the year 2016 but we exclude 2016 from Table A.3 since this is not the typical scenario.

Table A.4 summarizes all the variables used in our analysis and indicates in which equations they enter, noting in particular the use of our exclusion restrictions of family background and local college charcteristics in the choice equation.

Table A.3: Cohort chart

Calendar	Age																		
Year	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
1975	1959	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
1976	1960	1959	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
1977	1961	1960	1959	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
1978	1962	1961	1960	1959	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
1979	1963	1962	1961	1960	1959	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
1980	1964	1963	1962	1961	1960	1959	—	—	—	—	—	—	—	—	—	—	—	—	—	—
1981	—	1964	1963	1962	1961	1960	1959	—	—	—	—	—	—	—	—	—	—	—	—	—
1982	—	—	1964	1963	1962	1961	1960	1959	—	—	—	—	—	—	—	—	—	—	—	—
1983	—	—	—	1964	1963	1962	1961	1960	1959	—	—	—	—	—	—	—	—	—	—	—
1984	—	—	—	—	1964	1963	1962	1961	1960	1959	—	—	—	—	—	—	—	—	—	—
1985	—	—	—	—	—	1964	1963	1962	1961	1960	1959	—	—	—	—	—	—	—	—	—
1986	—	—	—	—	—	—	1964	1963	1962	1961	1960	1959	—	—	—	—	—	—	—	—
1987	—	—	—	—	—	—	—	1964	1963	1962	1961	1960	1959	—	—	—	—	—	—	—
1988	—	—	—	—	—	—	—	—	1964	1963	1962	1961	1960	1959	—	—	—	—	—	—
1989	—	—	—	—	—	—	—	—	—	1964	1963	1962	1961	1960	1959	—	—	—	—	—
1990	—	—	—	—	—	—	—	—	—	—	1964	1963	1962	1961	1960	1959	—	—	—	—
1991	—	—	—	—	—	—	—	—	—	—	—	1964	1963	1962	1961	1960	1959	—	—	—
1992	—	—	—	—	—	—	—	—	—	—	—	—	1964	1963	1962	1961	1960	1959	—	—
1993	—	—	—	—	—	—	—	—	—	—	—	—	—	1964	1963	1962	1961	1960	1959	—
1994	—	—	—	—	—	—	—	—	—	—	—	—	—	—	1964	1963	1962	1961	1960	1959
1995	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	1964	1963	1962	1961	1960
1996	1980	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	1964	1963	1962	1961
1997	1981	1980	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	1964	1963	1962
1998	1982	1981	1980	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	1964	1963
1999	1983	1982	1981	1980	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	1964
2000	1984	1983	1982	1981	1980	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
2001	—	1984	1983	1982	1981	1980	—	—	—	—	—	—	—	—	—	—	—	—	—	—
2002	—	—	1984	1983	1982	1981	1980	—	—	—	—	—	—	—	—	—	—	—	—	—
2003	—	—	—	1984	1983	1982	1981	1980	—	—	—	—	—	—	—	—	—	—	—	—
2004	—	—	—	—	1984	1983	1982	1981	1980	—	—	—	—	—	—	—	—	—	—	—
2005	—	—	—	—	—	1984	1983	1982	1981	1980	—	—	—	—	—	—	—	—	—	—
2006	—	—	—	—	—	—	1984	1983	1982	1981	1980	—	—	—	—	—	—	—	—	—
2007	—	—	—	—	—	—	—	1984	1983	1982	1981	1980	—	—	—	—	—	—	—	—
2008	—	—	—	—	—	—	—	—	1984	1983	1982	1981	1980	—	—	—	—	—	—	—
2009	—	—	—	—	—	—	—	—	—	1984	1983	1982	1981	1980	—	—	—	—	—	—
2010	—	—	—	—	—	—	—	—	—	—	1984	1983	1982	1981	1980	—	—	—	—	—
2011	—	—	—	—	—	—	—	—	—	—	—	1984	1983	1982	1981	1980	—	—	—	—
2012	—	—	—	—	—	—	—	—	—	—	—	—	1984	1983	1982	1981	1980	—	—	—
2013	—	—	—	—	—	—	—	—	—	—	—	—	—	1984	1983	1982	1981	1980	—	—
2014	—	—	—	—	—	—	—	—	—	—	—	—	—	—	1984	1983	1982	1981	1980	—
2015	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	1984	1983	1982	1981	1980

Table A.4: Variables included in Wage, ASVAB and Choice Equations

Variable	Wage	ASVAB	Choice
Individual background ($\mathbf{z}_i$)			
race dummies	✓	✓	✓
birth cohort dummies	✓	✓	✓
foreign born	✓	✓	✓
Family background ($\mathbf{f}_i$)			
mother's education (including missing indicator)			✓
father's education (including missing indicator)			✓
family income (including missing indicator)			✓
female-headed household at 14			✓
Local colleges ($\mathbf{c}_i$)			
presence of 4-year colleges in county			✓
number of 4-year colleges in county (per 100,000 people)			✓
tuition at public flagship			✓
Local labor market ($\mathbf{m}_{ia}$)			
county income per capita	✓		✓
county employment rate	✓		✓
Experience ($\mathbf{x}^r_{ia}$)			
months of school	✓		
months of only school			✓
months working in HS	✓		✓
months working in college	✓		✓
months working part-time	✓		✓
months working full-time	✓		✓
months in the military	✓		✓
months in other activities	✓		✓
experience and race interactions			✓
work experience and any school interactions	✓		
quadratic and cubic experience terms	✓		
binned experience terms			✓
Unobserved Factors ($\boldsymbol{\xi}_i$)			
Cognitive factor (ξ_{1i})	✓	✓	✓
Non-cognitive factor (ξ_{2i})	✓		✓

B Additional Descriptives and Structural Estimates at Age 32

In this section we report additional descriptive analyses. We also reproduce our main analysis from the body of the paper, evaluated at age 32 instead of age 29.

B.1 Comparison with CPS

In the table below, we compare the NLSY-aged birth cohorts in both the NLSY and CPS. We can only compare on a few dimensions, since the CPS does not collect information on family background or work history.

Table B.1: Demographics and Schooling Attainment of NLSY-Aged Cohorts in NLSY and CPS

	NLSY			CPS		
Variable	NLSY79	NLSY97	97–79	NLSY79	NLSY97	97–79
Demographics:						
White:	0.79	0.71	-0.08***	0.78	0.68	-0.10***
Black:	0.15	0.16	0.01	0.11	0.11	0.00
Hispanic:	0.07	0.14	0.07***	0.11	0.21	0.10***
Schooling attainment by age 29:						
% HS Dropouts	0.11	0.09	-0.01**	0.15	0.12	-0.03***
% HS Graduates	0.29	0.25	-0.05***	0.39	0.31	-0.08***
% Some College	0.38	0.40	0.03**	0.21	0.27	0.06***
% College Graduates	0.22	0.26	0.04***	0.25	0.31	0.06***
N	3,464	3,569		20,358	12,260	

Notes: *HS Graduates* included in this table are those who have either a GED or a diploma but who never attended college. *Some College* are those who attended college but did not graduate with a 4-year degree. *College Graduates* are those who graduated with a 4-year degree. Statistics weighted by CPS sampling weights. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

B.2 Local labor market and higher education conditions

The two cohorts we analyze differ in the economic conditions they faced over the early parts of their life cycles. We report differences in local labor market conditions at various ages, as well as access to and costs of college at age 16; the previous literature has found that these conditions play a crucial role in the human capital accumulation process (see also, e.g., Cameron and Heckman, 1998; Hotz et al., 2002). Table B.2 gives information about how our two county-level local labor market variables, employment rate and income per worker, evolve over the life cycle, as well as measures of four-year college availability and prices.[42] At all ages except 29, employment rate and income per worker grow across each cohort. By age 29, the employment rates are nearly equalized across cohorts, likely reflecting the effect of the Great Recession on the NLSY97 cohort.[43] There is a large and significant gap in income per worker between the two cohorts.

With regards to the higher-education landscape, the number of four-year colleges per 100,000 in the individual's age-16 county of residence dropped from 2.12 to 1.83. At the same time, tuition at the state flagship university in the individual's age-16 state of residence (deflated to 1982-84 dollars) more than doubled, from \$3,300 to \$6,800.

B.3 Structural estimates evaluated at age 32

Tables B.3 and B.4 are constructed in the same way as our main structural results (Tables 6–7) except that the marginal effects are evaluated at age 32.

Most of the marginal effects in Tables 6 and B.3 are independent of age, and thus these two tables are almost identical. However, the marginal effects in Tables 7 and B.4 are all age-dependent. Yet even here the marginal effects are remarkably similar. The one that is the most different is the marginal effect of a return to working full-time, where the return to a year of full-time work experience is 1 log point smaller. This is true with and without controlling for selection as well as for both cohorts. Thus, the change in the return across cohorts is mostly the same. There is also a difference in the return to schooling in NLSY79, where it is 0.5 log points higher at age 32. This is most noticeable in the return to Total College (4 year) in Panel (b), which is now more than 2 log points higher in NLSY79 at age 32, resulting in a smaller increase over time in the return to Total College (4 year).

[42] Note that "Employment rate" is used abusively here since it is computed as, for the respondent's county of residence at each age, the number of employees reported by employers divided by total population. Multiple job holding, among other reasons, can cause this number to diverge from the canonical employment rate measure.

[43] The NLSY97 cohort reached age 29 in 2009 through 2013.

Table B.2: Local labor market conditions at various ages and college access

Variable	NLSY79	NLSY97	97–79
County Employment Rate:			
At age 16	0.74	0.88	0.14***
At age 22	0.78	0.88	0.09***
At age 26	0.83	0.88	0.04***
At age 29	0.85	0.86	0.01**
County Ave. Income per Worker:			
At age 16	12.40	16.67	4.27***
At age 22	13.39	18.13	4.73***
At age 26	14.69	18.68	3.99***
At age 29	15.14	18.83	3.69***
Number of four-year colleges in county (per 100,000 people):			
At age 16	2.12	1.83	-0.30***
Share of youth with at least one four-year college in county:			
At age 16	0.85	0.82	-0.03***
Average tuition of state flagship university:			
At age 16	3.31	6.81	3.50***

Notes: Employment rate in the respondent's county of residence at each age is the number of employees reported by employers divided by population. Income per worker is the total wage and salary income of the county (in 1,000's of 1982-84$) divided by the number of workers. Number of colleges and college tuition are computed as of 1988 and 2005 for the respective NLSY panels. That is, we report college information for years 1988 and 2005 in the youth's county of residence at age 16. Summary statistics weighted by NLSY sampling weights. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

Table B.3: Measures of wage returns to schooling across specifications, at age 32

Specification	NLSY79	NLSY97	97–79
Panel (a): Return to Year of Schooling			
(i) Raw	0.077***	0.072***	-0.005
(ii) Mincer	0.036***	0.042***	0.006
(iii) HLT (2006)	0.067***	0.051***	-0.016**
(iv) + Background	0.055***	0.046***	-0.010
(v) + Actual Exper	0.011	0.004	-0.007
(vi) + Unobserved	0.019***	0.046***	0.028***
Panel (b) : Return to Graduation from HS (Sheepskin)			
(i) Raw	0.191***	0.197***	0.007
(ii) Mincer	0.101***	0.074***	-0.027
(iii) HLT (2006)	0.102***	0.073***	-0.029
(iv) + Background	0.104***	0.066***	-0.038**
(v) + Actual Exper	0.073***	0.049***	-0.023
(vi) + Unobserved	0.033**	0.049***	0.016
Panel (c) : Return to Graduation from College (Sheepskin)			
(i) Raw	0.401***	0.417***	0.016
(ii) Mincer	0.299***	0.294***	-0.005
(iii) HLT (2006)	0.261***	0.274***	0.013
(iv) + Background	0.238***	0.257***	0.019
(v) + Actual Exper	0.204***	0.227***	0.023
(vi) + Unobserved	0.187***	0.187***	0.001

Panel (a) is the wage return at age 29 of one extra year of schooling.
Panel (b) is the wage premium (sheepskin effect) of earning a high school diploma relative to not earning a diploma.
Panel (c) is the wage premium (sheepskin effect) of earning a bachelor's degree relative to a high school diploma.
(i) Indicates raw premium, controlling only for type-of-work dummies (in-school, part-time, full-time).
(ii) Adds to (i) a quadratic in potential experience (= age − years of schooling − 6), a linear term for years of schooling, and degree dummies.
(iii) Increases flexibility similar to Heckman et al. (2006a). Adds a cubic in schooling, a linear interaction between schooling experience and potential experience, and adds race/ethnicity indicators. Additionally, idiosyncratic error variance is allowed to be heteroskedastic by type of work.
(iv) Adds personal background characteristics and local labor market conditions.
(v) Replaces potential experience in (iv) with actual work experience type (in-school, part-time, full-time), military experience, and other experience. Also includes linear interaction between schooling and actual work experiences, except for military and other.
(vi) Adds person-specific random factors to account for dynamic selection. See Eq. (9)
All standard errors are clustered at the individual level and are on the order of 0.005–0.020. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

Table B.4: Measures of wage returns of work experiences at age 32 for selection- & non-selection-correction specifications

Variable	NLSY79	NLSY97	97–79
Panel (a): Full model without controlling for selection			
Years of School	0.011	0.004	-0.007
	(0.009)	(0.008)	(0.012)
Work in HS	0.028***	-0.006	-0.034***
	(0.010)	(0.008)	(0.013)
Work in College	0.062***	0.042***	-0.020
	(0.011)	(0.008)	(0.014)
Work PT Only	-0.048***	-0.045***	0.003
	(0.007)	(0.005)	(0.009)
Work FT Only	0.012***	0.030***	0.018***
	(0.001)	(0.002)	(0.002)
4-year college (no work)	0.250***	0.244***	-0.006
	(0.022)	(0.020)	(0.030)
4-year college (+ work)	0.317***	0.304***	-0.013
	(0.025)	(0.021)	(0.033)
Panel (b): Full model controlling for selection			
Years of School	0.019***	0.046***	0.028***
	(0.006)	(0.005)	(0.007)
Work in HS	0.000	-0.026***	-0.026***
	(0.008)	(0.005)	(0.009)
Work in College	0.064***	0.003	-0.061***
	(0.009)	(0.004)	(0.010)
Work PT Only	-0.018***	-0.008***	0.010*
	(0.005)	(0.003)	(0.006)
Work FT Only	0.009***	0.028***	0.019***
	(0.001)	(0.002)	(0.002)
4-year college (no work)	0.261***	0.373***	0.112***
	(0.015)	(0.011)	(0.018)
4-year college (+ work)	0.330***	0.376***	0.047**
	(0.017)	(0.011)	(0.021)

Panel (a) refers to wage equation marginal effects without correcting for selection on unobservables. This is specification (v) ("+Background") in Table 6.
Panel (b) refers to wage equation marginal effects correcting for selection on unobservables. This is specification (vi) ("+Unobserved") in Table 6.
"4-year College (no work)" is calculated as the sum of the marginal effect of "Years of School" (times 4), plus the "Return to Graduation from College (Sheepskin)" (from the relevant specification in Table 6).
"4-year College (+ work)" is calculated as the sum of 4-year college (no work) plus the marginal effect of "Work in College" (times the average years spent working in college).