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

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This paper investigates the wage returns to schooling and early work experiences and how these returns have changed across several recent cohorts of men. Much has been written about the growing importance of the wage returns to additional years of schooling and degree attainment. Most of these studies give little attention to the returns to the types and actual amounts of work experience young adults acquire and their influence on wages. This paper examines the returns to both school and work for men from three birth cohorts, using longitudinal data from the 1979 and 1997 panels of the National Longitudinal Survey of Youth. We develop and estimate a dynamic model of the schooling and work choices these men make in early adulthood and how they affect wage growth. We find that (i) ignoring the selectivity of accumulated work experiences results in sizable overstatements of the wage returns to schooling or degree attainment; (ii) with few exceptions, the returns to schooling and work experiences have trended downward over time; and (iii) decomposing the changes in the returns to skill reveals a downward trend in the level of unobserved ability of workers who acquire in-school work experience or who obtain formal educational degrees.

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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.[1] The characteristics and skill accumulation of American youth have also changed over this same time period.[2] College attendance has increased, college graduation has been delayed, and the amount of in-college work experience has gone up.[3] These underlying changes to the composition of youth are of immense importance in understanding how the overall premium for skill investment has evolved.

Our paper looks at three related research questions: What are the trends in the wage returns to schooling and early career work experience? How much of the evolution in the college wage premium actually reflects an increase of in-school, and, more generally, early work experience? What is the relative importance of changes in skill prices versus skill composition in explaining how the returns to skill have changed over the past 20 years? Failure to account for evolution in the incidence of early work experience may lead to an overestimation of the increase in the returns to schooling. In answering these questions, we control for both endogeneity and selection that plague estimates of the returns to skills. We do this by specifying and estimating, for a series of cohorts, a dynamic model of schooling and work decisions. We then decompose the evolution in the data into price and composition effects (see Oaxaca, 1973). By carefully accounting for selection in a dynamic setting, we also distinguish between changes in the price and composition of unobserved ability.

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[1] See, for example, Katz and Murphy (1992); Card and Lemieux (2001); Carneiro and Lee (2011); Valletta (2016)

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

[3] See, for example, Bacolod and Hotz (2006); Scott-Clayton (2012); Bound et al. (2012)

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 among three cohorts of individuals: (*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. As will be shown, these three cohorts differ markedly in their human capital investment decisions and the labor market conditions they faced while making such decisions.

While ours is not the first study to examine labor market trends over this time period, our use of longitudinal rather than repeated cross-sectional data allows us to more accurately measure early-career schooling and work experience and account for its endogeneity.[4] From each of the NLSY surveys, we construct comparable measures of schooling, work, and military histories from ages 16-29, along with comparable measures of earnings, educational attainment, ability, local labor market conditions, and personal and family background characteristics. From these histories, we are able to construct refined measures of human capital including whether or not work experience occurred simultaneously with schooling. Following many studies in the literature, we restrict our analysis to males.

Our analysis builds on the literature estimating the returns to schooling beginning with Mincer (1974), who popularized the Mincer model which interprets the coefficient on schooling in a log wage equation as a rate of return. More recently, Heckman, Lochner and Todd (2006b) show that using flexible methods yields more accurate estimates of the returns to schooling.[5] Extending the insights of Heckman et al. (2006b), we show that it is crucial to differentiate between *actual* and *potential* work experience when estimating the returns to schooling. Making this distinction allows us to separate human capital accumulation from age effects.

[4]Bacolod and Hotz (2006); Altonji et al. (2012); Böhm (2013); Castex and Dechter (2014) have all used NLSY data to make cross-cohort comparisons about the labor market.

[5]Specifically, the authors show that including flexible polynomials of schooling and potential work experience in the wage equation, as well as "sheepskin effects" for degree completion, is essential to accurately estimating the returns to schooling.

In order to obtain wage estimates that reflect selection-free, causal effects of human capital accumulation, we specify and estimate a dynamic model of schooling and work decisions that controls for person-specific unobserved heterogeneity. We linearly approximate the value functions (see Eckstein and Wolpin, 1989; Keane and Wolpin, 1997), but allow the idiosyncratic shocks to be correlated across choice alternatives. This correlation is induced by our factor-analytic approach inspired by Cameron and Heckman (1998, 2001) and Heckman et al. (2006a).[6] We use comparable cognitive test scores and the panel structure of the data to identify the heterogeneity factors. We emphasize our model's ability to separately account for work experience that is accumulated before graduation. Accurately accounting for this is important because such work experience may be rewarded upon post-schooling labor market entry. Failure to account for this pre-graduation work experience would bias estimates of the returns to schooling by incorrectly attributing the portion of the initial wage that corresponds to work experience.

Not only does our model account for the role of endogenous schooling and work decisions on wages, it also adds 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). As students take longer to complete college, borrowing constraints may lead them to work in order to financially support themselves during school. Working while in school may cause students to take longer to complete schooling, but 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 it is only the high-ability students who are able to graduate while holding down a job, then the policy implications are quite different than if in-school work experience causes higher future earnings for all participants.

[6]For other examples of factor models that estimate the returns to schooling, see Taber (2001); Hotz et al. (2002); Cunha et al. (2011).

After estimating the two-dimensional factor model, we examine the selection-corrected returns to schooling and work experience and how they have trended over the cohorts we study. We then use the model estimates to conduct counterfactual simulations (decompositions) which allows us to assess the role of price and composition effects in explaining changes in the wage structure over this period of time.[7] Our estimation of a factor-analytic structural model allows us to separately identify changes in wages due to observable characteristics from changes due to unobservable characteristics (see Fortin et al., 2011). Simulating our model allows us to observe how the extent of sorting on unobserved ability into various labor market skills has changed across cohorts.

We find that the failure of previous estimates of returns to schooling and degrees to account for selection into work experiences results in sizable overstatements of the wage returns to schooling or degree attainment, by as much as 60%. This bias is most strongly pronounced in estimates of the returns to schooling and least pronounced in the returns to a bachelor's degree.

Our results also show that the returns to various types of work experiences differ within and between cohorts. For example, we find evidence that the returns to an extra year of full-time work are larger than the returns to an extra year of schooling and have increased for more recent cohorts. At the same time, we document a general downward trend in the returns to most skills, the exceptions being in-high-school and full-time work experience. The skills with the highest returns in most recent cohorts are work experience attained during high school and college, which are rewarded on average at a rate of 5% per year.

Finally, we decompose the across-cohort changes in the returns to school and work experiences into secular changes in skill prices, changes in the amounts and composition of work experience and schooling, and changes in the selectivity of individuals who acquire them. We find strong effects, often in opposing directions,

[7]For examples of other studies that have used repeated cross-sectional data to decompose trends in the returns to education, see Fang (2006); Fortin (2006); Lee and Wolpin (2010); and Carneiro and Lee (2011). Two studies that have used panel data for these exercises are Taber (2001) and Cunha et al. (2011).

of both the composition of observable and unobservable skills in explaining trends in the returns to skill. 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. Our results are consistent with a story where the average level of unobserved ability among college students and graduates has declined due to expansion of enrollment in higher education institutions.

The remainder of the paper is organized as follows: Section I details the construction of the data and the descriptive trends over this time period; Sections II and III discuss the specification and estimation of our econometric model; Section IV discusses results of the model estimates; and Section V formulates counterfactual comparisons upon which we base our decompositions. Section VI concludes.

I. Differences in Wages, Skills and Skill Returns across Cohorts

In this section, we discuss the data used to describe differences in wages, education and work experiences across three birth cohorts over the last 30 years and to estimate our structural models for the wage returns to these experiences.

A. 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, health, and many others. The NLSY79 began interviewing a sample of respondents in the 1957-1964 birth cohorts in 1979, when they were between the ages of 14-22 and the respondents in the NLSY97 were from the 1980-1984 birth cohorts who were first interviewed in 1997 when they were ages 12-17.

From these data, we make several sample selections. First, as noted above, we restrict ourselves to male respondents.[8] Second, we restrict ourselves to the male

[8] We focus on males for two reasons: (*i*) because we would otherwise need to formally model marriage

respondents in the NLYS79 who were no more than age 20 in 1979 (i.e., were in the 1959-1964 birth cohorts), in order to minimize recall error at the first interview about their work and schooling experiences during adolescence. (No such restrictions were imposed on the NLSY97, given that the oldest respondents were only age 17 at the start of the latter survey.) Third, we dropped respondents in the military personnel and economically disadvantaged whites NLSY79 oversamples, since the former oversample was not followed after 1984 and the latter oversample was not followed after 1990. Finally, we dropped respondents in all other racial and ethnic groups but non-Hispanic whites, African Americans and Hispanics. After these restrictions, documented 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 of 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"). While other papers in the literature have typically grouped all birth cohorts of the NLSY79 together, we split them because our analysis focuses on wage returns at age 29, which means that we measure wages for the different NLSY79 cohorts over different calendar years. Given the swiftly changing market conditions (particularly manifesst in the college wage premium) between birth cohorts of the NLSY79 (Taber, 2001), dividing the NLSY79 in this way 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 life since the previous interview.[9] For example, the survey collects information on all jobs held between the current

and fertility decisions, which would be too cumbersome for the present analysis; and (*ii*) because the literature that has studied human capital formation (e.g. Keane and Wolpin, 1997) has focused on males.

[9] At the first interview, the survey asks extensive questions related to working and schooling history before the survey. For respondents who miss an interview, interviewers attempt to contact the individual during the next cycle.

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 are similarly rich. Linking the survey reports together, it is possible to get measures of employment, schooling enrollment, other activities (such as being in the military) and hourly wages for those employed on a month by month basis. Furthermore, we are able to can distinguish between work experience that occurred during school as opposed to over the summer between semesters and can we can differentiate work experience that occurred before and after schooling 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 of data we have for each of our three birth cohorts.

Our estimation subsample comprises 1,196 males in the NLSY79 old totaling 178,326 individual-month observations, 2,656 males in the NSLY79 young totaling 396,258 individual-month observations, and 4,443 males in the NLSY97 totaling 587,050 individual-month observations.[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.

In order to answer the research questions posed at the beginning of this article, we use data on the following topics: personal and family background characteristics; local labor market conditions; earnings (if employed); 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.

[10] We focus on males for two reasons: (*i*) because we would otherwise need to formally model marriage and fertility decisions, which would be too cumbersome for the present analysis; and (*ii*) because the literature that has studied human capital formation (e.g. Keane and Wolpin, 1997) has focused on males.

B. *Differences across Cohorts*

In this section, we present some stylized facts about the variation in the data across the three birth cohorts in our data. We begin by discussing the evolution in various exogenous variables, such as local labor market conditions, and personal and family characteristics. We then discuss the differences in the key endogenous variables of interest, namely schooling and employment decisions. We finish discussing how our outcome variable of interest, wage, varies with respect to these exogenous and endogenous variables.

Demographics

We start by presenting a description of differences across our three birth cohorts in economic, personal and family background characteristics. We analyze the role of local labor market conditions in the human capital accumulation process (see Cameron and Heckman, 1998; Hotz et al., 2002). Table 2 gives information about how our two county-level local labor market variables, "employment rate" and income per worker evolve over the life cycle. At all ages except 29, "employment rate" and income per worker grow across each successive cohort, with a much larger jump between the NLSY79 young and the NLSY97. By age 29, the "employment rates" are equalized across each of the cohorts, most likely because of the Great Recession's effect on the NLSY97 cohort. The gap in income per worker at age 29 is also equal within the NLSY79 cohorts, with a narrower gap between the NLSY97 and the NLSY79 cohorts.

While we do not model endogenous migration patterns that affect these results, we do note that accounting for the general evolution of labor market conditions is important when modeling wages and human capital investment decisions over the life cycle. In particular, the diminishing difference in local labor market conditions within the NLSY79 cohorts suggests that differences in labor market conditions can't explain why these two cohorts produce such different outcomes for wages.

We next discuss the change in Armed Forces Qualifying Test (AFQT) scores across these cohorts.[11] Table 3 lists the change in the median AFQT score and its dispersion. The overall median AFQT score has shown a slight U shape across cohorts, falling by 0.07 standard deviations and then rising by 0.08 standard deviations. However, this masks substantial heterogeneity by skill accumulation. The median AFQT score for college graduates has fallen in each successive cohort, while AFQT for high school dropouts has risen. The variance in AFQT for those completing some college is largely the same across cohorts. However, for all other education groups, the variance has increased across cohorts. These results are consistent with the findings of Altonji et al. (2012), who find that the skill distribution has widened.

Finally, we examine the changes across cohorts in the relationship between family background characteristics and educational attainment. This comparison is made in Table 4, where we consider four different characteristics: mother's education; father's education; family income; and female household headship. Between the NLSY97 and the NLSY79 cohorts, parental education grew by more than one grade level for mothers and more than four-fifths of a grade level for fathers. Within the two NLSY79 cohorts there was very little evolution in parental education. Mother's education grew most for college attendees, while father's education grew most for those who did not attend college. Of note is a sharp increase within the NLSY79 cohorts for high school dropouts, unmatched by any other educational group. Family income drops sharply between the two NLSY79 cohorts for all but high-school dropouts. However, across the NLSY79 young and NLSY97 there was a sharp increase in family income for college attendees, suggesting that family income is positively related with college attendance. Further, the difference in family income between high school dropouts and college graduates has also increased between the NLSY79 young and NLSY97 cohorts, by about 20%.

[11] The AFQT is a subset of the ASVAB. 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.

Finally, the incidence of female-headed households has increased by 9 percentage points between the NLSY97 and the NLSY79 young. However, this increase is almost exclusively for non-college graduates, who are 10 percentage points more likely to be in such a household.[12] We emphasize that these stark differences among all these cohorts further motivate the fact that they should be treated separately.

Work experience and educational attainment

We now discuss changes across the three cohorts in months of schooling and work experience as well as educational degrees attained. Table 5 computes the average levels of schooling and work experience attained by age 29, broken out by final education level. Consistent with Bound et al. (2012), we find that students in the NLSY97 are spending longer in school, and that this effect is most strongly pronounced among those who attend college.

Despite spending longer in school, these students have similar levels of overall work experience. To investigate how students are substituting between enrollment and work, we further distinguish between work experience that occurred during school. We find a positive trend across cohorts in the level of in-school work, particularly for in-college work among college graduates. Finally, we show that the level of out-of-school part-time work has risen slightly, but that the level of out-of-school full-time work has dropped sharply. These results show that the individuals in more recent cohorts appear to be supplementing longer spells in school with in-school work experience. The result is a much lower level of out-of-school work experience, but no change in the overall level of experience. These trends motivate our differential treatment of in-school and out-of-school work experience. Whether or not spending longer in school is detrimental to future wages is one of our primary empirical questions.

Table 6 lists various degree attainment probabilities among the cohorts. High

[12]This corresponds to roughly a 40% increase in the incidence for each of the non-college-graduate groups.

school graduation rates (or GED completion rates) improved by about two percentage points in recent years but were level between the two NLSY79 cohorts. Further, the probability of beginning college has steadily increased by about 5 percentage points per cohort. This significantly outpaced the increase in high school graduation rates, implying that most of the increase in college attendance came from those who previously would have graduated high school and not enrolled in college.

We compare college graduation rates at age 26 and 29 in order to show how time to degree has changed. By age 29, we see a steady 3 percentage point increase in the graduation rate across all three cohorts. However, at age 26 there is no increase between the NLSY79 young and the NLSY97 cohort. Together with the evidence in Table 5, this shows that time to a bachelor's degree has increased over this period, a finding consistent with Bound et al. (2012).[13] This increased time to college degree is possibly explained by an increase in the amount of in-college work experience, as documented in Table 5.

Wages

Finally, we turn to how wage profiles varied across our three cohorts. The next set of tables and figures examine the change in wage profiles by experience and educational attainment.

In order to see how wage premia associated with schooling and work experience has been rewarded, Table 7 examines the growth in full-time wages at age 29, broken out by different experiences and educational attainment. The overall pattern of differences across cohorts can be seen in the last panel, which groups individuals of all education levels together. Each row shows how much higher the average full-time wage is for an additional year of each type of experience. The highest growth rates to experience are for the NLSY79 cohorts. These range from full-time wages that are 9-10% *higher* at age 29 for an extra year of working

[13] These differences across cohorts also hold for graduation conditional on starting college.

in college to full-time wages that are 9-10% *lower* for an extra year of working part-time to virtually zero return to previous full-time work experience.

We also assess how wage premia associated with educational attainment have changed across these cohorts. Table 8 shows the 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 has also fallen over time, most steeply in recent years. While our finding of a decreasing college wage premium between the NLSY79 young and the NLSY97 appears to be at odds with other work—specifically Castex and Dechter (2014)—it is robust to a number of different specifications. In results not reported, we are able to replicate these trends using files provided in the online appendix of Castex and Dechter (2014).[14] While a large number of studies using CPS data show that the college wage premium has increased over this time period, our results are at least consistent with recent findings by Valletta (2016) showing a slowdown in the growth of the college wage premium. As a final note on Table 8, we discuss the change in the dispersion of wages varies by education group. Specifically, there has been increased wage dispersion for high school and college graduates, while there has been a tightening of the wage distribution for high school dropouts. These findings are generally consistent with Juhn et al. (1993) and Goldin and Katz (2007), who conclude that wage dispersion has increased over time, especially for those in the upper parts of the distribution.

We emphasize that our discussion has ignored the fact that selection may be present in these reduced-form wage profiles. In the next section, we introduce the model that we use to account for the potential selection and endogeneity that arise from differences in who acquired the various types of experiences. In our

[14] A detailed comparison of the various sources of discrepancy between our results and those of Castex and Dechter (2014) are available from the authors upon request.

final results, we present selection-corrected wage *returns*.

The differences we see in schooling and work experiences (endogenous choices) as well as demographic, family, and local labor market characteristics (exogenous characteristics) are the prime motivation for our structural model in which we attempt to assess the extent to which endogenous decisions have influenced the evolution of wage returns to skills.

II. The Model

Here we describe the underlying model of an agent's choice of work and schooling activities over their life cycle. We use this model to account for the endogenous change across cohorts in levels of schooling and early work experience and to obtain selection-free estimates of wage returns to these experiences.

A. 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, 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 at age a, where

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

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 has to occur in order to change the risk set. More formally:

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

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 $R_{ia} = 3$. The three risk sets and the activities associated with each are given in Table 1.

B. School and Work Experience

We are interested in the effects of accumulated "experiences" on various outcomes in this model. In particular, we are interested in accumulated *years* of school attendance, years of work experience, etc., as well as educational attainments, such as high school and college graduation. The vector of experiences is given by:

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

where the experience variables are: x_{1ia}, the number of years of schooling attendance as of age a; x_{2ia}^{r}, the number of years of work and school experience in 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 spent in other activities as of age a; $I_{ia}(R_{ia} < 3)$, 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. For $j = 1, 3, \ldots, 6$, the experience variables are accumulated since a starting age,

a_0, and we use $a_0 = 192$ (16 years old):

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

For $j = 2$, the experience term is either the number of years spent working in high school since a_0 if in the first risk set, $R_{ia} = 1$, or it is the number of years spent working while in college or graduate school, $R_{ia} > 1$:

$$x_{jia}^r = \begin{cases} \frac{1}{12} \sum_{\ell=a_0}^{a-1} d_{i\ell j} & \text{if } R_{ia} = 1 \\ \frac{1}{12} \sum_{\ell=a_{HS_i}}^{a-1} d_{i\ell j} & \text{if } R_{ia} > 1 \end{cases} \tag{5}$$

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

C. Wages

Let $W_{iaj'}$ denote the potential hourly wage rate that i would realize at age a if he chose activity j', $j' = 2, 3, 4$. We assume that $W_{iaj'}$ is determined by the individual's *human capital*, or *skills*, H_{ia} that he has as of the beginning of age a, measured in efficiency units; the occupation-specific skill price $P_{aj'}$ per efficiency unit that varies across time and/or ages, a, across the local labor market in which i resides at age a;[15] and idiosyncratic shocks, denoted by $e^{\varepsilon_{iaj'}}$, that are unanticipated by the individual:

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

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

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

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

where $p_{aj'} \equiv \ln P_{aj'}$, $h_{ia} \equiv \ln H_{ia}$, and $w^e_{iaj'} \equiv p_{aj'} + h_{ia}$ 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 $p_{aj'}$ is the following function of age/time and the conditions of the local labor market in which i resides at age a, $\mathbf{m}_{ia}$:

$$p_{aj'} = \beta^r_{0j'} + \boldsymbol{\beta}_{\mathbf{m}}\mathbf{m}_{ia}. \tag{8}$$

And we assume that the (log of the) individual's stock of human capital, h_{ia}, is determined by some observed personal characteristics, e.g., one's birth year, race, etc., denoted by the vector $\mathbf{z}_i$, the individual's accumulated schooling and work experiences, $\mathbf{x}^r_{ia}$, and the individual's unobserved personal characteristics, $\boldsymbol{\xi}_i$, which is broken out into elements pertaining to the individual's cognitive (ξ_{i1}) and non-cognitive (ξ_{i2}) abilities:

$$h_{aj'} = \boldsymbol{\beta}_{\mathbf{z}}\mathbf{z}_i + \boldsymbol{\beta}_{\mathbf{x}} g\left(\mathbf{x}^r_{ia}\right) + \beta_{\xi j'1}\xi_{i1} + \beta_{\xi j'2}\xi_{i2}. \tag{9}$$

It follows that

$$\begin{aligned} w_{iaj'} &= w^e_{iaj'} + \varepsilon_{iaj'}, \\ &= \beta^r_{0j'} + \boldsymbol{\beta}_{\mathbf{m}}\mathbf{m}_{ia} + \boldsymbol{\beta}_{\mathbf{z}}\mathbf{z}_i + \boldsymbol{\beta}_{\mathbf{x}} g\left(\mathbf{x}^r_{ia}\right) + \beta_{\xi j'1}\xi_{i1} + \beta_{\xi j'2}\xi_{i2} + \varepsilon_{iaj'} \end{aligned} \tag{10}$$

where $g(\cdot)$ contains: (i) a cubic polynomial in all types of accumulated experience, (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 (Heckman et al., 2006b). Note that schooling experience in $g(\cdot)$ is the sum of school-only and work-in-school experience so as to be comparable to the literature originating with Mincer (1974).

One of our primary interests is in obtaining consistent estimates of the parameters in (10). This will in turn allow us to isolate the role played by skill prices in the change across cohorts in returns to schooling and early work experiences. As we make clear below, the central obstacle is that the elements of $\mathbf{x}_{ia}^r$ are endogenous unless one conditions on the unobserved factors, $\boldsymbol{\xi}_i$. We now develop the nature of linkage through the sequences of activity choices individual i makes over his life cycle.

D. Activity Choice Value Functions

Let the value function to individual i who is age a who engages in activity d_j^r be denoted by V_{iaj}^r. These value functions depend on the elements of the individual's information set at age a: personal characteristics, $\mathbf{z}_{ia}$, family background characteristics, $\mathbf{f}_{ia}$, local labor market characteristics, $\mathbf{m}_{ia}$, accumulated school and work experiences $\mathbf{x}_{ia}^r$, and the individual's unobserved personal characteristics, $\boldsymbol{\xi}_i$. For computational simplicity, we approximate the V_{iaj}^r's for $j = 1, ..., J^r$ as a linear function of these characteristics:

$$\begin{aligned} V_{iaj}^r(\boldsymbol{\xi}_i) &= v_{iaj}^r(\boldsymbol{\xi}_i) + \omega_{iaj} \\ &= \boldsymbol{\alpha}_{\mathbf{f}j}^r \mathbf{f}_i + \boldsymbol{\alpha}_{\mathbf{z}j}^r \mathbf{z}_i + \boldsymbol{\alpha}_{\mathbf{m}j}^r \mathbf{m}_{ia} + \boldsymbol{\alpha}_{\mathbf{x}j}^r b(\mathbf{x}_{ia}^r, \mathbf{z}_i) + \alpha_{\xi j1}^r \xi_{i1} + \alpha_{\xi j2}^r \xi_{i2} + \omega_{iaj}, \end{aligned} \tag{11}$$

where $b(\cdot)$ contains: (i) a set of nine bin indicators for each type of accumulated experience, (ii) linear interactions between race/ethnicity and each type of accumulated experience, and (iii) no indicators for educational attainment, since these are already embedded in the choice sets.[16] 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 activity j from among the

[16] 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 essential in order to match the observed data.

activities in the current risk set, $R_{ia} = r$ so as to maximize his utility:

$$j_{ia}^{r*} = \underset{k}{\operatorname{argmax}}\, V_{iak}^{r}, \forall r. \tag{12}$$

E. Cognitive and Non-cognitive Ability

Our model incorporates two unobserved random factors representing unobserved cognitive and non-cognitive ability. To measure unobserved cognitive ability (ξ_{i1}), we use six subject tests from the ASVAB, each of which has been normalized to correct for different test taking ages and test media similar to Altonji et al. (2009).[17] For each subject test s, the z-scored test score y for individual i is defined as a function of personal characteristics, $\mathbf{z}_{ia}$, family background characteristics, $\mathbf{f}_{ia}$, and the cognitive ability ξ_{i1}

$$y_{is} = \gamma_{0s} + \boldsymbol{\gamma}_{\mathbf{f}s}\mathbf{f}_i + \boldsymbol{\gamma}_{\mathbf{z}s}\mathbf{z}_i + \gamma_{\xi s1}\xi_{i1} + \eta_{is}, \tag{13}$$

where η_{is} captures idiosyncratic variation in test scores not related to the cognitive ability or test score determinants.[18] We include the observable characteristics $\mathbf{z}_{ia}$ and $\mathbf{f}_{ia}$ in this equation in order to capture, for example, bias in testing related to racial and family background differences.

There is little overlap in the measures of non-cognitive traits across the two NLSY surveys.[19] Due to this data limitation, we are unable to measure non-cognitive ability consistently across NLSY cohorts. Instead, we use the panel nature of the data to identify the non-cognitive ability factor ξ_{i2}. Thus this second factor is defined as all unobserved person-specific factors influencing the

[17]The six subject tests we use are: Arithmetic Reasoning, Coding Speed, Mathematics Knowledge, Numerical Operations, Paragraph Comprehension, and Word Knowledge.

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

[19]The NLSY79 contains the Rotter locus of control score and Rosenberg self-esteem scale for all individuals. These have been used in other studies as non-cognitive measures (Heckman et al., 2006a; Cunha et al., 2011). The NLSY97 does not collect information on any of these tests, but instead collects information on risky behavior such as school suspensions, sexual promiscuity and substance abuse. Aucejo (2014) uses school suspensions, fights, "precocious sex," grade retention, and 8th grade GPA as non-cognitive measures.

agent's wage and decision process that are not in the clearly-defined cognitive factor.

III. Estimation

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 procedures we employ. For now, we continue to ignore the three different cohorts—the NLSY79 old, the NLSY79 young and the NLSY97—although we allow for all of the parameters of our model to be cohort group-specific and explicitly examine the across-cohort differences in the marginal returns to schooling and work experience in wages and in counterfactual analyses of cross-cohort differences in wages below.

A. 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 $\boldsymbol{\eta}_i$, for all a and i.[20] At the same time, because the choice of past activities determine the accumulated experiences in $\mathbf{x}_{ia}^r$ it is *not* the case that the elements of this vector are independent of $\boldsymbol{\xi}_i$, i.e.,

$$F(\mathbf{x}_i^r, \boldsymbol{\nu}_i) \neq f(\mathbf{x}_i^r) f(\boldsymbol{\nu}_i), \tag{14}$$

but

$$F(\mathbf{x}_i^r, \boldsymbol{\nu}_i \,|\, \boldsymbol{\xi}_i) = f(\mathbf{x}_i^r \,|\, \boldsymbol{\xi}_i) f(\boldsymbol{\nu}_i \,|\, \boldsymbol{\xi}_i), \tag{15}$$

where $\boldsymbol{\nu}_i \equiv \Big(\boldsymbol{\omega}_i + \boldsymbol{\xi}_i, \quad \boldsymbol{\varepsilon}_i + \boldsymbol{\xi}_i, \quad \boldsymbol{\eta}_i + \boldsymbol{\xi}_i\Big)$, $F(\cdot,\cdot)$ is the joint distribution function, and $f(\cdot)$ is the marginal distribution function. We further assume that $\boldsymbol{\xi}_i$ is

[20] Recall that $\boldsymbol{\eta}_i$ is the vector of test scores for individual i. This vector is allowed to be correlated through the factor structure introduced in equation (13).

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 independently distributed both across and at each age, a, and have mean zero and constant variances. That the vector of activity shocks, $\boldsymbol{\omega}_{ia}$, are 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 i.

B. Likelihood Function

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 this activity, conditional on $\boldsymbol{\xi}_i$, has the logistic form:

$$P^r_{iaj}\left(\boldsymbol{\xi}_i\right) = \frac{\exp\left(v^r_{iaj}\left(\boldsymbol{\xi}_i\right)\right)}{\sum_{k=1,\ldots,J^r} \exp\left(v^r_{iak}\left(\boldsymbol{\xi}_i\right)\right)} \tag{16}$$

where $v^r_{iaj}\left(\boldsymbol{\xi}_i\right)$ is the deterministic component of the value function, as defined in the first line of (11).

We assume that the idiosyncratic errors entering the wage function in (10) are normally distributed with zero mean and variance $\sigma^2_{wj'}$ and its probability density function is given by:

$$f_w(\boldsymbol{\xi}_i) = \frac{1}{\sigma_{wj'}}\phi\left(\frac{w_{iaj'} - \beta^r_{0j'} - \boldsymbol{\beta}_{\mathbf{m}}\mathbf{m}_{ia} - \boldsymbol{\beta}_{\mathbf{z}}\mathbf{z}_i - \boldsymbol{\beta}_{\mathbf{x}} g\left(\mathbf{x}^r_{ia}\right) - \beta_{\xi j'1}\xi_{i1} - \beta_{\xi j'2}\xi_{i2}}{\sigma_{wj'}}\right), \quad j' = 2, 3, 4, \tag{17}$$

where $\phi\left(\cdot\right)$ is the standard normal pdf.

We also assume that the idiosyncratic errors entering the ASVAB test score function in (13) are normally distributed with zero mean and variance σ^2_s and each probability density function is given by:

$$f_s(\xi_{i1}) = \frac{1}{\sigma_s}\phi\left(\frac{y_{is} - \gamma_{0s} - \boldsymbol{\gamma}_{\mathbf{f}s}\mathbf{f}_i - \boldsymbol{\gamma}_{\mathbf{z}s}\mathbf{z}_i - \gamma_{\xi s1}\xi_{i1}}{\sigma_s}\right). \tag{18}$$

It follows that the log likelihood function is given by:

$$\log \mathcal{L}\left(\boldsymbol{\theta}\right) = \sum_i \log \int \mathcal{L}_i\left(\theta \,|\, \boldsymbol{\xi}_i\right) f_\xi(\boldsymbol{\zeta}) d\boldsymbol{\zeta} \tag{19}$$

where

(20)

$$\mathcal{L}_i\left(\theta \,|\, \boldsymbol{\xi}_i\right) = \prod_s f_s\left(\xi_{i1}\right) \prod_a \prod_r \left[\prod_{j^r=1,5,6,7} P^r_{iaj}\left(\boldsymbol{\xi}_i\right)^{d^r_{iaj}} \prod_{k^r=2,3,4} \left[P^r_{iak}\left(\boldsymbol{\xi}_i\right) f_w\left(\boldsymbol{\xi}_i\right)\right]^{d^r_{iak}}\right]^{I(R_{ia}=r)}$$

and where $\boldsymbol{\theta} \equiv \begin{pmatrix}\boldsymbol{\alpha}' & \boldsymbol{\beta}' & \boldsymbol{\gamma}'\end{pmatrix}'$, $I(A)$ is the indicator function that is equal to one if A is true and zero otherwise, and $f_\xi(\cdot)$ is the pdf of $\boldsymbol{\xi}$. In the analysis that follows, we assume that $\boldsymbol{\xi}$ has a standard multivariate normal distribution with identity covariance matrix. Finally, the variance of the estimated parameters is recovered as the inverse of the estimated Hessian matrix, which has the desirable asymptotic properties for maximum likelihood estimators. In practice, we use quadrature to approximate the integral of the likelihood function using Gaussian quadrature with seven points of support for each dimension of the integral.

C. *Identification*

Here we informally discuss the identification of our model's parameters. Identification of the parameters relating observed outcomes to observed characteristics is straightforward. These parameters are identified by variation in the observed characteristics under various assumptions about the distribution from which the transitory errors are drawn. Identification of the parameters associated with the person-specific unobservables is less straightforward and requires more discussion.

To identify the role of unobserved effects, we cannot rely on instrumental variable techniques. Instrumenting for all the previous choices in a person's career would not be feasible in this framework, as such valid instruments would not exist. This further motivates the need for our structural model.

As discussed in Section III.A, we assume stochastic independence of $\boldsymbol{\xi}_i$ and the distributions of the observables, so that $\boldsymbol{\xi}_i$ are random effects with normalized mean and variance. The factor loadings $\boldsymbol{\alpha}_\xi$ and $\boldsymbol{\beta}_\xi$ represent the variance of the factors relative to their normalized values. Because $\boldsymbol{\xi}_i$ is vector-valued and appears in both the utility and wage equations, we impose three exclusion restrictions in order to be able to identify the factor loading parameters: (i) the factor ξ_{i2} does not enter the ASVAB test score equations; (ii) the population covariance between ξ_{i1} and ξ_{i2} is zero; and (iii) the vector of family background characteristics $\mathbf{f}_i$ does not enter the wage equation (see Willis and Rosen, 1979; Taber, 2001; Hotz et al., 2002).

In order to aid the interpretation of the factor loadings, we measure the first factor (representing cognitive skills) by utilizing ASVAB test scores. The intuition proceeds as follows: for a given vector of observables and outcomes (observed decisions, wages, and ASVAB subject test scores), the factor loading for ξ_{i1} in each of these equations measures the permanent covariance in the residuals among these alternatives, net of the other factor ξ_{i2}. The second factor ξ_{i2} (representing non-cognitive skills) is identified in a similar way, but because we have no common measures of non-cognitive skills across the two NLSY datasets, we use the panel nature of each dataset to identify this parameter vector. In this case, the factor loading on ξ_{i2} is identified from permanent covariance among outcome residuals holding fixed observables, ξ_{i1}, and transitory variation. Thus, individuals that have higher-than-expected outcomes over time conditional on observables and ξ_{i1} would have higher levels of ξ_{i2}. Because of our ability to find measurements of only ξ_{i1}, and not ξ_{i2}, we are unable to identify their covariance and thus instead restrict it to be zero.

We follow the previous literature (see Willis and Rosen, 1979; Taber, 2001; Hotz et al., 2002) in excluding family background characteristics $\mathbf{f}_i$ from the wage equations. While not crucial to identification in our context (because our selection specification is dynamic and by definition relies on panel data, as opposed to static sample selection specifications), this exclusion restriction helps pin down the factor loadings by allowing the set of observables to differ between the choice equations and the wage equations.

IV. Results

In this section we discuss the results of our estimation. While many of our questions will be answered in the next section, here we discuss the trends in the wage returns to in-school work experience. We begin by discussing the various model specifications that we use to evaluate our analysis, with a unique focus on how these specifications impact the returns to schooling. We then discuss the returns to various forms of experience and the returns to unobserved ability as measured by our factor loading estimates. Throughout we are interested in how the results differ across the three birth cohorts represented in our data.

A. Specification of the models

As discussed above, our full model allows us to estimate wage returns by accounting for the endogeneity of schooling and working choices early in the life cycle. As described, our full model of wage returns includes non-linear functions of school and experience variables, indicators for graduation attainment, demographic and background characteristics, and measures for unobserved cognitive and non-cognitive ability. We compare this specification with other models, specifically the classic Mincerian model (see Mincer, 1974) and the flexible specification introduced in Heckman et al. (2006b).

The classic Mincerian model allows for the 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). Some of the criticisms of this model include the strict linearity in the schooling terms, the quadratic in potential experience, and the restriction that the returns to experience be the same for all schooling levels. Heckman et al. (2006b) relax these assumptions, first by using indicators for each year of schooling, then using indicators for each year of potential experience, and finally by estimating the returns to potential experience separately for various different schooling classes (HS dropout, HS graduate, some college, college graduate). They find that the returns to schooling change drastically with the introduction of non-linearities in schooling and separability of returns by schooling class, leading them to harshly critique these assumptions of the classic Mincerian model.

To describe the implications of our model, we build on Heckman et al. (2006b)'s model in three different ways. The first is with respect to the experience variable. In our model, we are able to abstract away from *potential* work experience and instead use *actual* work experience. We break actual work experience into five different types: in-high-school, in-college, part-time, full-time, and military.

Next, to account for some selection on observable characteristics, we add in background characteristics such as nativity and birth year.[21]

Finally, and perhaps most importantly, our econometric strategy allows us to control for selection based on unobservables. As mentioned previously, we account for this by including random factors representing unobserved cognitive and non-cognitive ability and jointly estimating our structural model, which includes the wage, choice and ability equations. This allows us to more fully capture the remaining noise in the returns to school.

We examine the results of these different specifications in Tables 9 and 10. These results are in the form of marginal effects. For the graduation dummies, these are simply the estimate coefficients, since they enter the model linearly.

[21]We cannot include ASVAB nor interact it with educational attainment because ASVAB is our cognitive factor measure and doing so would remove all identifying power of the cognitive factor.

However, for the accumulated experience variables $\mathbf{x}_{ia}^{r}$ (schooling, work, military and other) that enter the model nonlinearly, we calculate the marginal effect on the full-time wage of an additional unit of experience k:

$$g_k'\left(\mathbf{x}_{ia}^{r}\right)=\frac{\partial w_{ia4}\left(\mathbf{x}_{ia}^{r}\right)}{\partial x_{kia}^{r}}, \tag{21}$$

where wage is subscripted by $j'=4$ to denote that we are examining full-time wages. Further, since this is a function of the experience terms, we need to choose a point of evaluation, which for this analysis is the average experience vector at age 29, $\overline{\mathbf{x}}_{29}^{r}$.[22] 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.[23]

B. *Returns to Schooling*

Table 9 shows the schooling estimates that emerge from our various specifications, as well as ones similar to Mincer and Heckman et al. (2006b). Our Mincerian specification is slightly different, in that it also contains indicators for HS and college graduates. Also our Heckman et al. (2006b) (HLT) is different. While it is still parametric, it is also very flexible with indicators for graduates, cubic polynomials in school and potential work experience, and an interaction between schooling and potential experience. Panel (a) shows the return to an additional year of schooling, while panels (b) and (c) illustrate the "sheepskin effects" of graduating high school and college, respectively.

We start by comparing our Mincer and HLT specifications. Across these two specifications, there is virtually no difference in the high-school wage premium, while the college wage premium drops by anywhere between 10-25%. However, the change in the return to an additional year of schooling increases dramatically between these specifications, with an increase of 20% for the NLSY97 cohort, and

[22]The full estimation results are available from the authors upon request.
[23]Estimating the returns even later in life would be interesting, but is not feasible for us given the data limitations.

a 10-fold increase for the NLSY79 old cohort. This implies that controlling for potential experience in our HLT specification results in a more linear specification.

When we replace potential experience with actual experience, we see significant changes in the HS wage premium as well as the return to another year of school and little change in the college wage premium. Specifically, the return to an additional year of education is 50-100% lower in this specification, verging to zero in the NLSY79 old. At the same time, the HS wage premium drops by 20-50% over this time frame. Thus much of the returns that were captured by schooling are now more accurately being attributed to the various forms of work experience, especially in-school work experience.[24]

Adding in indicators for nativity and birth year does not create a consistent change in most estimates. However, all returns to schooling in the NLSY97 did decrease, from between 7-75%, indicating a significant role for birth covariates for this cohort. Yet while the return to college graduation drops by about 7-15% for the NLSY79 cohorts, the return to another year of schooling and HS graduation increased 50-100% and 10-25%, respectively. [...]

Finally, we add in controls for selection on unobservable characteristics. Almost across the board, this leads to decreases in the sheepskin effects on the order of 0-80%, with the exception being the college wage premium in the NLSY79 old cohort which increased by 25%. This results in much smaller changes in the college wage premium over time, consistent with our prior of selection on unobservable characteristics playing an important role in the evolution of the college wage premium. Of special note is how the returns for the NLSY79 young changed, with a moderate increase in the per year return, but a significant drop in the HS wage premium.

[24]While not reported, the coefficients on in-college work are large and positive for all the cohorts. The coefficients on in-HS work are also large and significant for the NLSY79 cohorts, but negligible for the NLSY97 cohort.

C. Returns to experience

We continue by discussing the evolution across NLSY cohorts in the returns to various forms of human capital, under varying assumptions about selection on unobservables. As mentioned, we evaluate the return at the marginal effect for average experience levels by age 29, $g'_j\left(\bar{\mathbf{x}}^r_{29}\right)$. These returns can be found in Table 10. These estimates are calculated from our full model specification, which regresses the log wage on background characteristics, local labor market conditions, and demographic variables, as well as the experience terms. Panel (a) shows the results from a wage equation specification with no selection on unobservables, whereas panel (b) shows the estimates after controlling for selection by jointly estimating the wage equation with our choice model and ability equation. Note that the first variable, any school, is the same as panel (a) of Table 9.

The first three elements involve the returns to schooling, where the first line refers to the returns to any type of schooling, and the next two refer to the *additional* returns to working while in high school and college, respectively. Comparing these trends to each other allows us to answer one of our main research questions, specifically what are the trends in the wage returns to in-school work experience.

With regards to working while in high school, we see a stark U-shaped trend. Specifically, in the NLSY79 old cohort, working while in high school results in 2% higher wages than being in high school alone. However, for the NLSY79 young cohort these returns drop to almost -3%, almost washing away the gains from school. Then in the NLSY97 cohort, these returns increase to almost 3%, on top of the almost 3% he gets from already being in school. Thus there was a moderate increase between going from NLSY79 old to NLSY97 (1 log point), and a large increase between going from NLSY79 young to NLY97 (5.5 log points).

For working while in college, there is a consistent decreasing trend, though for all cohorts there is still a positive return. The trend goes going from 6.5% in the NLSY79 old, down to 2% in the NLSY97. This implies that the increase in the incidence of working while in college was not motivated by rising returns, but rather by items like paying for college, or shifts in the expectation of college life.

This provides a very useful comparison to the previous work found in Hotz et al. (2002). They examine only the NLSY79 young cohort and find the same results as ours for working while in high school, namely a smaller return than pure schooling. However, while they also find a smaller return for working while in college than pure schooling, we find a larger effect. Some potential explanations for this difference are our model having two factors and our model having a richer specification.

The other experience terms we are interested in are the full-time and part-time work experience variables. Not surprisingly, the returns to full-time work experience are always higher than those to part-time work experience. Further, they have remained steady at around 3%, causing the returns to full-time work and the returns to schooling to have become more comparable over time. When examining the returns to part-time work experience, we see once again the importance of controlling for selection. In panel (a) of Table 10, we find negative returns to part-time experience on full-time wages if we ignore selection. However, recognizing the role of selection in panel (b) shows that, while still negative, the effects are diminished. This finding is important, especially in light of recent discussion surrounding the detrimental impact of underemployment in the Great Recession. While these workers are still worse off than had they remained fully employed, the losses are not as profound as previously thought.

Recall that in section I.B we showed that the level of in-school work and time spent in school has increased at the expense of full-time work experience, and that the incidence of high school and college graduation has also increased. In this section, we have shown how the returns to these various activities and accomplishments have changed over time. In order to isolate the specific sources of these trends, we need to do a decomposition. The method and results of our decomposition are discussed in the next section.

D. *Factor loadings*

Before discussing the wage decompositions, it is useful to examine the contribution of the unobserved factors to the wages of young men. Table B.3 contains both the cognitive and non-cognitive factor loading estimates for the full-time wage equation in each cohort. Recall that the distribution of the factors is multivariate normal with mean zero and identity variance. Thus the interpretation of the estimates is the change in log wages (percent change in wage) due to a one standard deviation increase in the unobserved ability, holding fixed all observable characteristics and the other dimension of unobserved ability.

Our main finding is that the cognitive loading, at about 14-17 log points, provides a higher return to skill than the non-cognitive loading, which is around 11-12 log points. This is consistent with Cunha et al. (2011) who find that their measure of cognitive ability is the primary driver of the increase in the college wage premium in the 1980's. Across cohorts, the returns for each factor are lowest for the NLSY79 young cohort. The cognitive factor loading is highest for the NLSY79 old. Our results differ from Castex and Dechter (2014), who also look at the returns to ability between the NLSY79 and NLSY97 but find that the returns to AFQT have diminished greatly between the two. Our wage specification controls for selection in the wage equation that theirs does not account for. Thus, our finding that the return to unobserved ability (as measured by ASVAB components) has increased between the NLSY79 young and the NLSY97 can be explained by selection.

E. *Model fit*

Our decomposition exercise in the next section 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 (19). 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.[25] Next, we update the state space and repeat $T = 156$ times. Finally, we draw idiosyncratic wage shocks and compute wages in each period that a work activity was 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.[26]

V. Decompositions

In this section we use the parameter estimates of the model to run a set of decomposition exercises. 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, unlike previous studies, the estimates our model produces allow us to account for the endogenous nature of the changes in educational attainment and work experiences for each of the cohorts without relying on conditional independence assumptions.

[25]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.

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

A. Setup

Our approach differs from the canonical Oaxaca decomposition in three important ways: (*i*) we are interested in the difference across groups in (log) wage *premia* to skills rather than wage *levels*; (*ii*) we allow for a more flexible form of wages, allowing for identification of unobserved wage determinants; and (*iii*) our focus on wage *premia* leads us to analyze the role of the marginal effect of a skill. By formally discussing each of these differences, we are able to present the details of our decomposition approach, as well as highlight our contributions.

Wage premia vs wage levels

As mentioned, rather than focus on the difference in wage levels, we focus on the difference in wage premia. For example, the classic Oaxaca may look at the wages across the NLSY79 and NLSY97 cohorts to determine how much of the difference in the value of those wages is driven by price effects and how much by composition.[27] Our approach, however, aims to perform a similar decomposition, but instead of comparing the wage levels, we compare the wage premia to specific types of experience, say one more year of schooling, across groups, and then determine the relative importance of price and composition effects.

Our decomposition of average wage premia unfolds as follows. Denote by w the outcome of interest (log wage), s the skill of interest (e.g. college education or full-time work experience), a the group with the higher level of skill ("*a*bove" the mean), and b the group with the lower level of skill ("*b*elow" the mean). For example, college graduates in the NLSY79 cohort are in the $a79$ group, while high

[27] For the purpose of this decomposition, we will only be using the NLSY79 Young cohort. As such, we will use shorthand and refer to that cohort as NLSY79 and use the 79 superscript.

school graduates are in the $b79$ group. Thus, the return to skill s, R_s, is given by:

$$
\begin{aligned}
R_s &= \Delta w^s_{97} - \Delta w^s_{79} \\
&= (w^s_{a97} - w^s_{b97}) - (w^s_{a79} - w^s_{b79}) \\
&= \left(\overline{Z}_{a97} - \overline{Z}_{b97}\right)\hat{\beta}_{97} - \left(\overline{Z}_{a79} - \overline{Z}_{b79}\right)\hat{\beta}_{79} \\
&= \Delta\overline{Z}_{97}\hat{\beta}_{97} - \Delta\overline{Z}_{97}\hat{\beta}_{79} + \Delta\overline{Z}_{97}\hat{\beta}_{79} - \Delta\overline{Z}_{79}\hat{\beta}_{79} \\
&= \underbrace{\Delta\overline{Z}_{97}\Delta\hat{\beta}}_{\text{price}} + \underbrace{\Delta\Delta\overline{Z}\hat{\beta}_{79}}_{\text{composition}}
\end{aligned}
\tag{22}
$$

where $\hat{\beta}_j$ corresponds to the full-information maximum likelihood estimates of cohort j. The contribution that we bring in this analysis is evidenced here in the last line of Equation (22), where our focus on the difference in the difference of log wages (i.e, wage premia), results in a an extra layer of differences in the elements of the decomposition. In other words, we replace Oaxaca's X with ΔZ. To calculate this ΔZ for continuous covariates, we define the "above" group as observations in the interval $[\overline{s}, \overline{s} + 1 \text{ year}]$ and the "below" group as observations in the interval $[\overline{s} - 1 \text{ year}, \overline{s}]$, where $\overline{s}$ is the mean of the skill among full-time workers who are age 29.[28] For discrete covariates (i.e. high school graduation, college graduation), "above" is defined as those who have a degree (i.e. $s = 1$) and "below" is defined as those who do not ($s = 0$). As in the model, we compare college graduates with high school graduates only, and high school graduates with high school dropouts.

Unobserved Skills

In our model, we place specific structure on the functional form of wages, choices and ability. Doing so allows us to control for and estimate the effect of unobserved characteristics on wages for the different cohorts, based on assumptions of the distribution of the underlying unobservables. In order to be able to analyze the

[28]Recall that our data is in monthly format, which enables us to see multiple observations for individuals at points within that one-year time frame above and below the mean.

role of the unobserved covariates, we rely on simulated data to provide estimates for the actual value of each individual's unobserved characteristics (see Section IV.E). Thus we can further partition Z into components that are "observed" and components that are "unobserved." Denote by $\overline{Z}^{\text{unobs}}$ the unobserved components of Z and by α the factor loadings on these unobserved terms. If we redefine Z and β to represent the observed parameters and their estimates, then the last line of Equation (22) can be expanded as:

$$
\begin{aligned}
R_s &= \underbrace{\Delta\overline{Z}_{97}\Delta\hat{\beta}}_{\text{price}} + \underbrace{\Delta\Delta\overline{Z}\hat{\beta}_{79}}_{\text{composition}} \\
&= \underbrace{\Delta\overline{Z}_{97}\Delta\hat{\beta}}_{\text{obs price}} + \underbrace{\Delta\overline{Z}_{97}^{\text{unobs}}\Delta\hat{\alpha}}_{\text{unobs price}} + \underbrace{\Delta\Delta\overline{Z}\hat{\beta}_{79}}_{\text{obs composition}} + \underbrace{\Delta\Delta\overline{Z}^{\text{unobs}}\hat{\alpha}_{79}}_{\text{unobs composition}} .
\end{aligned}
\tag{23}
$$

These four terms represent all the price and composition effects, both observed and unobserved. We emphasize that the classic Oaxaca framework is preserved here. Our innovation is that, by placing additional structure on the wage process and simulating the estimated model, we can treat unobserved ability as observed. This allows us to directly compute the extent to which selection on unobserved ability 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.

Direct and indirect components

We now discuss one final step in deriving the different elements of our decomposition. Because we model a dynamic selection process that encompasses different dimensions of skill, these skill levels might be highly correlated with each other. In order to compute the wage change associated with increasing one skill (and not jointly increasing the levels of its correlated skills), we further partition the observed price effect into a direct effect and an indirect effect. We denote wage components that directly impact the skill of interest s with the subscript k (i.e. s

itself and its polynomial terms, if applicable), and wage components that are not directly related to s, but are still correlated with s with the subscript $-k$. The direct price effect as defined here matches closely with the selection-corrected marginal effects reported in Tables 9 and 10. The resulting formula builds on Equations (22) and (23), and is written as:

(24)
$$
\begin{aligned}
R_s &= \underbrace{\Delta\overline{Z}_{97}\Delta\hat{\beta}}_{\text{price}} + \underbrace{\Delta\Delta\overline{Z}\hat{\beta}_{79}}_{\text{composition}} \\
&= \underbrace{\Delta\overline{Z}_{97}\Delta\hat{\beta}}_{\text{obs price}} + \underbrace{\Delta\overline{Z}_{97}^{\text{unobs}}\Delta\hat{\alpha}}_{\text{unobs price}} + \underbrace{\Delta\Delta\overline{Z}\hat{\beta}_{79}}_{\text{obs composition}} + \underbrace{\Delta\Delta\overline{Z}^{\text{unobs}}\hat{\alpha}_{79}}_{\text{unobs composition}} \\
&= \underbrace{\Delta\overline{Z}_{97,k}\Delta\hat{\beta}_k}_{\text{obs direct price}} + \underbrace{\Delta\overline{Z}_{97,-k}\Delta\hat{\beta}_{-k}}_{\text{obs indirect price}} + \underbrace{\Delta\overline{Z}_{97}^{\text{unobs}}\Delta\hat{\alpha}}_{\text{unobs price}} + \underbrace{\Delta\Delta\overline{Z}\hat{\beta}_{79}}_{\text{obs composition}} + \underbrace{\Delta\Delta\overline{Z}^{\text{unobs}}\hat{\alpha}_{79}}_{\text{unobs composition}}
\end{aligned}
$$

B. Decomposition results

We present in Figure 1 the results of our decomposition exercise that decomposes the difference in differences of average wages in the NLSY97 and the NLSY79 young and just above and just below the mean of the skill. The figure contains seven separate bar graphs, which correspond to the seven separate skill premia that we decompose. To the right of each bar is the sum of all of the components, which corresponds to the change in the above-minus-below wage premium across the two NLSY cohorts.

As an example, Figure 1 shows that the wage premium to an additional year of schooling has risen over time by 2 log points. However, inspection of the bar shows that this overall effect is actually composed of three separate effects, one of which is negative. Consistent with the results of Table 10, the bar shows a negative change in the direct price effect. On the other hand, the price of skills related to schooling (i.e. working in high school) increased over this time period, and this had a positive effect on the premium to an additional year of schooling. Similarly, the observable characteristics of students have changed over time such that this contributes positively to the change in the wage premium to an additional year of schooling. Interestingly, we find little influence of unobserved skill or skill prices on the change in the wage premium to an additional year of schooling.

The other bars in Figure 1 show that the sign and magnitude of the observed direct price effect is consistent with the results in Tables 9 and 10. Looking at the premium for working in high school or college, we find that both observed and unobserved composition effects contributed negatively, and in roughly equal proportions. This finding is consistent with a story where in-school work is becoming increasingly negatively selected, in part due to the fact that expansion of higher education has attracted lower-quality students on average. This story is also at play when examining the premium to receiving a high school diploma or bachelor's degree. Here we see again large negative unobserved composition effects, although we find that observed composition effects are positive.

The results of the decomposition underscore the necessity of accounting for selection when analyzing how the wage premia to skills have changed over the past 20 years. It is specifically important to separately account for observed and unobserved composition effects, as these end up being quite large.

VI. Conclusion

This paper examines the returns to both school and work 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 in the evolution of work and schooling acquisition over the life cycle and its potential impact on measuring the wage returns to these experiences, we develop and estimate a dynamic model of the schooling and work choices these men make in early adulthood and how they affect wage growth.

Based on the estimates from this model, we produce several findings. First, the failure of previous estimates of returns to schooling and degrees to account for the influences of accumulated work experiences and their 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 work experiences differ within and between cohorts. For example, we find evidence that the returns to an extra year of full-time work are larger than the returns to an extra year of schooling and have increased for more recent cohorts. Finally, we decompose the across-cohort changes in returns to school and work experiences into secular changes in skill prices, changes in the amounts and composition of work experience and schooling and changes in the selectivity of individuals who acquire them.

We find evidence of a negative trend in the selectivity of workers who acquire in-school work experience and who obtain formal educational degrees. On the other hand, individuals are on average obtaining more schooling and work experience, which is contributing positively to the trend in wage returns to skill. We find little evidence that secular changes in the return to unobserved skill have had any impact on the across-cohort changes in returns to school and work experience. Our analysis highlights the necessity of accounting for selection when analyzing how the returns to skills have changed over the past 20 years.

References

Altonji, Joseph G., Prashant Bharadwaj, and Fabian Lange, "Constructing AFQT Scores that are Comparable Across the NLSY79 and the NLSY97," Working Paper, Yale University 2009.

_ , _ , and _ , "Changes in the Characteristics of American Youth: Implications for Adult Outcomes," *Journal of Labor Economics*, 2012, *30* (4), 783–828.

Atrostic, Barbara K., Nancy Bates, Geraldine Burt, and Adriana Silberstein, "Nonresponse in US Government Household Surveys: Consistent Measures, Recent Trends, and New Insights," *Journal of Official Statistics*, 2001, *17* (2), 209–226.

Aucejo, Esteban, "Explaining Cross-Racial Differences in the Educational Gender Gap," Working Paper, London School of Economics and Political Science 2014.

Aughinbaugh, Alison and Rosella M. Gardecki, "Attrition in the National Longitudinal Survey of Youth 1997," Working Paper, Bureau of Labor Statistics 2008.

Bacolod, Marigee and V. Joseph Hotz, "Cohort Changes in the Transition from School to Work: Evidence from three NLS surveys," *Economics of Education Review*, 2006, *25* (4), 351–373.

Böhm, Michael J., "Has Job Polarization Squeezed the Middle Class? Evidence from the Allocation of Talents," Discussion Paper 1215, CEP 2013.

Bound, John, Michael F. Lovenheim, and Sarah Turner, "Increasing Time to Baccalaureate Degree in The United States," *Education Finance and Policy*, Fall 2012, *7* (4), 375–424.

Cameron, Stephen V. and James J. Heckman, "Life Cycle Schooling and Dynamic Selection Bias: Models and Evidence for Five Cohorts of American Males," *Journal of Political Economy*, 1998, *106* (2), 262–333.

_ and _ , "The Dynamics of Educational Attainment for Black, Hispanic, and White Males," *Journal of Political Economy*, 2001, *109* (3).

Card, David and Thomas Lemieux, "Can Falling Supply Explain the Rising Return to College for Younger Men?," *Quarterly Journal of Economics*, 2001, *116* (2), 705–746.

Carneiro, Pedro and Sokbae Lee, "Trends in Quality-Adjusted Skill Premia in the United States, 1960-2000," *American Economic Review*, 2011, *101* (6), 2309–2349.

Castex, Gonzalo and Evgenia Kogan Dechter, "The Changing Roles of Education and Ability in Wage Determination," *Journal of Labor Economics*, 2014, *32* (4), 685–710.

Cunha, Flavio, Fatih Karahan, and Ilton Soares, "Returns to Skills and the College Premium," *Journal of Money, Credit and Banking*, 2011, *43* (5), 39–86.

Eckstein, Zvi and Kenneth I. Wolpin, "The Specification and Estimation of Dynamic Stochastic Discrete Choice Models: A Survey," *Journal of Human Resources*, 1989, *24* (4), 562–598.

Fang, Hanming, "Disentangling the College Wage Premium: Estimating a Model with Endogenous Education Choices," *International Economic Review*, 2006, *47* (4), 1151–1185.

Fortin, Nicole M., "Higher-education Policies and the College Wage Premium: Cross-state Evidence from the 1990s," *American Economic Review*, 2006, *96* (4), 959–987.

Fortin, Nicole, Thomas Lemieux, and Sergio Firpo, "Decomposition Methods in Economics," in Orley Ashenfelter and David Card, eds., *Handbook of Labor Economics*, Vol. 4A, Elsevier, 2011, pp. 1–102.

Goldin, Claudia and Lawrence F. Katz, "Long-Run Changes in the US Wage Structure: Narrowing, Widening, Polarizing," Working Paper 13568, National Bureau of Economic Research 2007.

Heckman, James J., Jora Stixrud, and Sergio Urzúa, "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior," *Journal of Labor Economics*, 2006, *24* (3), 411–482.

_ , Lance J. Lochner, and Petra E. Todd, "Earnings Functions, Rates of Return and Treament Effects: The Mincer Equation and Beyond," in Eric A. Hanushek and Finis Welch, eds., *Handbook of the Economics of Education*, Vol. 1, Elsevier, 2006, pp. 307–458.

Hotz, V. Joseph, Lixin Colin Xu, Marta Tienda, and Avner Ahituv, "Are There Returns to the Wages of Young Men from Working While in School?," *The Review of Economics and Statistics*, 2002, *84* (2), 221–236.

Juhn, Chinhui, Kevin M. Murphy, and Brooks Pierce, "Wage Inequality and the Rise in Returns to Skill," *Journal of Political Economy*, 1993, *101* (3), 410–442.

Katz, Lawrence F. and Kevin M. Murphy, "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," *Quarterly Journal of Economics*, 1992, *107* (1), 35–78.

Keane, Michael and Kenneth Wolpin, "The Career Decisions of Young Men," *Journal of Political Economy*, 1997, *105* (3), 473–522.

Lee, Donghoon and Kenneth I. Wolpin, "Accounting for Wage and Employment Changes in the US from 1968–2000: A Dynamic Model of Labor Market Equilibrium," *Journal of Econometrics*, 2010, *156* (1), 68–85.

Mincer, Jacob, *Schooling, Experience and Earnings*, New York: Columbia University Press for National Bureau of Economic Research, 1974.

Moretti, Enrico, "Local Labor Markets," in Orley Ashenfelter and David Card, eds., *Handbook of Labor Economics*, Vol. 4B, Elsevier, 2011, pp. 1237–1313.

Oaxaca, Ronald, "Male-Female Wage Differentials in Urban Labor Markets," *International Economic Review*, 1973, *14* (3), 693–709.

Scott-Clayton, Judith, "What Explains Trends in Labor Supply Among U.S. Undergraduates?," *National Tax Journal*, 2012, *65* (1), 181–210.

Taber, Christopher R., "The Rising College Premium in the Eighties: Return to College or Return to Unobserved Ability?," *The Review of Economic Studies*, 2001, *68* (3), 665–691.

Valletta, Robert G., "Recent Flattening in the Higher Education Wage Premium: Polarization, Skill Downgrading, or Both?," Discussion Paper 10194, IZA 2016.

Willis, Robert J. and Sherwin Rosen, "Education and Self-Selection," *Journal of Political Economy*, 1979, *87* (5), S7–S36.

Tables

Table 1—: Risk sets and activities

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

Table 2—: 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 3—: 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		
HS Graduates	0.79	0.85	0.89		
Some College	0.81	0.83	0.84		
College Graduates	0.52	0.56	0.62		
All Education Levels	0.93	0.96	0.96		
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 using bootstrapped standard errors of the median (500 replications).

Table 4—: Family background characteristics by final educational attainment

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

Table 5—: 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 5 – 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	1070	2415	2625		

AFQT distribution normalized so that the distribution including all cohorts is mean-zero, variance one. Significance reported at the 1% (***), 5% (**), and 10% (*) levels using bootstrapped standard errors of the median (500 replications).

Table 6—: 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

Table 7—: 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		

Estimates weighted by NLSY sampling weights. Estimates are coefficients from regressing log wage on each cumulative experience term separately. 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 8—: 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		
HS Graduates	0.37	0.39	0.39		
Some College	0.44	0.40	0.42		
College Graduates	0.39	0.37	0.43		
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.

Table 9—: Measures of wage returns to schooling across specifications

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***	-0.006***
(ii) Mincer	0.016***	0.033***	0.049***	0.017***	0.016***
(iii) HLT (2006)	0.107***	0.073***	0.058***	-0.035***	-0.015***
(iv) + Actual Exper	-0.002	0.012***	0.026***	0.014***	0.015***
(v) + Background	0.026***	0.024***	0.007***	-0.002	-0.018***
(vi) + Unobserved	0.052***	0.024***	0.013***	-0.028***	-0.011***
Panel (b) : Return to Graduation from HS					
(i) Raw	0.160***	0.156***	0.175***	-0.004	0.018***
(ii) Mincer	0.114***	0.089***	0.062***	-0.025***	-0.027***
(iii) HLT (2006)	0.115***	0.091***	0.060***	-0.024***	-0.031***
(iv) + Actual Exper	0.062***	0.061***	0.048***	-0.001	-0.012***
(v) + Background	0.081***	0.068***	0.037***	-0.014***	-0.030***
(vi) + Unobserved	-0.019***	0.020***	0.027***	0.039***	0.007*
Panel (c) : Return to Graduation from College					
(i) Raw	0.245***	0.420***	0.367***	0.175***	-0.053***
(ii) Mincer	0.203***	0.354***	0.252***	0.151***	-0.102***
(iii) HLT (2006)	0.148***	0.319***	0.235***	0.171***	-0.084***
(iv) + Actual Exper	0.145***	0.304***	0.222***	0.159***	-0.082***
(v) + Background	0.136***	0.253***	0.209***	0.117***	-0.044***
(vi) + Unobserved	0.177***	0.231***	0.186***	0.054***	-0.046***

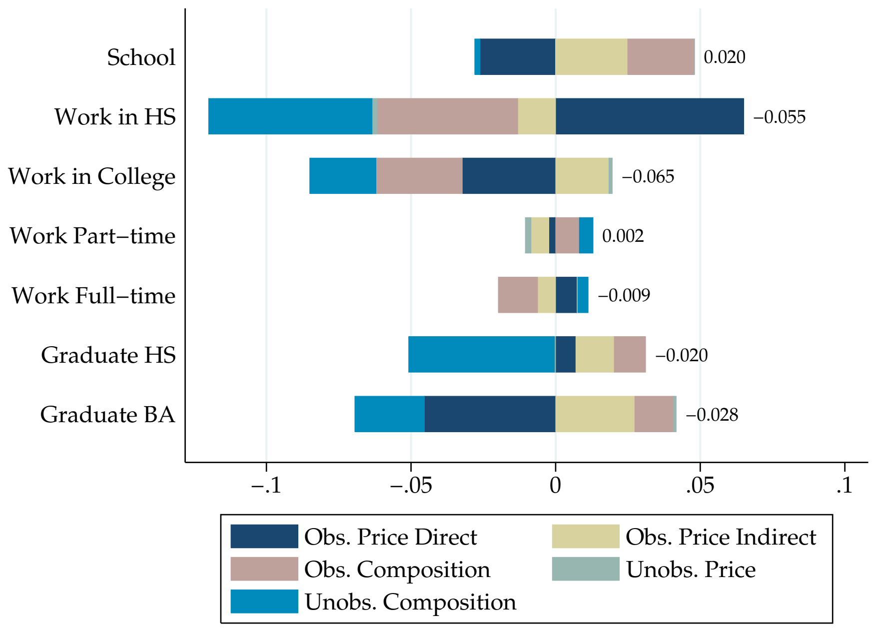
Panel (a) is the wage return at age 29 of one extra year of schooling.
Panel (b) is the wage premium of earning a high school diploma relative to not earning a diploma.
Panel (c) is the wage premium of earning a bachelor's degree relative to a high school diploma.
(i) Indicates raw premium without any controls.
(ii) Includes a quadratic in potential experience (age − years of schooling − 6), a cubic in years of schooling, and dummies for type of work (in-school, part-time, full-time) as the only set of controls.
(iii) Increases flexibility similar to Heckman et al. (2006b). Replaces the quadratic in potential experience with a cubic in potential experience, adds a linear interaction between schooling experience and potential experience, and adds race/ethnicity indicators.
(iv) Replaces potential experience with actual work experience type (in-school, part-time, full-time), military experience, and other experience.
(v) Adds personal background characteristics.
(vi) Adds discrete choice estimation and person-specific random factors for dynamic selection.
Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

Table 10—: Select wage equation marginal effects (+1 year at age 29)

Variable	NLSY79 Old	NLSY79 Young	NLSY97	79Y–79O	97–79Y
Panel (a): Full model without controlling for selection					
Yr of School	0.026***	0.024***	0.007***	-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					
Yr 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.

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 V.

Data Appendix

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 innate 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.

A1. Personal and family characteristics and innate 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.

A2. 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.[29] To create these local labor market variables, we make use of the restricted-access Geocode supplement of each of the NLSY surveys.

[29] "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.

A3. Wages and educational degrees

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

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

A4. 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 1.

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.

A5. 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.[30] 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).

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

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

Appendix Tables

B1. Sample Selection

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 $50 (in 1982-84$).

Table B.3—: 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 "Unobs het" column in Table 9. Significance reported at the 1% (***), 5% (**), and 10% (*) levels.

B2. Additional results

This subsection contains additional results including estimates of the factor loadings for each cohort and factor, model fit statistics for the simulated data used in the decomoposition exercise, and detailed decomposition results.

Table B.4—: 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 B.5—: Graduation and earnings in model and data

	Model			Data		
Outcome	79O	79Y	97	79O	79Y	97
Panel (a): Graduation rates by age 29						
Graduate HS	0.76	0.82	0.88	0.82	0.84	0.88
Graduate College	0.10	0.11	0.16	0.15	0.17	0.22
Panel (b): 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 (c): 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