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 overstatements 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, forthcoming). The characteristics and skill accumulation of American youth have also changed over this same time period.[1] 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, Lovenheim and Turner, 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 trends across cohorts in the wage returns to schooling and early career work experiences? Second, how much of the evolution in the college wage premium actually reflects an increase of in-school, and, more generally, early work experience? Third, what is the relative importance of changes in skill prices versus skill composition in explaining how the returns to skills have changed over the past 20 years? Answering these questions requires controlling for selection into schooling and work experiences. We do this by specifying and estimating, for three different cohorts, a dynamic model of schooling and work decisions. We then decompose the evolution in the premia to different skills into price and composition effects. By carefully accounting for selection in a dynamic setting, we also distinguish between changes in the price and composition of observed and unobserved skills.

Our analysis makes use of two longitudinal data sets, the 1979 and 1997 panels of the National Longitudinal Surveys of Youth (NLSY). We divide our analysis into three separate cohorts of individuals, all restricted to males: (*i*) NLSY79 respondents born in years 1959 and 1960; (*ii*) NLSY79 respondents born in years 1961 through 1964; and (*iii*) NLSY97 respondents, all of whom were born in years 1980 through 1984. We divide the cohorts in this way due to swiftly changing market conditions during the 1980s, specifically pertaining

[1] For example, Altonji, Bharadwaj and Lange (2012) note an increase in skills over time, but an overall widening of the skill distribution driven by trends in parental education.

to the college wage premium.[2]

Our use of longitudinal, rather than repeated cross-sectional, data allows us to more accurately measure early-career schooling and work experiences and account for their endogeneity.[3] From each of the NLSY surveys, we construct comparable measures of schooling, employment, and military histories from ages 16 through 29, along with comparable measures of earnings, educational attainment, cognitive skill, local labor market conditions, and personal and family background characteristics. From these histories, we are able to construct multidimensional measures of human capital investment, including whether or not work experience occurred simultaneously with schooling.

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, Lochner and Todd (2006) 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, Lochner and Todd (2006), we show that it is also crucial to differentiate between actual and potential work experience when estimating the returns to schooling, let alone the returns to accumulated work experiences.

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.[4] We follow Cameron and Heckman (1998, 2001) and Heckman, Stixrud and Urzúa (2006), among others, and use a factor model to reduce the dimensionality of the unobservable state space.[5] We use cognitive test scores and the panel structure of the data

[2]See Section 2.1 for further discussion.

[3]See also Bacolod and Hotz (2006); Altonji, Bharadwaj and Lange (2012); Böhm (2013); Castex and Dechter (2014); Lee, Shin and Lee (2015); Deming (2017), who have also used NLSY data to make cross-cohort comparisons about the labor market.

[4]See also recent work by Belzil and Hansen (2017) who estimate, using data from the NLSY79 and NLSY97, a dynamic model of schooling choices in which they control for dynamic selection on unobservables.

[5]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, Karahan and Soares (2011); Heckman, Humphries and Veramendi (forthcoming).

to identify the heterogeneity factors. Noteworthy, 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.[6]

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). Working while in school may cause students to take longer to complete schooling, or drop out altogether. However, accumulating work experience during school may also 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 selectivity 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 benefits of in-school work experience. We attempt to account for such selection in our econometric analyses.

After estimating our model, we examine the selection-corrected returns to schooling and work experiences, as well as to unobservable cognitive and non-cognitive skills, and how they have trended over the cohorts we study. We then use the model estimates to decompose the role of price and composition effects in explaining changes in the wage structure over this period of time.[7] Our framework allows us to separately identify changes in wages due to observable characteristics from changes due to unobservable characteristics (see Fortin, Lemieux and Firpo, 2011).

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

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

[7] For examples of other studies that have decomposed trends in the returns to education, see Taber (2001); Fang (2006); Fortin (2006); Lee and Wolpin (2010); Cunha, Karahan and Soares (2011); and Carneiro and Lee (2011). 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.

slight understatement of the wage returns to completed years of schooling. In addition, our selection-corrected estimates reveal a steady decline over time in the returns to an additional year of schooling, dropping from 5% to 1% in more recent cohorts. The returns to a high school degree have increased slightly over this time period, while the returns to a bachelor's degree have declined since the late 1980s.

Controlling for selection also reveals that in-school work experience increases wages later in life, especially for the most recent cohort. The return to working while in college is large, and only sees a small decline from 6% to 5% across the cohorts we analyze. For in-high-school work experience, however, the return fluctuates significantly, starting at 3% in the oldest cohorts, and increasing to 5% for the most recent cohorts. The return to in-high-school work experience is especially sensitive to accounting for selection. With regards to non-school-related work experience, we find that the return to full-time work experience has increased slightly from 3% to 3.4%, while the return to part-time work experience is small, often negative and does not change much across cohorts. We emphasize that the returns to non-part-time work experiences are in most cases larger than the return to schooling. This underscores the importance of accounting for actual – rather than potential – work experience in measuring the returns to human capital investment, especially work experience accumulated during school.

In addition to measuring the returns to work experiences, we also measure the returns to unobservable cognitive and non-cognitive skills. Both types of skills are rewarded slightly more today than 20 years ago. In addition, the return to a one-standard-deviation increase in cognitive skills is slightly higher (15-17%) than for non-cognitive skills (11-12%).

Finally, we decompose the across-cohort changes in the returns to schooling and work experiences into secular changes in skill prices, changes in the amounts and composition of work and schooling experiences, and changes in the selectivity of individuals who acquire them. We find that changes in the composition of both observable and unobservable skills play a large role in explaining trends in skill premia. These composition effects are most pronounced in the skills that are most highly rewarded: in-school work experience and graduation from high school and college. Overall, our results support the idea that the average level of cognitive and non-cognitive skills among college students and graduates has declined due to the expansion of enrollment in higher education institutions over our period of interest.

The remainder of the paper is organized as follows. Section 2 details the construction of the data and the descriptive trends over this time period; Sections 3 and 4 discuss the specification and estimation of our econometric model; Section 5 discusses results of the model estimates; and Section 6 formulates counterfactual comparisons upon which we base our decompositions. Finally, Section 7 concludes.

2 Differences in Wages, Skills & Skill Returns across Cohorts

In this section, we discuss the data used to describe differences in wages, education and types of work experience across three birth cohorts over the last 20 years, and to estimate our dynamic model of schooling and work decisions.

2.1 The Data

The data we use 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 following them through adulthood and contain information on education, employment, marriage and fertility, and health, among many others. The NLSY79 began with a sample of respondents born between 1957-1964 who were interviewed in 1979, when they were between the ages of 14-22. The respondents in the NLSY97 were born between 1980-1984, and were first interviewed in 1997 when they were between the ages 12-17.

From these data, we make several sample selections. First, as noted above, 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 between 1959 and 1964), in order to minimize recall error at the first interview about their work and schooling experiences

[8]We focus on males 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 males.

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 Tables B.1 and B.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 configure our data into three separate birth cohorts: (*i*) NLSY79 respondents born in years 1959 – 1960 (henceforth referred to as "NLSY79 Old" or "79O"); (*ii*) NLSY79 respondents born in years 1961 – 1964 (henceforth referred to as "NLSY79 Young" or "79Y"); and (*iii*) NLSY97 respondents (henceforth referred to as "NLSY97" or "97"). We choose to split the NLSY79 sample into two groups of cohorts because our analysis focuses on wage returns at a certain age (age 29), implying that we measure wages for the different cohorts over different calendar years. Given the swiftly changing market conditions between birth cohorts of the NLSY79 – particularly manifest in the college wage premium (see Taber, 2001) – dividing the NLSY79 into two cohort groups is pertinent to our analysis.

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

[9] At the first interview, the survey asked extensive questions related to working and schooling history before the survey. 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 recent completed interview.

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 three birth cohorts over the ages 16 through 29. (See Tables B.1 and B.2 for the number of person-months observations for each of our three birth cohorts.)

Our analysis is conducted on three samples: 1,196 males in the NLSY79 Old (178,326 individual-month observations), 2,656 males in the NSLY79 young (396,258 individual-month observations) and 4,443 males in the NLSY97 (587,050 individual-month observations).[10] 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 Tables B.1 and B.2.

In our analysis, we make use of variables that measure the following: personal and family background characteristics; local labor market conditions; earnings; and schooling and work histories, including military participation. For schooling and work histories, we observe for each calendar month the individual's schooling level and enrollment status along with his employment status and intensity (i.e. part-time or full-time). If an individual is employed, we observe his corresponding hourly wage. We discuss the exact construction of each of our variables in Appendix A.

2.2 Differences across Cohorts

In this section, we present some stylized facts about the variation in the data across the three birth cohorts. As mentioned previously, we construct comparable measures of cognitive ability test scores, personal and family background measures, earnings, education, schooling, employment, and military histories from the two NLSY surveys.[11] We begin by discussing the changes in background characteristics, such as personal and family characteristics, as well as in local labor market conditions, across cohorts before discussing the patterns for

[10] Our wage analysis comprises 100,293 observations in the NLSY79 Old, 228,180 observations in the NLSY79 Young, and 292,529 observations in the NLSY97.

[11] To make cognitive ability test scores comparable, we follow Altonji, Bharadwaj and Lange (2009) and Altonji, Bharadwaj and Lange (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).

key endogenous variables of interest, namely schooling and employment decisions. We then describe how wages vary with respect to these decisions.

2.2.1 Demographics

We start by describing the differences across our three birth cohorts in economic, personal and family background characteristics. We first examine the role of local labor market conditions in the human capital accumulation process (see also, e.g., Cameron and Heckman, 1998; Hotz et al., 2002). Table 1 gives information about how our two county-level local labor market variables, employment rate and income per worker, evolve over the life cycle.[12] At all ages except 29, employment rate and income per worker grow across each successive cohort. By age 29, the employment rates are equalized across each of the cohorts, likely reflecting the effect of the Great Recession on the NLSY97 cohort.[13] The gap in income per worker at age 29 is also negligibly small between the two NLSY79 cohorts, but there is a large and significant gap between the NLSY97 and the NLSY79 cohorts.

We next discuss the change in Armed Forces Qualification Test (AFQT) scores over time.[14] Table 2 displays the median and standard deviations of the AFQT scores for the various cohorts and how they changed across these cohorts. Median AFQT scores initially fall between the NLSY79 cohorts, with a statistically insignificant drop of 0.07 standard deviations for the overall sample which is driven by a large and significant 0.17 standard deviation drop for high-school graduates. AFQT scores for the NLSY97 cohort are, in general, higher than those for the NLSY79 Young cohort, with an overall increase of 0.08 standard deviations. However, while this is driven by a large 0.19 standard deviation increase for high-school dropouts, it is offset by a decrease in the median scores of college graduates

[12] 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.

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

[14] 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). However, to maintain comparability with previous literature, we report the change in the AFQT in this section.

by 0.12 standard deviations. These trends imply that the center of the distribution of cognitive skills declined across the cohorts for almost all of the educational categories, with the standard deviation of AFQT scores higher for the NLSY97 cohort among high-school dropouts and college graduates but little or no change for high school graduates or those with some college. These results are consistent with the findings of Altonji, Bharadwaj and Lange (2012), who document a widening of the AFQT distribution between the NLSY79 and NLSY97 cohorts.

Finally, we examine the changes across cohorts in the relationship between family background characteristics and educational attainment. This comparison is made in Table 3, where we consider four different characteristics: mother's education, father's education, family income, and living in a female-headed household. Between the NLSY97 and the NLSY79 cohorts, parental education increased by more than one grade level for mothers and more than four-fifths of a grade level for fathers. Between the two NLSY79 cohorts there was little change in parental education, an exception being the sharp and significant increase in father's education level between the two NLSY79 cohorts for high school dropouts. The mean of family income sharply declined across the two NLSY79 cohorts for high-school graduates and those with some college. With respect to the family income of the parental household in which the individual grew up, there was a sharp increase across the NLSY79 Young and NLSY97 for college attendees, while there was a small and insignificant decrease for high-school dropouts. This supports the idea that parents' family income has become more tightly associated with college attendance over this period. Finally, the share of the men in our samples that grew up in female-headed households increased by 9 percentage points between the NLSY97 and NLSY79 Young cohorts, with higher rates – 10–12 percentage points higher – among those without college degrees.

2.2.2 Work experience and educational attainment

We now consider the changes across the three cohorts in months of accumulated schooling and work experience as well as educational degrees attained. Table 4 computes the average levels of schooling and work experience attained by age 29 (beginning at age 16), broken out by final education level. Consistent with Bound, Lovenheim and Turner (2012), we find that students in the NLSY97 spent longer in school, and that this increase was most pronounced among those who attended college.

Despite spending longer in school, the young men in the most recent cohort who at least graduated from high school had accumulated similar amounts of total work experience by age 29 to the earlier cohorts. That said, there were changes in the types of work experience they accumulated. In particular, there was an increase across cohorts in the accumulated level of in-school work for those with at least a high school degree, particularly for in-college work among college graduates in the NLSY97. These patterns suggest that the longer time spent in school by the young men in more recent cohorts was due, in part, to their spending more time working while in school. Furthermore, while the overall level of out-of-school part-time work rose slightly across cohorts, the overall level of out-of-school full-time work sharply declined.

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. Specifically, one of our primary empirical questions is to assess whether or not spending longer in school (or working while in school) is detrimental to future wages. Finally, we note that young men who dropped out and never completed high school experienced a decline in accumulated work experience across our NLSY cohorts, with those in the NSLY97 cohort having accumulated almost 10 months less work experience by age 29 and this decline largely the result of being employed fewer months in out-of-school, full-time jobs. This interaction between completed schooling and human capital investment highlights the importance of using a sufficiently flexible model to estimate the returns to schooling and work experiences.

Table 5 lists various degree attainment frequencies among the cohorts. High school graduation (or GED completion) rates increased by about two percentage points for the NLSY97 cohorts but were at the same level between the two NLSY79 cohorts. Further, college attendance has steadily increased by 4–5 percentage points across the cohorts. This across-cohort increase in college attendance, significantly outpaced the across-cohort increase in high school graduation rates, suggesting that most of the across-cohort increase in college attendance came from those who previously would have graduated high school and not enrolled in college.

In Table 5, we also compare college graduation rates at age 26 and 29 in order to assess how time-to-degree has changed. By age 29, we observe a steady 3 percentage point increase in the graduation rate across all three cohorts. However, as of age 26 there is no difference in graduate rates between the NLSY79 Young and the NLSY97 cohorts. Together with the evidence in Table 4, this latter evidence in Table 5 indicates that time to a bachelor's degree has increased over this period, a finding consistent with Bound, Lovenheim and Turner (2012).[15] Some of this increased time to college degree might be explained by an increase in the amount of in-college work experience that is documented in Table 4.

2.2.3 Wages

Finally, we examine how wage profiles have varied across our three cohorts. We first document how wages at age 29 for different schooling levels and levels of accumulated work experience have 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 be interpreted as causal effects. Below, in Section 4, we develop a econometric model to estimate the causal effects of schooling and work experience on wages.

Table 6 reports the wage premia to experiences for those working full-time at age 29. Each row shows how much higher the average full-time wage is for an additional year of each type of experience for the four different education groups (HS dropouts, HS graduates, some college, and college graduates). In addition, the overall pattern of differences across cohorts can be seen in the last panel, which groups individuals of all education levels together. In this last panel, the wage premia are highest for working in college, in the range of 8% to 11%. On the other hand, part-time work (while not in school) experience is associated with lower wages, in the range of 0 to -5% for an additional year of experience.[16] For full-time work, the wage premia are around 4% to 5%. While the overall returns to the various work experiences increased between both NLSY79 cohorts, they have generally declined between

[15] Note that these differences across cohorts also hold for graduation conditional on starting college, though all differences lack statistical significance.

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

the NLSY79 Young and NLSY97, with the returns to full-time work being the most stable over time. These findings point to significant across-cohort changes in either the composition of those engaging in these work activities, or the return to these skills, or both. The model we introduce in the next section allows us to distinguish between these different mechanisms.

We also assess how the observed wage premia associated with educational attainment have changed across these cohorts. Table 7 shows average log wages, wage premia and dispersion associated with high school graduation, completion of some college, and college graduation across the three cohorts. The high school wage premium exhibits a U-shape across the three cohorts, while the college wage premium exhibits a hump shape. The premium for completing some college is constant across the NLSY79 cohorts, but falls steeply in the NLSY97 cohort.

While our finding of a decreasing college wage premium between the NLSY79 Young and the NLSY97 is at odds with some previous research (Böhm, 2013; Castex and Dechter, 2014; Deming, 2017), it is consistent with some recent studies of changes in wages over time and is robust to a number of different specifications.[17,18] While a large number of studies using CPS data show that the college wage premium has increased over this time period, our results are closer to those in recent studies by Beaudry, Green and Sand (2014) and Valletta (forthcoming) who find a slowdown in the growth of the wages of college workers and of the college wage premium, respectively, for younger workers since 2000, which includes the period when the NLSY97 cohorts reached age 29.[19]

[17] In particular, we are able to replicate these trends using files provided in the online appendix of Castex and Dechter (2014). Specifically, the differences in results are due to two implementation choices made by Castex and Dechter (2014): (*i*) focusing on individuals aged 16 at the time of taking the ASVAB test; and (*ii*) including a three-year moving average of the national unemployment rate. Using their data, we show that dividing the NLSY79 into two cohorts and removing the three-year moving average of the national unemployment rate yields estimates of the college wage premium that are identical to ours, i.e. a large spike within the NLSY79 followed by a slight decrease from the NLSY79 Young to the NLSY97. These results are not reported for brevity, but are available upon request.

[18] Deming (2017) also analyzes changes in the wage returns to skills using the NLSY79 and NLSY97. Using his replication files, we are able to show that there has been a decline in the college wage premium if we divide the NLSY79 into two cohorts. While Deming allows the returns to skill to vary by NLSY cohort in his analysis, he does not allow the returns to completed education to vary. Neither Castex and Dechter (2014) nor Deming (2017) account for actual work experience when measuring returns to skills.

[19] Valletta (forthcoming) finds that among workers age 25-34 the college-only wage premium fell from 2001-2004 and has remained fairly flat through 2015 (see Panel (a) of his Figure 4). Beaudry, Green and Sand (2014) find that wage profiles for college workers in more recent birth cohorts have fallen since 2000 and exhibited lower growth rates (see Panel (b) of their Figures 1 and 2). Both of these studies use data

In Table 7 we also present estimates of the dispersion of wages by education group for our three cohorts. We find that wage dispersion for high school and college graduates increased across cohorts, while it declined across the cohorts for high school dropouts. These findings are generally consistent with the secular trends in Goldin and Katz (2007) and Lee, Shin and Lee (2015), who show that wage dispersion has increased over time, especially for those in the upper parts of the distribution. To our knowledge, the across-cohort trends in wage dispersion among high school dropouts have not been documented in the existing literature.

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 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 demographic, family, and local labor market characteristics are the prime motivation for our model in which we attempt to estimate the evolution of wage returns to skills by accounting for these changes in composition.

3 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 three birth cohorts.

from the CPS. That said, the remaining differences in the evolution of the college wage premium between the CPS – as used by Valletta (forthcoming) and Beaudry, Green and Sand (2014) – and those in Table 7 based on NLSY data may be explained by differences in composition in the two samples, in the way wages are measured, and the fact that the CPS is a series of cross-sections of the U.S. population while the NLSY samples are collected longitudinally for a set of birth cohorts.

3.1 Activities and Risk Sets

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 *risk set* of activities, where the risk set at any point in time 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. In practice, we estimate the model separately for each cohort c – namely NLSY79 old, NLSY79 young, and NLSY97 – so all the parameters should be understood as cohort-specific. Let R_{ia} denote the risk set for individual i at age a, where we assume that there are K possible risk sets, i.e., $R_{ia} = r \in 1, \ldots, K$. Then, conditional on facing risk set $R_{ia} = r$, individual i chooses from among J^r activities, where we define

$$d^r_{iaj} = \begin{cases} 1 & \text{if } i \text{ is in activity } j \text{ from risk set } r \text{ at age } a \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

and $\sum_{j=1}^{J^r} d^r_{iaj} = 1$, for all i, a and r.

After the initial risk set ($R_{ia} = 1$), we allow for *attainment-contingent* risk sets, i.e., some attainment activity (j^*) has to occur in order to change the risk set. More formally:

$$R_{ia} = r \text{ iff } d^{R_{i\tilde{a}}}_{i\tilde{a}j^*} = 1 \text{ at some age } \tilde{a}, \tilde{a} < a, \tag{2}$$

for $r > 1$. In our case, the relevant activities are graduation from high school, which changes the risk set to $R_{ia} = 2$, and graduation from college, which changes the risk set to $R_{ia} = 3$, and thus $K = 3$. The three risk sets and the activities associated with each are given in Table 8.

3.2 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:

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

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 risk 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[20] as of age a; $I_{ia}(R_{ia} > 1)$, 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 $j = 1, 3, \dots, 6$, the experience variables are accumulated from a starting age, $a_0 = 192$ (16 years old):[22]

$$x_{jia} = \frac{1}{12} \sum_{\ell=a_0}^{a-1} d_{i\ell j}. \tag{4}$$

For $j = 2$, if the individual is in the first risk set ($R_{ia} = 1$), then 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 in the other risk sets ($R_{ia} > 1$), 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 graduate school, $x_{2_{COL}ia}$. Thus,

$$\mathbf{x}_{2ia}^{r} \equiv \begin{cases} \Big(x_{2_{HS}ia}\Big) & \text{if } R_{ia} = 1 \\ \Big(x_{2_{HS}ia}, \quad x_{2_{COL}ia}\Big) & \text{if } R_{ia} > 1, \end{cases} \tag{5}$$

[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}.

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.

3.3 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 time and/or ages, a, and 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:

$$W_{iaj} = P_{iaj} H_{ia} e^{\varepsilon_{iaj}}, \tag{6}$$

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

$$\begin{aligned} w_{iaj} &= p_{iaj} + h_{ia} + \varepsilon_{iaj} \\ &= w^e_{iaj} + \varepsilon_{iaj}, \end{aligned} \tag{7}$$

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

$$p_{iaj} = \beta_{0j} + \boldsymbol{\beta}_{\mathbf{m}} \mathbf{m}_{ia}. \tag{8}$$

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

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

by the vector $\mathbf{z}_i$, the individual's accumulated schooling and work experience and degree completion,[24] $\mathbf{x}_{ia}^r$, 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}):

$$h_{ia} = \boldsymbol{\beta}_{\mathbf{z}}\mathbf{z}_i + \boldsymbol{\beta}_{\mathbf{x}} g\left(\mathbf{x}_{ia}^r\right) + \beta_{\xi 1j}\xi_{1i} + \beta_{\xi 2j}\xi_{2i}. \tag{9}$$

It follows that

$$\begin{aligned} w_{iaj} &= w_{iaj}^e + \varepsilon_{iaj}, \\ &= \beta_{0j} + \boldsymbol{\beta}_{\mathbf{m}}\mathbf{m}_{ia} + \boldsymbol{\beta}_{\mathbf{z}}\mathbf{z}_i + \boldsymbol{\beta}_{\mathbf{x}} g\left(\mathbf{x}_{ia}^r\right) + \beta_{\xi 1j}\xi_{1i} + \beta_{\xi 2j}\xi_{2i} + \varepsilon_{iaj}, \end{aligned} \tag{10}$$

where $g(\cdot)$ contains: (i) a cubic polynomial in all types of accumulated experience,[25] (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, Lochner and Todd, 2006).

One of our primary interests is in obtaining consistent estimates of the parameters in (10). These estimates, in turn, allow us to isolate the role played by skill prices, as opposed to skill composition, in the change across cohorts in returns to schooling and types of work experience. As we make clear below, the central obstacle to this differential attribution 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 linkage through the sequences of activity choices individual i makes over his life cycle.

3.4 Activity-specific Value Functions

Let the value function for individual i who is of age a and who engages in activity j in risk set r be denoted by V_{iaj}^r. These value functions depend on the elements of the individual's information set at age a, namely, personal characteristics, $\mathbf{z}_i$, family background characteristics, $\mathbf{f}_i$, local labor market characteristics, $\mathbf{m}_{ia}$, accumulated school and work experiences

[24] Since risk set is tantamount to degree completion, these act as risk-set specific intercepts.

[25] 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.

$\mathbf{x}_{ia}^r$, and the individual's unobserved characteristics, $\boldsymbol{\xi}_i$. For computational simplicity, we approximate the V_{iaj}^r's as a linear function of these characteristics:[26]

$$\begin{aligned} V_{iaj}^r(\boldsymbol{\xi}_i) &= \boldsymbol{\alpha}_{\mathbf{f}j}^r \mathbf{f}_i + \boldsymbol{\alpha}_{\mathbf{z}j}^r \mathbf{z}_i + \boldsymbol{\alpha}_{\mathbf{m}j}^r \mathbf{m}_{ia} + \boldsymbol{\alpha}_{\mathbf{x}j}^r b\left(\mathbf{x}_{ia}^r, \mathbf{z}_i\right) + \alpha_{\xi 1j}^r \xi_{1i} + \alpha_{\xi 2j}^r \xi_{2i} + \omega_{iaj} \\ &= v_{iaj}^r(\boldsymbol{\xi}_i) + \omega_{iaj}, \end{aligned} \tag{11}$$

where $b(\cdot)$ contains: (i) a set of nine bin indicators for each type of accumulated experience, and (ii) linear interactions between race/ethnicity and each type of accumulated experience.[27] 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_{ia}^{r*} from among the activities in the current risk set $(R_{ia} = r)$ that yields the highest value:

$$j_{ia}^{r*} = \underset{j}{\operatorname{argmax}}\, V_{iaj}^r. \tag{12}$$

3.5 Cognitive and Non-Cognitive Abilities

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.[28] We chose to include these subjects 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

[26] In the following, we make the dependence of V_{iaj}^r on $\boldsymbol{\xi}_i$ explicit, which will be convenient when discussing the estimation of the model in the next section.

[27] 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: 10 months, 20 months, 30 months, 40 months, 50 months, 60 months, 70 months, and 80 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.

[28] 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, Humphries and Veramendi (forthcoming).

of personal characteristics, $\mathbf{z}_i$, family background characteristics, $\mathbf{f}_i$, and the cognitive ability ξ_{1i}, namely

$$y_{is} = \gamma_{0s} + \boldsymbol{\gamma}_{\mathbf{f}s}\mathbf{f}_i + \boldsymbol{\gamma}_{\mathbf{z}s}\mathbf{z}_i + \gamma_{\xi 1s}\xi_{1i} + \eta_{is}, \tag{13}$$

where η_{is} captures idiosyncratic variation in test scores not related to the cognitive ability or other test score determinants.[29]

There is little overlap in the measures of non-cognitive traits across the two NLSY surveys.[30] Due to this data limitation, we are unable to include comparable measures of non-cognitive ability for all three of our NLSY cohorts. For this reason, we rely on the panel nature of the data to identify the residual (non-cognitive) ability factor ξ_{2i}. Thus, this second factor is defined as all unobserved person-specific determinants of the agent's wage and decision process that are not in, and orthogonal to, the clearly-defined cognitive factor.

4 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 distinguish between the three different cohorts – NLSY79 Old, NLSY79 Young and NLSY97 – although we allow all of the parameters of our model to be cohort-specific and we explicitly examine the across-cohort differences in the estimated marginal returns to schooling and work experiences. Finally, we also discuss the identification of the model.

4.1 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, $\mathbf{z}_i$, $\mathbf{f}_i$, $\mathbf{m}_{ia}$, and of the unobservables, $\boldsymbol{\omega}_{ia}$, $\boldsymbol{\varepsilon}_{ia}$, and

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

[30] 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, Stixrud and Urzúa, 2006; Cunha, Karahan and Soares, 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 (2017) who use school suspensions, fights, precocious sex, grade retention, substance abuse, and 8th grade GPA as non-cognitive measures.

$\boldsymbol{\eta}_i$, for all a and i. At the same time, because the choice of past activities determines the accumulated experience in $\mathbf{x}_{ia}^r$ it is not the case that the elements of this vector are independent of $\boldsymbol{\xi}_i$.

We further assume that $\boldsymbol{\xi}_i$ is mean zero and has identity covariance matrix. With respect to $\boldsymbol{\omega}_{ia}$, $\boldsymbol{\varepsilon}_{ia}$, and $\boldsymbol{\eta}_i$, respectively, we assume that they are mutually independent, and independently distributed both across 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 before the actual realizations of wages are known by individual i.

4.2 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 activity j in risk set r, conditional on $\boldsymbol{\xi}_i = \boldsymbol{\xi}$, has the logistic form:

$$P_{iaj}^r(\boldsymbol{\xi}) = \frac{\exp\left(v_{iaj}^r(\boldsymbol{\xi})\right)}{\sum_{k=1,\ldots,J^r}\exp\left(v_{iak}^r(\boldsymbol{\xi})\right)}, \tag{14}$$

where, as defined in the first line of (11), $v_{iak}^r(\boldsymbol{\xi})$ is the component of the value function associated with activity k that is deterministic from individual i's viewpoint.

Additionally, we assume that the idiosyncratic errors entering the wage function in (10) are normally distributed with zero mean and variance, $\sigma_{w_j}^2$, and the corresponding contribution to the likelihood, conditional on $\boldsymbol{\xi}_i = \boldsymbol{\xi}$, is given by:

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

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

We also assume that the idiosyncratic errors entering the ASVAB test score function in (13) are normally distributed with zero mean and variance $\sigma_{y_s}^2$, and that the likelihood

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

contribution, conditional on $\xi_{i1} = \xi_1$, is given by:

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

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

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

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

$$\mathcal{L}_i(\theta \mid \boldsymbol{\xi}) = \prod_s f_{y_{is}}(\xi_1) \prod_a \prod_r \left[\prod_{j=1,5,6,7} P^r_{iaj}(\boldsymbol{\xi})^{d^r_{iaj}} \prod_{k=2,3,4} \left[P^r_{iak}(\boldsymbol{\xi}) f_{w_{iak}}(\boldsymbol{\xi}) \right]^{d^r_{iak}} \right]^{I(R_{ia}=r)}, \tag{17}$$

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]

4.3 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 variable techniques, as finding valid instruments for these sequences of past choices over individuals' careers is challenging. 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, Stixrud and Urzúa (2006). In what follows, we discuss how identification is achieved within this

[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 for the parameters, we use perturbed point estimates from the specification of the model without unobserved heterogeneity. Finally, the covariance matrix of the estimated parameters is estimated as the inverse of the estimated Hessian matrix.

econometric framework.

First, one can use the results of Hu and Shum (2012) to show nonparametric identification of the conditional choice probabilities, $P^r_{iaj}(\boldsymbol{\xi})$. This identification result relies on the first-order Markov structure, and the resulting dynamic exclusion restrictions implied by our dynamic discrete choice model.[33] 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, $P^r_{iaj}(\boldsymbol{\xi})$.

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, 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.[34] 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, than one 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 measurements dedicated to that factor. Here, the panel structure 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 are key to the identification of the returns to unobserved factors, (ξ_1, ξ_2), in the outcome and choice equations.

Finally, we exclude the vector of family background characteristics, $\mathbf{f}_i$, from the wage

[33] 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.

[34] The existence of a set of measurements dedicated to the first factor, ξ_1, is not only useful in terms of identification, but it also helps with the interpretation of the factors, with ξ_1 being interpreted as a cognitive factor, and the second factor, ξ_2, which enters the choice as well as the wage equations, as a non-cognitive factor.

equations (see Willis and Rosen, 1979; Taber, 2001; Hotz et al., 2002, for similar restrictions). The assumption that these background characteristics affect wages only indirectly through individual decisions is instrumental in identifying the wage equation parameters from the observed wages of the selected group of labor market participants.

5 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 show that generalizing the classic Mincer model by controlling for observed and unobserved selection, produces returns to schooling estimates that are much lower than those produced by wage equation specifications that control only for potential experience or control for actual work experience but fail to account for the endogeneity of the latter. This highlights the importance of selection on observables and unobservables in determining these returns. 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 over time.

5.1 Specifications of the 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, demographic and 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, Lochner and Todd (2006). While our version of the latter specification (referred to as HLT hereafter) is parametric, it remains very flexible and includes controls for race, 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-wage 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, Lochner and Todd (2006) 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, Lochner and Todd (2006) in three notable ways. The first one relates to work experience. In our model, we use *actual* work experience instead of *potential* work experience, distinguishing between in-high-school, in-college, part-time, full-time, and military work experiences. Second, we include controls for observable characteristics, in particular nativity (native-born or foreign-born) and birth year, and local labor market conditions (employment rate and income per capita).[35] Third, and most importantly, we control for selection into schooling and work experience levels based on unobservable characteristics. We do so by allowing the cognitive and non-cognitive ability factors, (ξ_1, ξ_2), to enter the wage equation.

We report the marginal effects associated with these different specifications and different variables of interest in Tables 9 and 10.[36] For the accumulated experience variables, $\mathbf{x}_{ia}^r$, 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 ($\overline{\mathbf{x}}_{29}^r$).[37]

[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 observation in our panel. Estimating the returns even later in life would be interesting, but is not feasible given data limitations. Note that, on the other hand, in this specification the returns to graduation do not depend on age as graduation dummies enter the model linearly.

5.2 Returns to Schooling

Table 9 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 report six different specifications on separate rows in each Panel, beginning with raw premia and ending with our preferred specification.

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 10% to 22% lower than the Mincer specification for the NLSY97 and NLSY79 Old cohorts, respectively. In contrast, the estimated returns to an additional year of schooling [Panel (a)] are dramatically larger for the HLT specification compared to the Mincer one, with the return to an extra year of schooling based on the former specification being 38% larger than the latter specification for the NLSY97 cohort and five times larger for the NLSY79 Old cohort.

In row (iv) of the Panels in Table 9, 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 high school graduation [Panel (b)] and an extra year of schooling [Panel (a)] in row (iv) are much lower, while the estimated returns to college graduation in row (iv) are not that different from those in the preceding rows of Panel (c). This finding suggests that a sizable part of the estimated returns to schooling in the previous rows actually may be returns to the work experiences individuals acquire during their transition from school to work.[38]

In row (v) of the Panels in Table 9 we extend the above specification to include controls for the local labor market conditions and demographic background characteristics displayed in Tables 1 and 3, respectively. Adding these variables does not result in estimated returns for years of schooling and degrees that differ substantially from those in the preceding rows

[38] In results not reported, but available upon request, we find that the primary driver of the decline in row (iv) is due to controlling for in-school work experience.

of the Panels. The one exception is with the return to college graduation, which declines by 5%-15% when one adds controls for demographics and labor market conditions.

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 9. This specification accounts for selection by jointly estimating the wage equation with our choice model and ability measurement equations, as described in Section 4.2. Compared to the estimates for our other specifications, accounting for selection reduces the returns to high school [Panel (b)] and college degrees [Panel (c)], but increases the returns to each additional year of schooling [Panel (a)]. The returns to schooling and degrees in row (vi) are much lower than the unadjusted ones in row (i) of each Panel, with this difference attributable in part to holding constant actual work experiences, in part to controlling for observable characteristics and, finally, in part to accounting for selection on unobservables. Below, in Section 6, we quantify the relative importance of these components and how much they account for changes in the returns to education (and work experiences) across the cohorts we analyze.

Finally, we compare how our estimates of the returns to schooling when one controls for selection in row (vi) have changed across our three cohorts. These changes are recorded in the last two columns of Table 9 for each panel. The estimated returns to an additional year of schooling [Panel (a)] declined across the three cohorts, while the return to a high school degree [Panel (b)] increased, albeit at a decreasing rate. The across-cohort change in the return to obtaining a college degree [Panel (c)] followed an inverse U-shape. Finally, we note that the across-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.

5.3 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 10. Panel (a) displays results for the wage equation specification that corresponds to the controls of demographics and local labor market conditions and was used to produce row (v) in Table 9, while Panel (b) is based on the selection-corrected wage equation used to produce the returns to education estimates in rows (vi) of Table 9. The first row of both Panel (a) and Panel (b) of Table 10 (*Year of School*) is the same as rows (v) and (vi) of Panel (a) of Table 9, respectively. The second and third rows of both Panels display the additional returns to working while in high school and college, respectively. Finally, rows (iv) and (v) display the estimated returns to part- and full-time out-of-school work experience, respectively. As before, the estimated returns to the various types of work experiences are measured at age 29.

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, ranging between 4 and 6 percent, which 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. Comparing the estimates for the returns to this form of work experience across Panels (a) and (b), we find that they are not particularly sensitive to whether or not one controls for unobserved heterogeneity. Finally, we note that these returns are highest for the NSLY79 Old cohort (6%) and are a bit lower (5%) for the two more recent cohorts.

With respect to the returns to working while in high school, Table 10 shows that they are, in almost every instance, lower than the corresponding returns to working while in college. Moreover, they are more sensitive to whether or not one controls for unobserved heterogeneity. In particular, the returns to working while in high school initially vary from 0% to 2.5% and are decreasing over time. After controlling for unobserved heterogeneity, the range of these returns widens to -1% to 5% and is U-shaped across the three cohorts.[39]

[39] Our estimates of the returns to working while in high school are similar to those found in Hotz et al. (2002) who also estimate the wage returns to early work experiences using data from the NLSY79 Young cohort. In contrast, Hotz et al. (2002) find much smaller returns to working in college than we do. This discrepancy likely results from differences in the specifications of the random factors used in each paper. In

With respect to non-school related work experiences, we find an estimated return of between 3% and 3.5% to wages from an additional year of full-time, non-school work experience. This return does not vary much across our three cohorts and is robust to the inclusion of unobserved heterogeneity. In contrast, the estimated returns to part-time, non-school related experience are quite sensitive to controls for unobserved heterogeneity. In particular, with no controls for unobserved heterogeneity [Panel (a)], it appears that returns to part-time, non-school work are always negative and are sizable, with a negative return between -4.5% and -2.2%. Once we control for unobserved heterogeneity, these negative returns shrink by a factor of 5 or more and are not statistically significant for the NLSY79 Young cohort. 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, non-school work for the subsequent wages of young men.

In summary, we find that the returns to in-school and full-time work experiences tend to be large, larger in fact in many cases than the returns to an additional year of schooling. We also find that the returns to work experiences, especially those for in-high-school and part-time work experiences, differ substantially depending on whether one controls for or does not control for unobserved heterogeneity, which has large impacts on the implied trends in the returns to work experiences.

5.4 Returns to Unobserved Skills

Finally, we examine the contribution of the unobserved factors to the wages of young men. Table 11 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 unobserved ability, holding fixed all observable characteristics and the other dimension of unobserved ability.

this paper, we use a two-factor specification, with one of the factors measuring cognitive ability, while Hotz et al. (2002) use a single-factor specification that is not explicitly linked to cognitive skills.

We find that the wage return to cognitive ability (or cognitive skills) of young men is between 15% and 17% for a one-standard-deviation increase in cognitive skills and is slightly higher than the return to non-cognitive skills, which is between 11% and 12% for a one-standard-deviation increase. Across cohorts, the returns to each factor are lowest for the NLSY79 Young cohort. The cognitive factor loading is highest for the NLSY79 Old, while the non-cognitive factor loading is highest for the NLSY97, although the estimated returns to non-cognitive skills are fairly stable across cohorts.[40]

6 Decomposing Changes in Skill Wage Premia

In this section we use the parameter estimates of the model to conduct a set of decomposition analyses of the sources of changes in skill wage premia. Specifically, we assess the relative importance of the changes in prices of skills versus changes in the composition of skills across the three NLSY cohorts in accounting for the observed changes in the wage premia to these skills. A key feature of our decomposition approach is that it allows us to account for the endogenous nature of the changes in educational attainment and types of work experience for each of the cohorts.

6.1 Setup

Our approach differs from the canonical Oaxaca decomposition in two important ways. First, we are interested in the difference across groups in wage premia to skills, rather than differences in wage levels. Second, as noted above, our decomposition explicitly accounts for unobserved wage determinants. This approach allows us to quantify the extent to which wage premia for various skills have changed over time due to changes in the (causal) returns to skills (i.e. price effects), or changes in the selectivity of those who accumulate the skills (i.e. composition effects), where selection can be either on observable or unobservable

[40]Our results contrast with Castex and Dechter (2014) and Deming (2017), who also examine the wage returns to skills between the NLSY79 and NLSY97 but find that the returns to cognitive skills (as measured by AFQT) have diminished greatly between the two. This likely reflects the fact that our empirical framework differs from both of theirs in several important ways. Most importantly, we estimate the returns to skills after controlling for selection on observables *and* unobservables. Additionally, our factor model explicitly acknowledges the fact that cognitive skills are measured with error by the ASVAB test scores.

characteristics.

6.1.1 Price versus Composition Effects in Changes in Skill Wage Premia

To distinguish between changes in prices and composition of skills in accounting for the changes in the skill wage premia, we decompose the wage premia as follows. Denote by w the outcome of interest (log wage) and s the skill of interest (e.g. college graduation, or full-time work experience). We partition individuals into two skill groups, denoting the group with the higher level of skill by h, and the lower skill group by l. We use the 79 and 97 subscripts to denote the cohort group.[41] Thus, for example, with respect to college graduation, college graduates in the NLSY79 cohort are in the $(S = h, C = 79)$ skill group, while high school graduates in the NLSY79 cohort are in the $(S = l, C = 79)$ group.

Using this notation, the (population-level) across-cohort change in the wage premium to the skill s $(\Delta_t R_s)$ is then given by:

$$\begin{aligned} \Delta_t R_s \equiv & \left[E\left(w|S=h, C=97\right) - E\left(w|S=l, C=97\right)\right] - \\ & \left[E\left(w|S=h, C=79\right) - E\left(w|S=l, C=79\right)\right] \\ = & \underbrace{(\beta_{97} - \beta_{79})\Delta_s E(Z_{97}|S=s)}_{\text{price}} + \\ & \underbrace{\beta_{79}\left(\Delta_s E(Z_{97}|S=s) - \Delta_s E(Z_{79}|S=s)\right)}_{\text{composition}}. \end{aligned} \tag{18}$$

where Δ_t denotes the differencing across the cohorts, Δ_s denotes the simple differencing operator between $s = h$ and $s = l$, ands β_c (Z_c) denotes the wage equation parameters (characteristics) associated with cohort c. Using our model and parameter estimates, we consistently estimate both components of the decomposition by replacing β_c with their maximum likelihood estimates, $\hat{\beta}_c$ from Tables 9, 10 and 11 that control for unobserved heterogeneity, and by replacing the conditional expectations, $E(Z_c|S = s)$, with their sample analogues.

In practice, we use the following partitions of skill levels to group individuals in our data.

[41] For expositional purposes, we focus on comparing the NLSY79 Young cohort with the NLSY97 cohort. As such, we will use shorthand and refer to that cohort as NLSY79 and use the 79 subscript. We show decomposition results for both pairwise cohort comparisons later on.

For continuous measures, such as full-time work experience level, we define the high-skill group h as individuals whose skill level falls in the interval $(\overline{s}, \overline{s}+1]$, while the low-skill group l corresponds to the interval $(\overline{s}-1, \overline{s}]$, where $\overline{s}$ denotes the average skill level among full-time workers who are age 29, where $\overline{s}$ is specific to each cohort and measured in number of years. For discrete measures (i.e. high school graduation and college graduation), the high-skill (low-skill) group is simply defined as those who have obtained (not obtained) the degree, i.e. $s = 1$ ($s = 0$).

6.1.2 Accounting for Unobserved Skills

As noted above, the random factor specification we use allows us to analyze the role of changes in the prices and composition of unobserved cognitive and non-cognitive abilities across cohorts. In order to do so, we draw a vector of ability factors, (ξ_1, ξ_2), from the population distribution and use our model and parameter estimates to simulate individual paths of decisions and outcomes conditional on the unobserved factors and initial conditions, such as demographics and family background. We then estimate the conditional expectations of the unobserved skills $E(\xi_1|S = s)$ and $E(\xi_2|S = s)$ using sample analogues from this simulated dataset (see Appendix C for a more detailed discussion).

Using the notation introduced in the previous section, we can partition the vector of characteristics Z into components that are observed and those that are unobserved (to the econometrician). Let Z^{unobs} (Z^{obs}) denote the unobserved (observed) components of Z and let β^{unobs} (β^{obs}) denote the parameters associated with these characteristics. Then, we can extend the decomposition in (18) as follows:

$$
\begin{aligned}
\Delta_t R_s = & \underbrace{(\beta_{97}^{\text{obs}} - \beta_{79}^{\text{obs}})\Delta_s E(Z_{97}^{\text{obs}}|S=s)}_{\text{observed price}} + \\
& \underbrace{(\beta_{97}^{\text{unobs}} - \beta_{79}^{\text{unobs}})\Delta_s E(Z_{97}^{\text{unobs}}|S=s)}_{\text{unobserved price}} + \\
& \underbrace{\beta_{79}^{\text{obs}}\left(\Delta_s E(Z_{97}^{\text{obs}}|S=s) - \Delta_s E(Z_{79}^{\text{obs}}|S=s)\right)}_{\text{observed composition}} + \\
& \underbrace{\beta_{79}^{\text{unobs}}\left(\Delta_s E(Z_{97}^{\text{unobs}}|S=s) - \Delta_s E(Z_{79}^{\text{unobs}}|S=s)\right)}_{\text{unobserved composition}}.
\end{aligned}
\tag{19}
$$

Values for each of these four components – observed price, unobserved price, observed composition and unobserved composition – in the specification for returns in (19) are calculated using the parameter estimates for the wage equation and school and work payoff functions and the simulation procedure described above and detailed in Appendix C. By extending the classic Oaxaca decomposition to account for unobserved skills, we can quantify the extent to which selection on unobserved skills contributes to the observed wage premia for different skills, and how changes across cohorts in this selection process have affected the changes in skill premia.

Finally, we further decompose the observed price effects in specification (19) into the sum of a direct and an indirect effect. We define the direct effect as the portion of the observed price effect that is attributable to the skill of interest itself (i.e. S itself and its polynomial terms, if applicable), with the indirect effect being the residual portion that is attributable to the other skills that are imperfectly correlated with the skill of interest (e.g. full-time work experience for S = years of schooling).[42]

6.2 Decomposition Results

In Figures 1 and 2, we summarize the findings of our decomposition analysis of the changes in wage premia for different types of skills between the NLSY97 and NLSY79 Young cohorts and

[42]Note that for the case of the high school and college graduation dummies, the direct price effect is simply given by the across-cohort difference in the wage coefficients associated with these indicators, where the wage coefficients come from the model specification that includes the random factors.

the NLSY79 Young and NLSY79 Old cohorts, respectively. Each figure contains a bar graph with seven bars, which correspond to the seven different skill premia that we decompose. Each bar contains five parts, which represent the relative contribution to the overall change in the wage premium of each separate component of interest, namely: observed price directly related to the skill, observed price indirectly related to the skill, observed composition, unobserved price, and unobserved composition. To the right of each bar is the sum of all of the five components of wage changes; it corresponds to the cross-cohort change in the skill premium, or $\Delta_t R_s$ as defined in (18).[43]

Consider the decomposition of the across-cohort changes in the returns to additional years of school across the NLSY79 Young and NLSY97 cohorts. Figure 1 shows that the wage premium to an additional year of schooling has increased by 2 percentage points across these two cohorts for those working full-time at age 29. This increase in the wage premium for an additional year of schooling is almost completely acounted for by three equal-sized effects. The first is the observed direct price effect, which is negative and is taken from the estimated change in the returns to schooling recorded in the last column of Panel (b) of Table 10. The second is the observed indirect price effect, i.e., the combined effects of changes in the returns to the work-related experiences (skills) that are correlated with years of schooling and thus indirectly impact the wage premium to an additional year of schooling. Again, we use the across-cohort changes to work-related experiences recorded in the last column of Panel (b) of Table 10 to calculate this indirect price effect. This observed indirect price effect is positive. Finally, there is an effect of changes in the composition of observed skills across cohorts. This skill composition effect also is positive and is driven, in part, by the rise in accumulated work experience associated with those with higher levels of schooling.

Looking at the decomposition results for the other types of skill across the NLSY79 Young and NLSY97 cohorts displayed in Figure 1, we find that wage premia for most of these skills declined across these two cohorts. The decline is especially pronounced for the changes in premia for in-school work experience and the graduation attainment. This decline is primarily driven by the decline across these cohorts in the amounts of both observed and

[43]The quantities presented in Figures 1 and 2 are computed from simulated data. See Appendix C for more details.

unobserved skills attained by age 29, and indicates that those who worked in school (both high-school and college, though more pronounced in high school) ended up, overall, with lower amounts of productive skills. This latter finding is consistent with the idea that the across-cohort increase in the amount of in-school work for a given amount of education may have resulted from the increases in college education and tightening of credit to finance higher education, thus leading the members of the NLSY97 cohort to work more while in school in order to fund higher college costs.[44]

The decline in the wage premia for graduating from either high school or college across these two cohorts that is displayed in Figure 1 is heavily influenced by changes in the composition of unobserved skills, implying that those who completed degrees had lower amounts of unobserved skills in the NLSY97 than they did in the NLSY79 young. Overall, with some exceptions, we find that the decline in premia is mostly due to the general decline in the composition of skills between the NLSY79 Young and NLSY97, especially as it relates to unobserved skills. And finally, for each skill we find little to no role of unobserved price effects. This reflects the relative stability over time in the returns to these skills as noted in Table 11.

The decomposition in wage changes across the NLSY79 Old and Young cohorts displayed in Figure 2 also points to significant roles played by the unobserved skills for the NLSY79 Old and NLSY79 Young cohorts, though primarily in the opposite direction. Here we see that those working in school and those graduating college had significantly higher levels of skills (both observed and unobserved) in the NSLY79 Young than in the NLSY79 Old. In particular, we find that most of the well-documented sharp increase in the college wage premium in the 1980s was due to selection on unobservable skills.

In summary, a key finding that emerges from our decomposition analysis of wage premia to different types of skills is that changes in the composition of both observable and unobservable skills play an important role in explaining trends in skill premia. This is particularly true for unobserved skills, where changes in the composition of such skills make up a large share of the across-cohort changes in the wage premia for in-school work experiences,

[44] See Lochner and Monge-Naranjo (2012) for summary of the trends and findings concerning credit constraints in education.

high-school graduation and college graduation.

7 Conclusion

This paper examines the returns to both schooling and various forms of work experience for men from three birth cohorts, using longitudinal data from the 1979 and 1997 panels of the National Longitudinal Survey of Youth. To deal with selectivity 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 individuals make in their early adulthood and how they affect subsequent wages for each of these cohorts. Building on previous work by Heckman, Lochner and Todd (2006), 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 differentiates among various forms of work experience that were actually attained by the individual; and, importantly, (*iv*) it accounts for individual-specific multi-dimensional unobservable heterogeneity to correct for the endogeneity of past human capital investment decisions.

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 schooling or degree attainment. Second, we find that the returns to various types of school and work experiences significantly differ both within and between cohorts. For example, we find evidence that the returns to an extra year of in-school or full-time work are larger than the returns to an extra year of schooling and have increased for more recent cohorts. Third, we decompose the across-cohort changes in wage premia to schooling and various types of work experience into secular changes in skill prices, and changes in the composition – both in terms of observable and unobservable characteristics – of groups of individuals who acquire different types and amounts of schooling and work experiences. Our results point to the existence of sizable composition effects, both in terms of observable and unobservable skills, which play an important role in explaining across-cohort changes in skill premia.

Our analysis highlights the need to account for dynamic selection and changes in composition of skills – both those that result from different schooling and accumulated work experiences and those reflecting unobserved cognitive and non-cognitive 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 across-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: Local labor market conditions at various ages

Experience	NLSY79 Old	NLSY79 Young	NLSY97	79Y–79O	97–79Y
County Employment Rate:					
At age 16	0.72	0.75	0.88	0.03***	0.13***
At age 22	0.76	0.79	0.88	0.03***	0.09***
At age 26	0.81	0.84	0.88	0.03***	0.04***
At age 29	0.85	0.85	0.85	0.00	0.00
County Ave. Income per Worker:					
At age 16	12.04	12.40	16.54	0.36***	4.14***
At age 22	12.53	13.71	18.13	1.18***	4.42***
At age 26	13.96	14.83	18.65	0.87***	3.82***
At age 29	14.94	14.98	18.52	0.04	3.54***

"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. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

Table 2: Median AFQT score and dispersion by final educational attainment

	NLSY79 Old	NLSY79 Young	NLSY97	79Y–79O	97–79Y
Median AFQT score:					
HS Dropouts	-0.97	-0.97	-0.77	0.00	0.19**
HS Graduates	0.05	-0.13	-0.14	-0.17**	-0.02
Some College	0.43	0.38	0.45	-0.05	0.07
College Graduates	1.22	1.18	1.05	-0.04	-0.12***
All Education Levels	0.40	0.33	0.42	-0.07	0.08*
Standard deviation of AFQT score:					
HS Dropouts	0.68	0.78	0.94	0.10***	0.16***
HS Graduates	0.79	0.85	0.89	0.06*	0.04
Some College	0.81	0.83	0.84	0.02	0.01
College Graduates	0.52	0.56	0.62	0.04	0.06***
All Education Levels	0.93	0.96	0.96	0.03	0.00
Sample Sizes:					
N HS Dropouts	179	379	416		
N HS Graduates	338	774	923		
N Some College	391	939	1,358		
N College Graduates	188	453	748		
N All Education Levels	1,096	2,545	3,445		

AFQT distribution normalized so that the distribution including all cohorts is mean-zero, variance one. Significance reported at the 1% (***), 5% (**), and 10% (*) levels. 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. Sample sizes may differ from those reported in Table B.1 due to missing AFQT scores.

Table 3: Family background characteristics by final educational attainment

	NLSY79 Old	NLSY79 Young	NLSY97	79Y–79O	97–79Y
Mother's education:					
HS Dropouts	9.78	10.17	11.22	0.39	1.05***
HS Graduates	11.12	10.91	11.93	-0.21	1.02***
Some College	11.95	11.82	12.97	-0.13	1.15***
College Graduates	13.34	13.38	14.52	0.04	1.14***
All Education Levels	11.78	11.76	12.86	-0.02	1.10***
Father's education:					
HS Dropouts	8.88	9.89	11.08	1.01***	1.19***
HS Graduates	11.02	10.87	11.79	-0.15	0.92***
Some College	12.60	12.21	12.94	-0.39*	0.73***
College Graduates	14.10	14.38	14.98	0.28	0.60***
All Education Levels	12.09	12.14	12.97	0.06	0.82***
Family Income:					
HS Dropouts	20.04	20.58	19.64	0.54	-0.94
HS Graduates	31.42	26.58	25.88	-4.84***	-0.70
Some College	35.45	31.46	33.98	-3.99***	2.52**
College Graduates	47.04	45.16	49.44	-1.88	4.28**
All Education Levels	34.95	31.87	33.82	-3.08***	1.94***
Share lived in female-headed HH					
HS Dropouts	0.18	0.19	0.31	0.01	0.12***
HS Graduates	0.13	0.14	0.25	0.01	0.11***
Some College	0.11	0.14	0.24	0.03	0.10***
College Graduates	0.08	0.10	0.12	0.02	0.02
All Education Levels	0.12	0.13	0.23	0.02	0.09***
Sample Sizes:					
HS Dropouts	206	409	603		
HS Graduates	373	800	1,202		
Some College	420	978	1,696		
College Graduates	197	462	873		
All Education Levels	1,196	2,649	4,374		

Family income is in 1,000's of 1982-84$. Education is highest grade of the respondent's biological parents. Female-headed household is from survey round 1 in NLSY79 and age 14 in NLSY97. Significance reported at the 1% (***), 5% (**), and 10% (*) levels. Sample sizes may differ from those reported in Table B.1 due to missing variables of interest.

Table 4: Average end-of-panel experience by final educational attainment

	NLSY79 Old	NLSY79 Young	NLSY97	79Y–79O	97–79Y
Total months of schooling:					
HS Dropouts	14.11	14.92	18.92	0.81	4.00***
HS Graduates	23.47	22.53	25.03	-0.94*	2.51***
Some College	42.15	38.47	48.77	-3.68***	10.31***
College Graduates	75.29	75.16	87.37	-0.12	12.21***
All Education Levels	39.96	40.59	50.31	0.63	9.71***
Total months of work experience:					
HS Dropouts	96.01	95.35	85.84	-0.66	-9.51***
HS Graduates	105.23	102.20	101.76	-3.03	-0.44
Some College	97.61	99.54	100.41	1.93	0.87
College Graduates	86.72	99.59	100.53	12.87***	0.93
All Education Levels	97.55	99.87	99.40	2.31**	-0.46
Months of school only:					
HS Dropouts	11.09	9.07	11.89	-2.02**	2.82***
HS Graduates	16.33	12.00	13.18	-4.33***	1.18**
Some College	23.10	16.94	19.44	-6.16***	2.50***
College Graduates	42.35	33.22	33.68	-9.13***	0.46
All Education Levels	23.63	18.77	20.97	-4.87***	2.20***
Months of work in high school:					
HS Dropouts	3.03	5.86	7.04	2.83***	1.18*
HS Graduates	7.13	10.53	11.85	3.39***	1.32***
Some College	6.33	10.55	12.24	4.22***	1.69***
College Graduates	4.93	11.29	12.06	6.36***	0.76
All Education Levels	5.91	10.23	11.60	4.32***	1.37***
Months of work in college:					
Some College	12.72	10.97	17.09	-1.74**	6.12***
College Graduates	28.01	30.65	41.64	2.64	10.99***
All Education Levels	10.42	11.60	17.74	1.18*	6.14***

Continued on next page

Table 4 – continued from previous page

	NLSY79 Old	NLSY79 Young	NLSY97	79Y–79O	97–79Y
Months of part-time work:					
HS Dropouts	16.87	18.69	21.57	1.82	2.87***
HS Graduates	12.79	15.80	19.43	3.01***	3.63***
Some College	12.74	14.43	16.31	1.68**	1.88***
College Graduates	9.22	10.98	9.38	1.76***	-1.60***
All Education Levels	12.49	14.41	15.73	1.92***	1.32***
Months of full-time work:					
HS Dropouts	76.11	70.81	57.24	-5.30*	-13.56***
HS Graduates	85.31	75.87	70.48	-9.44***	-5.39***
Some College	65.82	63.59	54.77	-2.24	-8.82***
College Graduates	44.56	46.67	37.45	2.11	-9.22***
All Education Levels	68.73	63.63	54.33	-5.11***	-9.30***
Sample sizes:					
N HS Dropouts	177	348	301		
N HS Graduates	338	722	693		
N Some College	381	898	1029		
N College Graduates	174	447	602		
N All Education Levels	1,070	2,415	2,625		

Note: All counts begin at age 16, thus the average high school dropout had 14 months of high school enrollment after age 16 in the NLSY79 Old.
Significance reported at the 1% (***), 5% (**), and 10% (*) levels.
Sample sizes may differ from those reported in Table B.1 due to survey attrition.

Table 5: Graduation probabilities by age

Variable	NLSY79 Old	NLSY79 Young	NLSY97	79Y–79O	97–79Y
At Age 26:					
Pr(Grad HS)	0.87	0.88	0.90	0.00	0.02**
Pr(Start College)	0.55	0.59	0.64	0.04**	0.05***
Pr(Grad College)	0.19	0.22	0.22	0.03	0.01
Pr(Grad College | Start Col)	0.35	0.37	0.35	0.02	-0.02
N	1,099	2,456	3,607		
At Age 29:					
Pr(Grad HS)	0.87	0.89	0.91	0.01	0.02**
Pr(Start College)	0.56	0.61	0.65	0.04**	0.05***
Pr(Grad College)	0.20	0.23	0.26	0.03**	0.02*
Pr(Grad College | Start Col)	0.36	0.38	0.39	0.02	0.01
N	1,064	2,400	1,930		

Notes: High school graduation includes earning either a GED or a diploma. Starting college refers to enrolling in either a 2- or 4-year institution. Significance reported at the 1% (***), 5% (**), and 10% (*) levels. Sample sizes may differ from those reported in Table B.1 due to survey attrition.

Table 6: Average growth in full-time wages due to various experiences by final educational attainment

Experience	NLSY79 Old	NLSY79 Young	NLSY97	79Y–79O	97–79Y
High School Dropouts:					
Work in HS	0.050	0.079	0.048	0.029	-0.031*
Work part time	-0.045	0.026	-0.046	0.072***	-0.073***
Work full time	0.034	0.052	0.050	0.018***	-0.002
N	1,070	1,899	1,513		
High school graduates:					
Work in HS	0.038	0.024	0.070	-0.014	0.046***
Work part time	0.007	-0.029	-0.005	-0.036***	0.024***
Work full time	0.036	0.058	0.058	0.023***	0.000
N	2,223	4,295	4,550		
Some College:					
Work in HS	-0.005	0.072	0.024	0.076***	-0.048***
Work in college	0.065	0.071	0.073	0.006	0.002
Work part time	-0.032	0.035	-0.031	0.067***	-0.066***
Work full time	0.054	0.068	0.066	0.013***	-0.002
N	2,001	4,523	5,584		
College Graduates:					
Work in HS	-0.001	0.057	-0.006	0.057**	-0.062***
Work in college	0.061	0.039	0.039	-0.022	0.001
Work part time	0.016	0.041	-0.088	0.025	-0.129***
Work full time	0.106	0.114	0.097	0.007	-0.016**
N	691	1,730	2,231		
All Education Levels:					
Work in HS	0.027	0.070	0.044	0.044***	-0.026***
Work in college	0.080	0.109	0.092	0.028***	-0.017***
Work part time	-0.019	-0.003	-0.055	0.017**	-0.053***
Work full time	0.038	0.053	0.047	0.015***	-0.006***
N	5,985	12,447	13,878		

The sample is conditional on working full-time at age 29. Estimates weighted by NLSY sampling weights. Estimates are coefficients from separate bivariate regressons of log wage on each cumulative experience term. One monthly observation per year per individual is included in N. HS Graduates included in this table are those who never attended college. "Some College" are those who attended college (either 2- or 4-year) but did not graduate with a 4-year degree. College Graduates are those who graduated with a 4-year degree but who never attended graduate school. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

Table 7: College and HS Wage Premium and dispersion at age 29 for full-time workers

	NLSY79 Old	NLSY79 Young	NLSY97	79Y–79O	97–79Y
Average log wages:					
HS Dropouts	1.86	1.81	1.75	-0.05***	-0.05***
HS Graduates	2.00	1.92	1.91	-0.09***	-0.01
Some College	2.14	2.05	2.01	-0.09***	-0.04***
College Graduates	2.31	2.35	2.28	0.04***	-0.08***
Average wage premium:					
High school Wage Premium	0.14	0.11	0.16	-0.04**	0.05***
Some College Wage Premium	0.13	0.13	0.09	0.00	-0.04***
College Wage Premium	0.31	0.44	0.37	0.13***	-0.07***
Standard deviation of log wages:					
HS Dropouts	0.39	0.38	0.35	-0.01	-0.03***
HS Graduates	0.37	0.39	0.39	0.02***	0.00
Some College	0.44	0.40	0.42	-0.04***	0.02***
College Graduates	0.39	0.37	0.43	-0.02***	0.06***
Sample sizes:					
N HS Dropouts	1,205	2,154	1,188		
N HS Graduates	2,727	5,452	3,403		
N Some College	2,820	6,528	5,317		
N College Graduates	1,296	3,578	3,526		

Summary statistics weighted by NLSY sampling weights. All monthly log wage observations during the last year of the panel are included in N. HS Graduates included in this table are those who never attended college. “Some College” are those who attended college (either 2- or 4-year) but did not graduate with a 4-year degree. College Graduates are those who graduated with a 4-year degree but who never attended graduate school. “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. Significance reported at the 1% (***), 5% (**), and 10% (*) levels. For standard deviations of log wages, the significance comes from two-tailed F-tests of the ratio of the variances.

Table 8: Definitions of Activities by Educational Risk 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 9: Measures of wage returns to schooling across specifications, at age 29

Specification	NLSY79 Old	NLSY79 Young	NLSY97	79Y–79O	97–79Y
Panel (a): Return to Year of Schooling					
(i) Raw	0.054***	0.075***	0.068***	0.020***	-0.007*
(ii) Mincer	0.022***	0.026***	0.042***	0.004	0.016***
(iii) HLT (2006)	0.107***	0.073***	0.058***	-0.034***	-0.015***
(iv) + Actual Exper	0.035***	0.023***	0.006***	0.012***	-0.017***
(v) + Background	0.026***	0.024***	0.006***	-0.002	-0.018***
(vi) + Unobserved	0.052***	0.024***	0.013***	-0.028***	-0.011***
Panel (b) : Return to Graduation from HS (Sheepskin)					
(i) Raw	0.160***	0.156***	0.175***	-0.004	0.019***
(ii) Mincer	0.118***	0.084***	0.060***	-0.034***	-0.024***
(iii) HLT (2006)	0.115***	0.091***	0.060***	-0.024***	-0.031***
(iv) + Actual Exper	0.076***	0.066***	0.042***	-0.010***	-0.024***
(v) + Background	0.081***	0.068***	0.037***	-0.013***	-0.031***
(vi) + Unobserved	-0.019***	0.020***	0.027***	0.039***	0.007*
Panel (c) : Return to Graduation from College (Sheepskin)					
(i) Raw	0.245***	0.420***	0.367***	0.175***	-0.053***
(ii) Mincer	0.191***	0.360***	0.260***	0.169***	-0.100***
(iii) HLT (2006)	0.148***	0.319***	0.234***	0.171***	-0.085***
(iv) + Actual Exper	0.142***	0.303***	0.231***	0.161***	-0.072***
(v) + Background	0.136***	0.253***	0.209***	0.117***	-0.044***
(vi) + Unobserved	0.177***	0.231***	0.186***	0.054***	-0.046***

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, Lochner and Todd (2006). 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) Replaces potential experience in (iii) 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.
(v) Adds personal background characteristics and local labor market conditions.
(vi) Adds person-specific random factors to account for dynamic selection. See Eq. (10)
All standard errors are on the order of 0.002. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

Table 10: Measures of wage returns of work experiences at age 29 for selection- & non-selection-correction specifications

Variable	NLSY79 Old	NLSY79 Young	NLSY97	79Y–79O	97–79Y
Panel (a): Full model without controlling for selection					
Year of School	0.026***	0.024***	0.006***	-0.002	-0.018***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Work in HS	0.025***	0.024***	-0.003**	-0.001	-0.027***
	(0.003)	(0.002)	(0.001)	(0.004)	(0.002)
Work in College	0.067***	0.043***	0.040***	-0.024***	-0.003
	(0.003)	(0.002)	(0.001)	(0.004)	(0.002)
Work PT Only	-0.041***	-0.022***	-0.045***	0.019***	-0.023***
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Work FT Only	0.034***	0.035***	0.035***	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Panel (b): Full model controlling for selection					
Year of School	0.052***	0.024***	0.013***	-0.028***	-0.011***
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)
Work in HS	0.031***	-0.010***	0.050***	-0.042***	0.060***
	(0.003)	(0.002)	(0.001)	(0.004)	(0.002)
Work in College	0.060***	0.049***	0.047***	-0.011***	-0.002
	(0.003)	(0.002)	(0.001)	(0.004)	(0.002)
Work PT Only	-0.008***	0.001	-0.006***	0.010***	-0.007***
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Work FT only	0.030***	0.029***	0.034***	-0.001	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Panel (a) refers to wage equation marginal effects without correcting for selection on unobservables. This is specification (v) ("+Background") in Table 9.

Panel (b) refers to wage equation marginal effects correcting for selection on unobservables. This is specification (vi) ("+Unobserved") in Table 9.

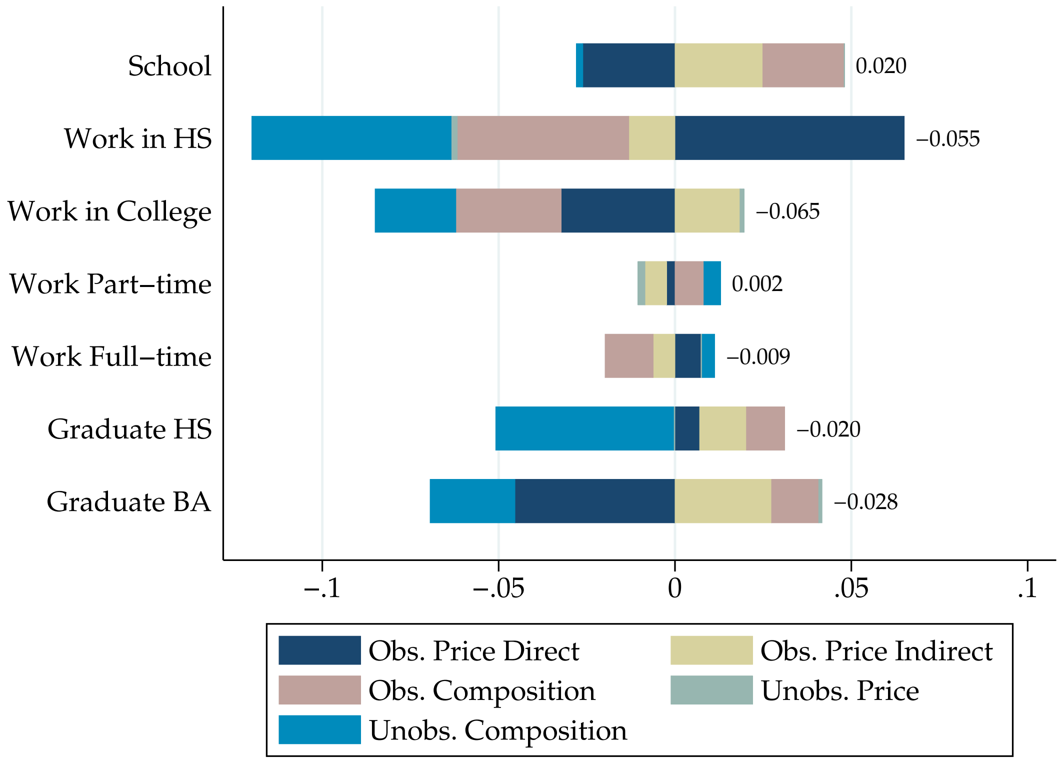
Marginal effects are evaluated at the cohort-specific sample averages at age 29 for 1 additional year of each component of experience. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

Table 11: Full-time wage factor loading estimates

Variable	NLSY79 Old	NLSY79 Young	NLSY97	79Y–79O	97–79Y
Cognitive	0.174***	0.145***	0.163***	-0.030***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Non-Cognitive	0.114***	0.108***	0.117***	-0.006***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

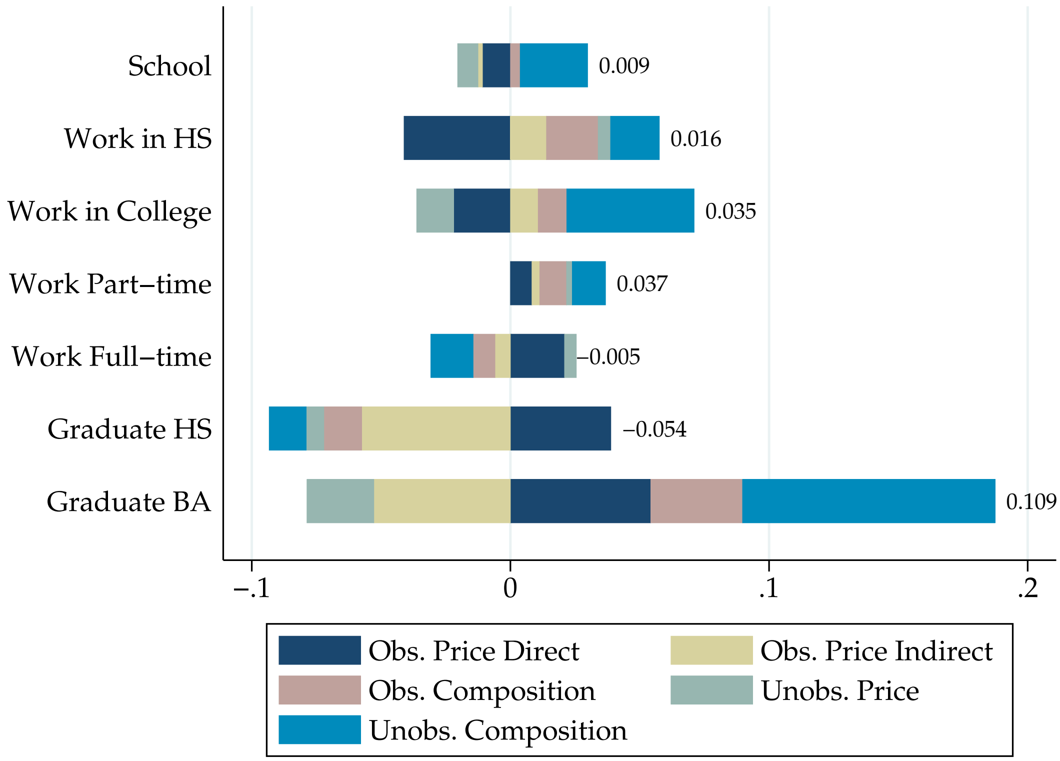
Factor loading estimates are from the specification found in the "+ Unobserved" row in Table 9. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

Figure 1: Components of Changes in Skill Premia between NLSY79 Young and NLSY97 Cohorts



Notes: Above are results of our decomposition of the change in skill premia between the NLSY79 young and NLSY97 cohorts. Numbers to the right of the bars correspond to the total of all components. Further details regarding the decomposition method can be found in Section 6.

Figure 2: Components of Changes in Skill Premia between NLSY79 Old and NLSY79 Young Cohorts



Notes: Above are results of our decomposition of the change in skill premia between the NLSY79 old and NLSY79 young cohorts. Numbers to the right of the bars correspond to the total of all components. Further details regarding the decomposition method can be found in Section 6.

A Data Appendix (for online publication)

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 of variables: personal and family background characteristics and cognitive ability; local labor market conditions; earnings and educational degrees; school and work activity variables; and finally we discuss 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 age 14.

A.2 Local labor market conditions

We observe local labor 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"), along with the income per worker in the county.[45] To create these local labor market variables, we make use of the restricted-access Geocode supplement of each of the NLSY surveys.

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

[45] "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.

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 risk 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 risk set would be work during high school. Similarly, work in school in the second risk set would be work during college. In addition to these activities, the individual can transition to another risk 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 risk sets. The full set of possibilities is displayed in Table 8.

The primary monthly activity variable within each risk 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 months, 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 14-17 for the NLSY79 young and aged 18-21 for the NLSY79 old), 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.[46] 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 old (i.e. those who were 20 or older at the time of the first interview).

The second difference between the two surveys has to do with attrition rates. In the NLSY97, attrition rates are much higher than in the NLSY79. For example, after 12 interviews in the NLSY79, the non-response rate was 10%, compared with about 17% for the NLSY97. While the higher attrition rate in the recent panel might be cause for concern, Aughinbaugh and Gardecki (2008) show that the additional attrition in the NLSY97 does not affect estimates of labor market outcomes. Furthermore, as discussed in Atrostic et al. (2001), attrition rates increased in six different U.S. government surveys during the 1990s.

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

We take these conclusions as evidence that differing attrition rates between the two NSLY surveys is not a major problem for our analysis.

B Appendix Tables (for online publication)

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

Table B.1: Choice Sample Selection

Category	NLSY79 Old[a]	NLSY79 Young[b]	NLSY97
Starting persons	6,741	5,945	8,984
Drop females	3,355	2,928	4,599
Drop older birth cohorts[c]	1,698	0	0
Drop non-race oversamples[d]	492	251	0
Drop other race	0	0	40
Resulting No. of persons (males)	1,196	2,666	4,559
Survey Waves	15	15	15
Survey person-years[e]	12,628	33,983	57,522
Add retrospective data years[f]	2,920	675	843
Potential person-years	15,548	34,658	58,365
Potential person-months	186,576	415,896	688,903
Drop missing interview months[g]	8,250	19,638	101,853
Resulting person-months	178,326	396,258	587,050
Final No. of persons	1,196	2,656	4,443
Final No. of person-months	178,326	396,258	587,050
Ave. No. of months per person	149.1	149.2	132.1
Max. No. of months per person	156	156	156

[a] Birth years 1957-1960.
[b] Birth years 1961-1964.
[c] Birth years 1957 and 1958.
[d] Oversamples of military personnel and disadvantage white individuals are both excluded from the analysis.
[e] This refers to the number of survey rounds available before an individual turns 28.
[f] This refers to adding retrospective data for the years 1974-1978 or 1993-1996 (if applicable).
[g] This refers to dropping any right-censored missing interview spells or any observations during or after a spell of 3+ missed interviews.

Table B.2: Wage Sample Selection

Category	NLSY79 Old	NLSY79 Young	NLSY97
Potential wage observations[a]	117,559	264,547	386,461
Drop self-employed wages	6,502	13,278	23,699
Drop outlying wages[b]	1,693	4,669	27,581
Drop non-reported wages	9,071	18,420	42,742
Final wage observations	100,293	228,180	292,529

[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\$).

C Forward Simulation (for online publication)

Our decomposition exercise allows for unobservable skills and skill prices to explain changes in the returns to education and work experience. In order to adequately characterize unobservable skills, we simulate our model and perform the decompositions on the simulated data. This section first explains how we simulate the model and then shows that the simulated data match key moments of the NLSY data quite well.

We compute the simulated data through forward simulation, using the parameter estimates of the likelihood function in (16). Specifically, we begin by drawing an unobserved factor vector for each individual from the population distribution (a standard multivariate normal). We then draw preference shocks and compute choice probabilities using the observed states (i.e. the demographic, family background, and local labor market characteristics, along with the unobserved factor drawn at the beginning of the simulation) and the parameter estimates of the choice equations.[47] Next, we update the state space and repeat $T = 156$ times.[48] Finally, we draw idiosyncratic wage shocks and compute wages in each period that a work activity is chosen. We perform this forward simulation 150 times for each individual in the NLSY79 estimation samples, and 100 times for each individual in the NLSY97.[49]

[47] In the simulation after $t = 1$, the choice probabilities are a function of the demographic, family background, and local labor market characteristics, the unobserved factors, and the endogenous experience variables.

[48] See Table C.1 for a comparison of choice frequencies between the model and the data, as well as Table C.2 for a comparison of wage premia in the model and the data.

[49] The reason for this is that the NLSY97 has many more individuals than either of the NLSY79 samples.

Table C.1: Choice frequencies in model and data

	Model			Data		
Activity	79O	79Y	97	79O	79Y	97
Panel (a): Pre-high school graduate risk set						
School only	12.61	7.89	8.71	10.69	7.89	9.80
Work in HS	3.08	6.27	7.20	3.72	5.98	7.79
Work PT (no school)	3.53	4.69	3.66	2.67	3.41	3.19
Work FT (no school)	8.60	6.72	4.31	9.81	8.44	5.80
Military	0.12	0.06	0.01	0.20	0.22	0.03
Other	11.71	8.91	6.76	7.29	6.83	6.73
Graduate from HS	0.49	0.52	0.57	0.55	0.55	0.63
Panel (b): High school gradute risk set						
School only	3.45	4.17	4.60	4.22	4.23	5.23
Work in College	3.72	4.36	9.37	5.47	5.79	10.16
Work PT (no school)	7.45	8.85	10.54	6.05	6.26	7.26
Work FT (no school)	32.03	30.63	27.60	32.50	30.51	24.96
Military	0.93	1.39	0.56	2.75	4.70	2.69
Other	7.80	10.66	9.96	7.25	7.88	8.02
Graduate with BA	0.07	0.07	0.11	0.10	0.11	0.14
Panel (c): College Graduate risk set						
School only	0.56	0.30	0.54	0.41	0.33	0.37
Work in College	0.40	0.38	0.72	0.61	0.75	0.84
Work PT (no school)	0.21	0.30	0.57	0.41	0.46	0.75
Work FT (no school)	2.90	3.41	3.84	4.68	5.16	5.08
Military	0.08	0.11	0.05	0.20	0.13	0.13
Other	0.25	0.31	0.31	0.43	0.37	0.41

Table C.2: Graduation and earnings in model and data

	Model			Data		
Outcome	79O	79Y	97	79O	79Y	97
Panel (a): Raw wage premia (any age)						
HS wage premium	0.18	0.22	0.27	0.18	0.20	0.22
BA wage premium	0.26	0.41	0.39	0.26	0.44	0.40
Panel (b): Raw wage premia (full-time work at age 29)						
HS wage premium	0.25	0.17	0.16	0.22	0.20	0.21
BA wage premium	0.25	0.37	0.32	0.26	0.38	0.30