The Effects of High School Career and Technical Education for Non-College Bound Students

Michael Robert LaForest
Charlottesville, Virginia

B.S. Economics & Political Science, University of Michigan, 2007
M.A. Economics, University of Virginia, 2012

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Abstract*

I present a dynamic structural model of individual choice regarding high school education curricula, post-secondary education attainment, and early labor market opportunities. I estimate the model to investigate the returns to education from different types of U.S. high school curricula, with a particular focus on career and technical education (CTE) for non-college bound students. I estimate the model using panel data on students' high school course selection and labor market outcomes from the Education Longitudinal Study of 2002, and I account for high school curriculum self-selection by including instruments in the model for high school CTE and academic opportunities along with local labor market controls. The estimates suggest that, relative to general education courses, trade CTE courses improve a non-college bound student's later labor market wages and chance of being employed in a skilled occupation, while business CTE courses improve wages in low-wage / high-non-pecuniary utility occupations. In addition, the estimates suggest that increased CTE opportunities decrease a non-college bound student's propensity to drop out of high school but also that CTE courses decrease a high school graduate's likelihood to pursue a post-secondary education degree. Policy simulations suggest that incorporating vocational certification into high school CTE curricula would cause more students to take CTE courses and improve their labor market outcomes and that instituting a German-style high school tracking system in the United States would improve the education and labor market outcomes of high school graduates at the expense of their non-pecuniary utility in high school. Policy simulations also suggest that providing free tuition to community college would cause more students to take general education courses in high school, increase graduation from community colleges, slightly increase graduation from four-year colleges and universities, and slightly increase average wages in the population.

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1. Introduction

In 2014, 32% of U.S. high school graduating seniors did not attend any post-secondary institutions following graduation (Bureau of Labor Statistics, 2015). For many non-college bound students, taking career and technical education (CTE) courses in high school, which prepare them for trade and business careers, may be preferable to concentrating solely on general education courses.[2] An important question is which type of high school education is most advantageous for these students. Learning particular labor market skills while attending high school may improve the ability of these students to find well-paying jobs after graduation. Alternatively, these students may be better served over their lifetimes by learning a wide range of non-honors English, math, and science courses in high school and waiting to learn job-specific skills after graduation in the labor market.

There is disagreement among researchers and policy makers about the merits of high school career and technical education.[3] Some researchers and policy makers see high school CTE as an alternative to college which helps students find well-paying careers, while others see high school CTE as a system that limits students' future post-secondary education and labor market options. A third set of policy makers see high school CTE as a system that can prepare students to attend post-secondary education institutions as well as prepare them to enter the labor market. Partially due to this lack of consensus, high school education policy has favored an expansion of academic and general education curricula alongside a reduction in CTE curricula over the last 30 years, which has caused the number of high school students in the United States concentrating in a vocational field to fall from one-third to one-fifth since 1982 (U.S. Department of Education, 2013). However, the Council of Economic Advisors (2010) has recently projected faster growing labor market demand for individuals with technical college degrees and specific training than for those with full university degrees. Little empirical research has been conducted on the benefits and drawbacks of high school CTE, and there remains general disagreement

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[2] The terms "Career and Technical Education" and "Vocational Education" are used synonymously by different sets of policy makers and researchers throughout the field and literature. I use the terms synonymously throughout this paper.

[3] For a discussion of these disagreements, see Silverburg et al. (2004), Bozick and Dalton (2013), Levesque et al. (2008), U.S. Department of Education (2013), and Independent Advisory Panel of the NACTE (2014).

among researchers about its effects, as discussed in Section 2 below.

In addition, the percentage of students who drop out of high school is sizable as is the percentage of students who begin but never complete a post-secondary education (PSE) degree. Specifically, 10% of the potential high school class of 2012 had not received a high school diploma or General Educational Development (GED) certificate by age 21 (Flood et al., 2015).[4] As well, only 29% of students who began PSE certificate / associate degree programs in 2009 had completed them in three years or less, and only 59% of students who began PSE bachelor's degree programs in 2006 had completed them in six years or less (National Center for Education Statistics, 2015). These sizable attrition rates motivate three additional questions. The first is how taking high school CTE affects the labor market outcomes of high school dropouts and students who begin but never complete PSE degrees. The second is how the availability of high school CTE affects students' propensity to drop out of high school, and the third is how taking high school CTE affects students' propensity to complete PSE degrees.

I contribute to the literature by providing the most thorough empirical analysis of the returns of different types of high school education for different types of students to date. I estimate how different types of high school education curricula impact students' PSE attainment, later-life wages, probability of employment in a skilled occupation (as opposed to being unemployed or working in a minimum wage job), and probability of dropping out of high school. To evaluate these effects, I construct and estimate a comprehensive yet tractable dynamic structural model of high school education, post-secondary education, and labor market decisions, and I account for high school curriculum self-selection by including high school vocational and academic opportunity instruments at each student's school along with local labor market controls. Finally, I use the model to conduct policy

[4] To describe the high school dropout rate, the literature usually uses a combination of two statistics: the graduation rate (percentage of students who graduate on time with a regular diploma, 81% in 2012) and the status dropout rate (the percentage of individuals ages 16-24 who are not enrolled in school and have not earned a high school degree or equivalent, 7% in 2012) (National Center for Education Statistics, 2015). Alternatively, I describe the high school dropout rate as the percentage of 21 year olds who have not earned a high school degree or equivalent, because 21 is the age at which a U.S. high school student is no longer allowed to attend high school if she has not yet graduated (the age varies slightly across states as discussed in section 3.1).

simulations.

The model, described in detail in Section 3, is constructed as follows. Education and labor market decisions are modeled as one of 15 distinct choices each period. Each year, an individual chooses between attending high school in one of five fields (trade CTE, business CTE, general education, academic, and other), completing the general education development (GED) exam, working in one of five types of occupations (professional, skilled manual labor, skilled non-manual labor, skilled other, and unskilled), attending one of three types of post-secondary education institutions (trade school, community college, and four-year university), and neither working nor attending school. An individual's present choices affect her future wage offers, and she chooses between these education and labor market options each period in order to maximize her expected lifetime utility.

The model is estimated using data from the restricted-use version of the Educational Longitudinal Study of 2002 (ELS:2002). The data set follows 16,200 students from the start of their high school education until eight years after high school graduation and includes a variety of detailed education and labor market information about each student, such as each student's high school transcript, PSE attainment, occupation data by year, and wage data by year. Details about the ELS:2002 data set and variable construction are provided in Section 4.

I estimate the parameters of the dynamic structural model using maximum simulated likelihood estimation. Section 5 describes the estimation strategy in detail, including estimation assumptions, how the likelihood function is constructed, what identifies each of the parameters in the model, and the extent to which the instruments are exogenous. Section 6 presents the parameter estimates of the structural model and compares them to parameter estimates of linear models of later-life wages and employment that are estimated using two-stage least squares (2SLS) regression analysis.

The parameter estimates from the 2SLS regressions indicate that, relative to general education courses, trade vocational courses improve a student's later labor market wages and chance of being employed in a skilled occupation while business vocational courses decrease a student's wages but have little effect on employment. Structural estimates support these findings but suggest that the lower wages associated with business vocational courses are driven by occupation composition effects and occupational selection. Specifically, concentrating in a business vocational curriculum improves wages in low-wage / high-non-pecuniary utility occupations, incentivizing business vocational concentrators to choose low-wage / high-non-pecuniary utility occupations. The structural parameters also show that the positive returns to trade vocational education are generally confined to skilled manual labor occupations and the positive returns to business vocational education are generally confined to skilled non-manual labor occupations. Individuals who complete trade and business high school curricula are more likely to work in skilled manual labor and skilled non-manual labor occupations (respectively) than to work in unskilled occupations, relative to individuals who complete a general education high school curriculum. Next, the structural estimates suggest that concentrating in a trade or business vocational field slightly decreases the propensity to pursue a PSE degree after high school relative to concentrating in a general education field. In addition, the estimates show that an increased availability of vocational course offerings and vocational opportunities decreases a student's propensity to drop out of high school. Finally, the estimates suggest that, after I allow for two types of unobserved heterogeneity in the population, individuals in the population can be split between those who will always graduate from high school (two-thirds of the population) and those who are at high risk of dropping out of high school (one-third of the population). The estimates show that individuals who are at high risk of dropping out of high school are also less likely to attend PSE institutions, less likely to be employed, and (conditional on employment) less likely to be employed in skilled occupations. The results imply that the effects of high school vocational education are concentrated among the one-third of the population that is at high risk of dropping out of high school and of experiencing adverse labor market outcomes.

I conduct five policy simulations using the structural model and estimates, which I discuss in Section 7. First, I simulate the effect of requiring vocational curricula to be taught at every high school nationwide. This simulation causes an additional 4.9% of high school students to concentrate in vocational education curricula but has very minor effects on PSE and labor market outcomes. Second, I simulate the effect of removing vocational course offerings and opportunities nationwide. This simulation causes 3.2% of students who would have concentrated in vocational education curricula to instead concentrate in non-vocational curricula but, similar to the first simulation, has very minor effects on PSE and labor market outcomes. Third, I simulate the effect of incorporating vocational certification directly into high school vocational curricula.[5] The simulation causes an additional 2.9% of U.S. high school students to take vocational courses. The simulation also predicts an increase in the number of individuals working in skilled manual labor and skilled non-manual labor occupations, a decrease in the number of individuals working in unskilled occupations, and an increase in average wages and average welfare across the population.

Fourth, I simulate the effects of instituting a German-style high school tracking system in the United States, which divides students into vocational, general education, and academic tracks when they enter secondary school based on their standardized test scores and for which students on the vocational track receive vocational certification in addition to a high school diploma. The simulation predicts that more students graduate in both academic and vocational fields as a greater percentage of students are forced into these fields and away from the general education track. However, restricting high school options also causes more students to drop out of high school and instead pursue GEDs. The additional students on the academic track each have a higher propensity to pursue bachelor's degrees, the additional GED completers each have a lower propensity to pursue bachelor's degrees, and the additional students on the vocational track each receive vocational certificates with graduation. For individuals who graduate from high school, the additional PSE degrees and high school academic and vocational degrees increase average wages and increase the likelihood of being employed, while individuals who drop out of high school have lower wages and a lower likelihood of being employed. The simulation shows that, for a high school graduate, these later labor market benefits come at the cost of the individual's non-pecuniary utility in high school, as she does not enjoy

[5] Vocational certification is historically pursued after high school graduation and is needed to work in various vocational occupations. The number of high school vocational programs that confer vocational certification has dramatically increased since 2006 (two years after the students in the ELS:2002 sample graduated high school), largely due to the Carl D. Perkins Career and Technical Education Act of 2006 (U.S. Department of Education, 2013).

the academic and vocational courses she is forced to take as much as she would have enjoyed the general education courses she would have taken had they been available.

Finally, I simulate the effects of free community college for all United States high school graduates, which was recently proposed by President Barack Obama and incorporated into the education policy platforms of Bernie Sanders and Hillary Clinton (Obama, 2015; Sanders, 2016; Clinton, 2016). I find that, under this policy, more individuals complete associate degrees, more individuals pursue general education courses in high school, and a few more individuals complete bachelor's degrees. Average wages slightly increase, largely driven by the increase in bachelor's degree attainment, and average utility in the population increases, particularly prior to entering the labor market. However, these utility gains do not offset the costs of the policy proposal (under conservative welfare assumptions).

2. Literature Review

The question of the effects of different types of high school curricula has not been adequately addressed in the previous literature. The studies that have been conducted in the past have largely suffered from self-selection issues which bias their results. These self-selection issues are caused by each student endogenously choosing her own high school curriculum. As students get to choose which classes they take in high school, students with different unobserved characteristics (e.g., motivation and ability in a particular high school field) may self-select into different types of classes. If these unobserved characteristics also affect labor market outcomes, such as wages and employment prospects, a researcher cannot determine whether differences in students' labor market outcomes were caused by students having taken different classes or by the unobserved factors that motivated the students to take different classes in the first place. Without controlling for endogenous self-selection, a researcher may conclude that concentrating in a particular high school field increases later life wages when, in reality, the choice to concentrate in that field and the higher later life wages are both affected by the student's unobserved characteristics. Not addressing this self-selection issue biases the results of non-causal studies comparing the effects of different high school education curricula.

A majority of previous studies have not adequately controlled or instrumented for endogenous high school curriculum selection. In addition, they have reached contradictory conclusions using data from the same data sets (The National Longitudinal Study of the High School Class of 1972 (NLS-72), High School and Beyond (HS&B), and The National Education Longitudinal Study of 1988 (NELS:88)) due to different choices of empirical specifications. Meyer and Wise (1982), Stromback (2010), and Davis and Obenauf (2011) found no significant effect of high school CTE training on early labor force experiences, while Arum and Shavit (1995), Mane (1999), and Bishop and Mane (2004) found that taking CTE courses significantly improved non-college bound students' wages and employment chances. I briefly discuss the differences in empirical strategies across these studies, which drive their contradictory conclusions, below.

Mane (1999), Bishop and Mane (2004), and Davis and Obenauf (2011) used variations of linear regression models with different specifications of explanatory and dependent variables. Mane (1999) used the total number of academic courses and total number of vocational courses completed by each student as his explanatory variables along with quadratic terms for how the number of academic and vocational courses completed by each student varied from the average across the sample. He also controlled for college attendance but did not include any instruments for endogenous high school curricula selection. Bishop and Mane (2004) split high school curriculum into five categories and ran nine different linear regressions on different wage and employment dependent variables. They controlled for college attendance and included two high school vocational characteristic control variables to control for high school curricula self-selection: whether the school was a vocational school and the percentage of full-time faculty who were vocational teachers. Davis and Obenauf (2011) ran a linear regression of wages on high school curriculum after splitting curriculum into three mutually exclusive categories. They included a single variable to control for high school curricula self-selection: each student's self-reported interest in high school.

Meyer and Wise (1982), Aram and Shavit (1995), and Stromback (2010) used more complex estimation methods but did not attempt to control or instrument for high school curricula self-selection in any way. Meyer and Wise (1982) investigated the effects of taking different high school curricula by using maximum likelihood estimation to jointly estimate tobit regressions of weeks worked, logit regressions of school attendance, and linear equations of labor market log wages. Aram and Shavit (1995) investigated the effects of high school curricula using a multinomial logit model of occupation choice with occupation separated into five distinct occupation groups. Finally, Stromback (2010) used data from the Longitudinal Survey of Australian Youth. He estimated the effects of high school vocational education using propensity score matching of high school completion and vocational education on earnings after excluding individuals from the sample who attended college. Generally, there has been a lack of consensus about the effects of taking high school CTE throughout the literature as well as an absence of rigorous, empirical studies investigating its effects.

One additional study merits discussion. Meer (2007) used data from NELS:88 and dealt with the problem of high school curriculum self-selection using the Heckman (1979) correction in addition to including a set of high school vocational opportunity instruments. He estimated a static model with one observation of high school education in 1992 and one observation of income in 2000 for each individual. He found that there were minor positive effects of high school CTE on later-life earnings for a particular subset of the population but that a majority of individuals in that subset were already concentrating in high school vocational curricula. My research goes beyond Meer in several dimensions: it uses education and employment data from every year available in the panel data set; it uses a student's path of choices over time to infer additional information about her unobserved heterogeneity; it estimates interaction terms between the effects of high school curriculum and post-secondary education degree attainment; and it estimates the effects of CTE education on an individual's high school dropout propensity and employment outcomes jointly with the effect on her wages. In addition, the dynamic structural model allows me to separately identify the present and future benefits of education and labor market choices (e.g., present wage and utility benefits relative to future wage and utility benefits). Finally, by estimating a dynamic structural model, I am able to conduct policy simulations.

My estimation methodology generally follows the previous literature on dynamic structural models of individual behavior such as Berkovec and Stern (1991), Keane and Wolpin (1997), Eckstein and Wolpin (1999), Diermeier et al. (2005), and Chan (2013). Differences include that my model is the first to look at high school curriculum choice and that it models a broader range of lifetime choices (6-12 choices in any given period, 15 choices across an individual's lifetime) than any previous model. For example, Eckstein and Wolpin (1999) included a total of six high school education and part-time / full-time work options in their model, and Chan (2013) included a total of eight labor supply and welfare participation options in his model. In addition, my estimation methodology is the first to deal with unobserved and partially unobserved choice data in some periods for some individuals in a longitudinal data set. Instead of dropping these individuals, I simulate the state vector in every period where choice data is observed, by first simulating choice outcomes in every period where choice data is unobserved, as described in Section 5.3.

3. Model

An individual's schooling and work decisions are modeled using a dynamic discrete choice model. Every year, an individual chooses among mutually exclusive education and labor market options in order to maximize her lifetime utility, knowing that current education and labor market decisions affect future wages and educational opportunities. The individual's decision each year depends on the utility she receives from her decision in the current year as well as her knowledge about how that decision will affect her in the future.

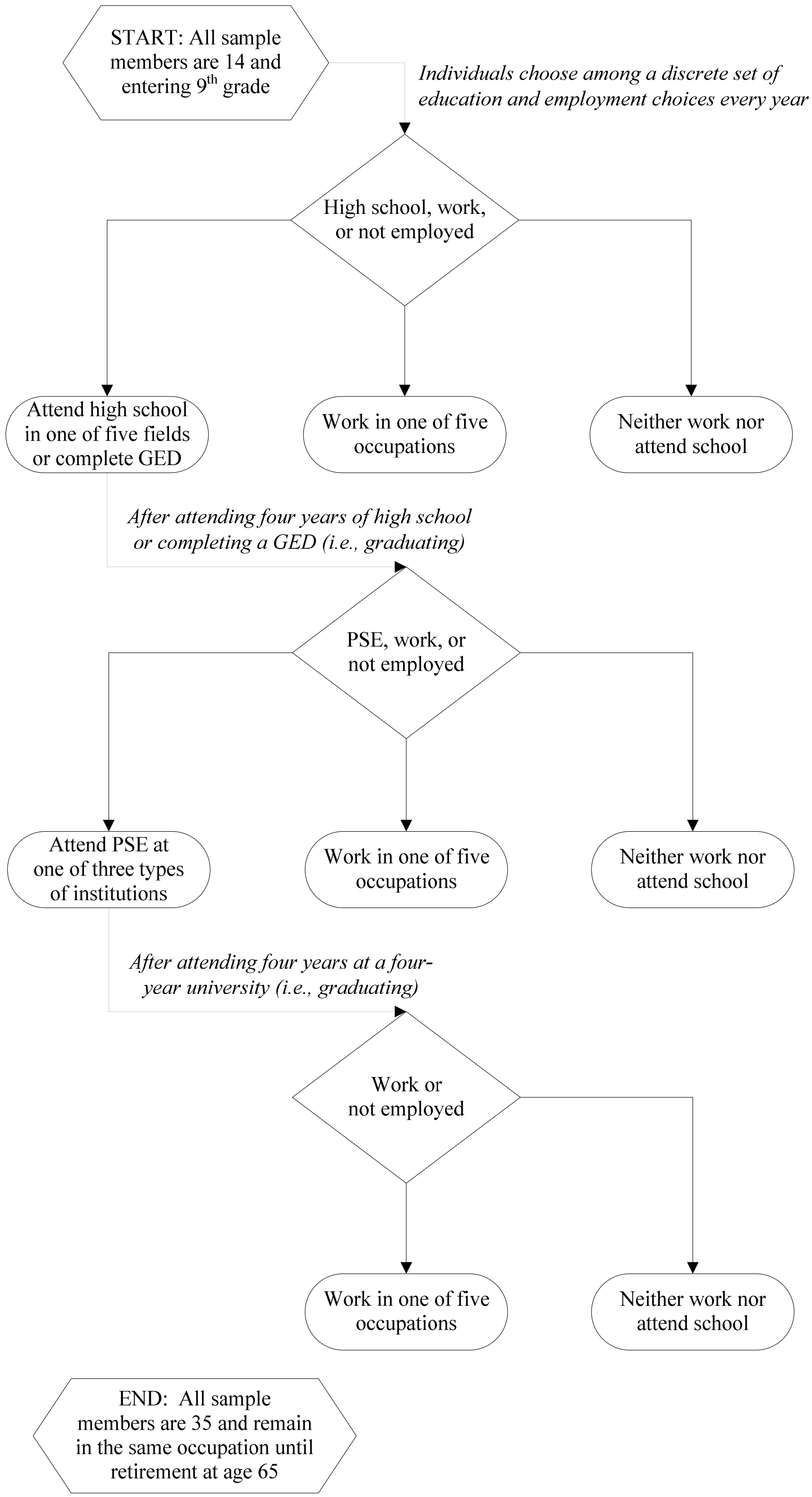
The rest of Section 3 provides details about the model. Discussion of how the data relates to the model is postponed until Section 4.

3.1 Choices

As illustrated in Figure 1, the model is structured as follows: an individual begins making choices in her first year of high school when she is 14 years old. In each period, which is one year long, she chooses among:

(A) Attending high school in one of five fields: *Academic, General Education, Business Vocational, Trade Vocational, or Other (agriculture, health, art, physical*

Figure 1: Individual Choices



education, etc.);

(B) Working in one of five types of occupations: *Professional, Skilled Non-Manual Labor, Skilled Manual Labor, Skilled Other, or Unskilled;*

(C) Neither working nor attending school: *Not Employed.*[6]

Once the individual has completed four years of high school, she graduates. As soon as the individual graduates, she receives a high school diploma that reflects her aggregate curriculum across her four years of high school.[7] Denote the number of years individual *i* has completed in high school field *k* prior to the start of period *t* as F_{it}^{k}. After completing her fourth year of high school ($\sum_j F_{it}^{j} = 4$), individual *i*'s aggregate curriculum vector, H_{it}, is updated to indicate the field that she chose for a plurality of the four years that she completed:

$$H_{it}^{k} = 1 \quad \text{iff} \quad k = \underset{j}{\text{argmax}}\left[F_{it}^{j}\right] \quad .$$[8]

If the individual devoted the same number of years to multiple fields, the most recently taken field is assigned as her aggregate high school curriculum. The student is aware of how aggregate curriculum will be assigned when she makes her high school field choice each year. Her decision is driven by the enjoyment she receives from taking classes in a particular field during the current year, her knowledge of how the choice will affect her overall high school curriculum, and her knowledge of how her overall high school

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[6] See Section 4.2 for a discussion of how high school field and labor market occupation categories in the model were chosen to roughly follow the high school field and occupation categories used in previous studies.

[7] Yearly high school field choices are modeled, as opposed to modeling a single overall high school field choice, to capture an individual's propensity to drop out of high school over time and change her high school field over time. A single high school curriculum type is assigned at graduation, as opposed to keeping track of all four yearly high school field choices, to decrease the size of the state space over which the likelihood function must be evaluated when estimating the model. See Appendix A.3 for a comparison of curriculum outcomes under my chosen construction rule relative to curriculum outcomes under two alternative specifications.

[8] In practice, the aggregate curriculum construction rule is slightly more complicated than this with regard to the general education and other fields: students were assigned an overall general education curriculum or other curriculum only if they concentrated in that field for twice as many years as they concentrated in any academic or vocational field and if they chose that field during their senior year. The reason for this complexity is that students who are considered academic and vocational concentrators in the U.S. high school education system generally still take some general education and alternative (art, health, physical education, etc.) courses in high school in addition to their academic and vocational courses, particularly during their first two years of high school. This specification is similar to other specifications used in the literature such as Meer (2007).

curriculum will affect her future wage offers and PSE choices (discussed below).

The individual cannot drop out of high school prior to age 16 due to compulsory school attendance laws.[9] The individual cannot choose to attend high school after age 21 due to high school attendance age requirements.[10] If the individual is any age over 18 and has not yet graduated from high school, in addition to her other choices, she can choose to:

(D) Complete the General Educational Development exam: *GED.*

After completing the GED exam, individual *i*'s aggregate curriculum vector (H_{it}) is updated to indicate that she earned a GED:

$$H_{it}^{GED} = 1 \quad \text{iff} \quad F_{it}^{GED} = 1 \quad .$$

After graduating from high school or receiving a GED, the individual can no longer choose any of the five high school education options or the GED option. Instead, in addition to working and non-employment, she can choose to:

(E) Attend one of three types of post-secondary education institutions: *Trade School, Community College, or Four-Year University.*[11]

The individual can pursue any of the PSE degrees each year, in any order. Once an individual has attended and passed one year at a trade school, two years at a community college, or four years at a four-year university, she receives a degree from that institution and can no longer attend that type of PSE institution. Let N_{it}^{k} denote the number of years individual *i* has completed at PSE institution type *k* prior to the start of period *t*. Her PSE graduation vector, P_{it}, is constructed as

$$P_{it}^{4yr} = 1 \quad \text{iff} \quad N_{it}^{4yr} = 4 \quad ,$$
$$P_{it}^{CC} = 1 \quad \text{iff} \quad N_{it}^{CC} = 2 \quad ,$$
$$P_{it}^{1yr} = 1 \quad \text{iff} \quad N_{it}^{1yr} = 1 \quad .$$

[9] These laws vary slightly across states. All states set their compulsory school attendance age at either 16, 17, or 18, though many states provide some exceptions which allow students to drop out prior to reaching the compulsory school attendance age (Education Commission of the States, 2015).
[10] These requirements vary slightly across states, but a majority of states set the age cutoff at 21 (29 states). A minority of states set the age cutoff at 19 (1 states), 20 (9 states), 22 (1 state), 26 (1 state), or provide no age cutoff at the state level (9 states) (Education Commission of the States, 2013).
[11] Throughout this paper "trade school" refers to any vocational certificate granting PSE institution, "community college" refers to any associate degree granting PSE institution, and "four-year university" refers to any bachelor's degree granting PSE institution.

After the individual graduates from a four-year university, she can choose among only work options and the "not employed" option. That is, an individual who receives her bachelor's degree cannot choose to attend a community college at a future date to pursue an associate degree.[12] The student is aware of these PSE institution graduation rules when making her choice each year.[13] Overall, there are 15 total options available to a person over her lifetime: five high school education fields, one GED exam, five occupations, three types of PSE institutions, and the not employed option.[14]

The individual can choose among education and labor market options until she turns 35, after which she remains in her most recently chosen occupation for the rest of her career. This assumption conforms with labor market evidence that individuals seldom change occupations over the second half of their careers (e.g., Neal, 1999) and follows the treatment of future utility used in the previous literature (e.g., Berkovec and Stern, 1991, and Francesconi, 2002). Once the individual turns 65, she retires. Following retirement, all individuals receive the same amount of utility which is independent of previous choices.[15]

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[12] This assumption is made to simplify the choice set available to bachelor's degree completers. Only 0.2% of individuals in the data set attended a two-year community college or a one-year trade school after attaining a bachelor's degree.

[13] Approximately 20% of individuals who enroll in a two-year community college eventually transfer to a four-year university (Hossler et al., 2012). The amount of community college credit that is transferable varies widely from 0% to 100%, with an average of around 70% among transferees, which takes into account that many transfer credits do not give specific course credit towards graduation (Monaghan and Attewell, 2014). Potential future work involves expanding the model to allow community college credit to transfer to four-year universities with a certain probability, realized after community college courses are taken. Note that I currently recode community college transfers who attain bachelor's degrees as having attended four-year universities for four years.

[14] Marriage and child birth choices are left out of the model to avoid another level of model complexity and to preserve estimation tractability. Omitting child birth may add additional self-selection bias to the model if individuals who plan to have children choose specific high school concentrations and choose not to participate in the labor market. Similar to other high school curriculum self-selection bias in the model, this bias is dealt with by including instruments for high school curriculum choice and by estimating the distribution of unobserved heterogeneity in the population, as discussed in Section 5.5.

[15] As an individual makes no decisions after age 35, expected lifetime utility after age 35 can be re-written as a single lump sum. The particular way this utility is distributed across periods after age 35 does not affect the individual's expected future utility except by changing the magnitude of this lump sum and by changing the extent to which early career educational attainment and occupation-specific human capital affect this lump sum.

3.2 Utility Function

The individual receives utility each period from both her current wage, if working, and the non-pecuniary characteristics of her current choice. Each period, the individual receives a wage offer in each of the five occupations.[16] Specifically, the wage offer for person *i* in occupation *k* in period *t* is

$$w_{it}^{k} = X_i\tilde{\beta}_X^k + H_{it}\tilde{\beta}_H^k + P_{it}\tilde{\beta}_P^k + P_{it}^{1yr}H_{it}\tilde{\beta}_{PH}^k + O_{it}\tilde{\beta}_O^k + \tilde{u}_i^k + \tilde{\varepsilon}_{it}^k \quad . \qquad (1)$$

The symbol "~" denotes wage parameters and wage error terms. The vector X_i is comprised of time-invariant characteristics of the individual, detailed in Section 3.3 below. Vectors H_{it} and P_{it} are comprised of dummy variables for high school graduation curriculum and PSE institution graduation as defined in Section 3.1. As P_{it}^{1yr} is a binary variable that takes the value of zero or one, vector $P_{it}^{1yr}H_{it}$ is comprised of dummy variables for whether the individual completed a particular high school track as well as completed a PSE trade school degree / certification.[17] Vector O_{it} is comprised of the occupation-specific human capital the individual has gained in each of the five occupations. The error terms $\tilde{u}_i^k$ and $\tilde{\varepsilon}_{it}^k$ are discussed later in this section. For non-occupation options, w_{it}^k is equal to zero.

Next, the individual receives non-pecuniary utility each period from her current choice. The total utility she receives in a period is assumed to be a linear function of her wage, if working, and the non-pecuniary utility she receives from her choice. Specifically, individual *i*'s total utility flow from choice *k* at time *t* is

$$U_{it}^k = \varphi w_{it}^k + X_i\beta_X^k + H_{it}\beta_H^k + u_i^k + \varepsilon_{it}^k \quad . \qquad (2)$$

The coefficient φ represents the utility value of wages relative to non-pecuniary utility.

[16] I assume the individual receives a wage offer in every occupation every period with 100% certainty, an assumption which is used in a variety of other structural models (e.g., Eckstein and Wolpin, 1999). An individual who, in reality, did not receive a wage offer in an occupation in a period is represented in the model as having received an extremely low wage offer in that occupation in that period.

[17] These interaction terms are included to investigate whether there is an additional benefit to wages from both concentrating in a particular vocational curriculum in high school and graduating from a one-year PSE trade school in addition to the benefits of graduating from each individually.

The vector $\beta_H^k = 0$ for all non-PSE choices.[18] For PSE options, β_H^k captures how the utility an individual gains from attending each type of post-secondary institution is affected by her previous high school education choice (H_{it}). This is because her previous education choice affects whether she is accepted into colleges, her net tuition, and whether she knows other material that may help her in college, giving her more incentive to attend. All of these effects cumulatively make up β_H^k. For the "Not Employed" option, U_{it}^k is standardized to zero.

The stochastic error terms $\tilde{\varepsilon}_{it}^k$ and ε_{it}^k (associated with wage offers and non-pecuniary utility, respectively) vary across individuals, across choices, and across time. Each $\tilde{\varepsilon}_{it}^k$ is distributed $iid\ N(0, \sigma_{\tilde{\varepsilon}}^2)$, and each ε_{it}^k is distributed $iid\ EV(0,1)$.[19] The error terms $\tilde{u}_i^k$ and u_i^k vary across individuals and across choices but are constant over time. These error terms reflect the individual unobserved heterogeneity which motivates each person to make specific choices in the model conditional on her observables.[20] For example, $\tilde{u}_i^k$ and u_i^k include the effects of an individual's unobserved motivation and ability in each education field and labor market occupation.

3.3 Individual Characteristics X_i

The specific individual characteristics that constitute X_i (which affects wages and non-pecuniary utility as defined in Section 3.2) vary across the 15 education and labor market options in the model.[21] Specifically, the effect of individual characteristics on wages in each occupation ($X_i\tilde{\beta}_X^k$) can be written as

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[18] P_{it} and H_{it} do not affect occupation non-pecuniary utility as I assume that the labor market returns to education are exclusively wage-related. That is, I assume that taking particular classes in high school will increase wages in each occupation but will not directly increase the non-pecuniary enjoyment of working in each occupation.

[19] Error terms $\tilde{\varepsilon}_{it}^k$ and ε_{it}^k are each assumed to be independent across individuals, choices, and time. The error term associated with the wage in each occupation each year, $\tilde{\varepsilon}_{it}^k$, can be thought of as a yearly wage bonus in each occupation that changes from year to year. The error term associated with the non-pecuniary utility of each choice each year, ε_{it}^k, can be thought of as stochastic randomness in an individual's life that changes her enjoyment of that choice from year to year.

[20] No assumptions on the distribution of the pre-realized $\tilde{u}_i^k$ and u_i^k need to be made.

[21] Age/year variables are omitted from the model to decrease the parameter set. See Section 6.3 for a discussion of how their omission affects the estimation results.

$$X_i\tilde{\beta}_X^k = \tilde{\alpha}^k + C_i\tilde{\beta}_C^k + M_i\tilde{\beta}_L^k \qquad \text{for occupation choices,}$$

and the effects of individual characteristics on the non-pecuniary utility of each choice ($X_i\beta_X^k$) can be written as

$$X_i\beta_X^k = \alpha^k + C_i\beta_C^k \qquad \text{for occupation choices,}$$

$$X_i\beta_X^k = \alpha^k + C_i\beta_C^k + I_i\beta_I^k \qquad \text{for high school field and GED choices,}$$

$$X_i\beta_X^k = \alpha^k + C_i\beta_C^k + A_i\beta_A^k \qquad \text{for PSE insitution choices.}$$

The vectors C_i and M_i correspond to personal characteristics about the individual and the local labor market where the individual's high school was located, respectively. Vectors I_i and A_i correspond to characteristics about the individual's high school related to curriculum selection and college attendance, respectively, such as the high school's vocational course offerings and opportunities, career counseling availability, and college preparatory programs.[22] The variables $\tilde{\alpha}^k$ and α^k are constant terms.

3.4 Value Function

Define $\tilde{\varepsilon}_{it}$ and ε_{it} as the vectors of all wage time-specific error terms and non-pecuniary time-specific error terms, respectively, for individual *i* in period *t*. Define S_{it} as the state vector for individual *i* at the start of period *t*, which consists of relevant time-invariant characteristics about the individual ($X_i, \tilde{u}_i^k, u_i^k$), vectors of past education and employment decisions ($F_{it}, H_{it}, N_{it}, P_{it}, O_{it}$), and vectors of current period time-specific stochastic error terms $\tilde{\varepsilon}_{it}$ (wage utility) and ε_{it} (non-pecuniary utility). Time-invariant characteristics about the individual ($X_i, \tilde{u}_i^k, u_i^k$) do not change in S_{it} over time. The variables F_{it+1}^k and N_{it+1}^k increase by one with certainty every year the individual chooses to attend high school in a specific field and chooses to attend a specific type of PSE institution, respectively. H_{it+1} and P_{it+1} change, as defined in Section 3.1, when the individual graduates from high school and from each type of PSE institution. Each $\tilde{\varepsilon}_{it}^k$ and ε_{it}^k is *iid*.

Every year an individual works in an occupation, she has a chance to gain

[22] See Section 5.3 for a discussion of how including I_i, A_i, and L_i in the model helps to account for high school curriculum self-selection.

occupation-specific human capital in that occupation (O_{it}^{k}). Specifically, the law of motion of occupation-specific human capital in each occupation is

$$O_{it+1}^{k} = O_{it}^{k} + \psi_{it} \quad \text{iff} \quad k_{it} = k \quad \& \quad \underset{j}{sum}(O_{it}^{j}) < 2,$$

$$O_{it+1}^{k} = O_{it}^{k} \qquad \text{otherwise,}$$

where ψ_{it} is a random variable distributed iid $Bernoulli(\theta_e)$ and realized at the end of period t.[23] The probability an individual gains occupation-specific human capital, θ_e, can take on five different values that depend upon the individual's highest level of educational attainment (i.e., no high school diploma or equivalent (θ_{noHS}), high school diploma or equivalent (θ_{HS}), PSE trade certificate (θ_{1yr}), associate degree (θ_{CC}), or bachelor's degree (θ_{4yr})). An individual's level of occupation-specific human capital is allowed to vary between low ($O_{it}^{k} = 0$), medium ($O_{it}^{k} = 1$), and high ($O_{it}^{k} = 2$) in each occupation to reflect the discrete raises an individual receives, after controlling for inflation, in her occupation throughout her lifetime. Also, note that an individual can accumulate only up to two levels of occupation-specific human capital across all occupations ($sum_j(\mathrm{O}_{\mathrm{it}}^{\mathrm{j}}) \leq 2$) over her lifetime, which follows the results of previous studies that have shown that individuals rarely accrue high levels of occupation-specific human capital in multiple occupations (e.g., Topel and Ward, 1992, and Pavan, 2010).[24]

Denote individual i's choice in period t as k_{it}. I define the transition of the state vector described in the two preceding paragraphs as

$$S_{it+1} = G(S_{it}, k_{it}, \psi_{it}, \tilde{\varepsilon}_{it+1}, \varepsilon_{it+1}) \quad . \tag{3}$$

Note that today's choice between available education and labor market options (k_{it}) affects future choices ($k_{i\tau}, \tau > t$) by increasing the stock values of $F_{it}, H_{it}, N_{it}, P_{it}$, and O_{it} for every future period $\tau = t+1, t+2, \dots, T$. These increased stock values affect the value of utility for each choice in every future period $\tau = t+1, t+2, \dots, T$.

[23] Depreciation of occupation-specific human capital over time is omitted from the model in order to avoid another level of model complexity.

[24] The assumptions that occupation-specific human capital accrues probabilistically and is constrained to a small number of possible states follow Sullivan (2010) and are made to greatly decrease the size of the state space.

The individual chooses between her education and employment options, in each period t from when she enters high school at age 14 ($t = 1$) to when she retires at age 65 ($t = T$), to maximize her expected lifetime utility in that period. The individual's expected lifetime utility, i.e., value function, at the start of period t can be written as

$$V_{it}(S_{it}) = \max_{\{k_{it}\}} \left[U_{it}^{k_{it}}(S_{it}) + E\left(\sum_{\tau=t+1}^{T} \delta^{\tau-t} \max_{\{k_{i\tau}\}} U_{i\tau}^{k_{i\tau}}(S_{i\tau}) \right) \right]$$

where δ is the discount factor, $U_{it}^{k_{it}}(S_{it})$ is the current period utility from choosing option k_{it} given state vector S_{it}, and $S_{i\tau}$ follows the transition of the state vector described in equation 3. The mean $E(\cdot)$ is over the joint distribution of future error terms $\psi_{i\tau}$, $\tilde{\varepsilon}_{i\tau}$, $\varepsilon_{i\tau}$ for every period $\tau = t+1, t+2, \ldots, T$. The construction of the value function is similar to the construction used in other dynamic discrete choice models such as Keane and Wolpin (1997).

Define $\bar{S}_{it}$ as the pre-period state, prior to the start of period t, which consists of everything in state vector S_{it} except period t error term vectors $\tilde{\varepsilon}_{it}$ and ε_{it}. The expected value of lifetime utility from period t until retirement, prior to realizing the error term vectors $\tilde{\varepsilon}_{it}$ and ε_{it} that are drawn at the start of period t, can be written as

$$V_{it}^{*}(\bar{S}_{it}) = E\left[\sum_{\tau=t}^{T} \delta^{\tau-t} \max_{\{k_{i\tau}\}} U_{i\tau}^{k_{i\tau}}(S_{i\tau}) \right]$$

where the mean $E(\cdot)$ is over the joint distribution of future error terms $\psi_{i\tau}$, $\tilde{\varepsilon}_{i\tau}$, $\varepsilon_{i\tau}$ in every period $\tau = t, t+1, t+2, \ldots, T$. Next, the net present value of choosing choice k today, after realizing today's error term vectors $\tilde{\varepsilon}_{it}$ and ε_{it}, can be rewritten using Bellman's equation as

$$V_{it}^{k}(S_{it}) = U_{it}^{k}(S_{it}) + \delta V_{it+1}^{*}(\bar{S}_{it+1}) \quad .$$

Note that tomorrow's pre-period state ($\bar{S}_{it+1}$) is determined based on today's state vector (S_{it}) and today's choice (k_{it}) as defined in Equation 3. Because the non-pecuniary error terms for each choice (ε_{it}^{k}) are distributed $iid\ EV(0,1)$, the expected value of lifetime utility from period t until retirement, prior to realizing today's time-specific error terms, has a closed-form solution. Specifically,

$$V_{it}^{*}(\bar{S}_{it}) = \int ln\left(\sum_j \exp\{\bar{V}_{it}^{j}(S_{it})\}\right) f(\tilde{\varepsilon}_{it}) d\tilde{\varepsilon}_{it} \quad (4)$$

$$\text{where } \bar{V}_{it}^{j}(S_{it}) = V_{it}^{j}(S_{it}) - \varepsilon_{it}^{j} \; .$$

The integral over $\tilde{\varepsilon}_{it}$ corresponds to integrating over each of the normal $\tilde{\varepsilon}_{it}^{k}$ error terms associated with wages in each of the five occupations. The derivation of $V_{it}^{*}(\bar{S}_{it})$ is similar to the derivation used in other dynamic discrete choice models such as Chan (2013).

4. Data

4.1 Summary Statistics

I estimate the model using data from the restricted-use version of the Educational Longitudinal Study of 2002 (ELS:2002). This study, conducted by the U.S. Department of Education, followed a nationally representative random sample of 16,200 students from 750 different high schools across the United States.[25] The study collected data from August 2000, when the respondents began high school, until May 2012, eight years after the majority of the respondents had graduated from high school. The initial survey was conducted in 2002 and was succeeded by three follow-up surveys in 2004, 2006, and 2012. In addition to student surveys, supplementary information was collected from each student's parents, teachers, high school administrators, high school librarians, and high school counselors. High school transcripts and post-secondary education transcripts were collected for a majority of the students.

Summary statistics about the personal characteristics of the students (C_i) are displayed in Table 4.1.[26] Overall, 50% of the sample was male, 56% of the sample was

[25] The sample is nationally representative of U.S. high school sophomores in 2002 with two exceptions. First, the ELS:2002 study oversampled individuals attending private schools in order to increase the sample size of individuals attending private schools, as noted in Table 4.1. Second, the number of high school dropouts in the sample is lower than the population average, as discussed in Section 4.2.

[26] Indicator variables for missing information are used for each variable that is missing information for some individuals in the data set (e.g., Test Score in Table 4.1). In Table 4.1, population averages for gender, race, urbanicity, and region are from the U.S. Census Bureau (2000). Population averages for gender, race, and region are over all individuals in the U.S. in the year 2000 aged 15-17, 14-17, and 5-17, respectively. Population averages for urbanicity are over all individuals in the U.S. population. In Table 4.1, population averages for public versus private secondary school enrollment in the year 2000 are from the National Center

Table 4.1: Personal Characteristics

Variable	Mean	Std Dev	2000 U.S. HS Pop Avg
Male	0.500	0.500	0.515
Black	0.134	0.341	0.146
Hispanic	0.150	0.357	0.152
Other Race	0.158	0.365	0.150
Socio-Economic Status	0.000	1.000	--
Test Score	0.000	1.000	--
Midwest	0.249	0.432	0.231
South	0.363	0.481	0.352
West	0.205	0.404	0.234
Suburban	0.479	0.500	0.508
Rural	0.182	0.386	0.210
Catholic School	0.122	0.327	0.054
Non-Catholic Private School	0.090	0.286	0.040

Notes:
1) Baseline options are as follows: Race - White; Region - Northeast; Urbanicity - Urban; School - Public.
2) Total # observations is 16,200 for all variables except Test Score. Total # observations is 15,890 for Test Score. Sample sizes are rounded to the nearest ten to comply with secure data disclosure requirements.

white, and the other 44% of the sample was fairly equally split among black, Hispanic, and "other race" individuals.[27] The sample was fairly evenly split geographically across the U.S., with a larger percent of the sample from areas that identified as suburban than from areas that identified as urban or rural. Socio-Economic Status (SES) is a constructed variable in the ELS:2002 data set which aggregates together, into a single variable, the number of parents that were in a student's household, whether the parents were employed, and parental income in 2002. Test score is the cumulative sum of a student's test scores on the ELS:2002 math and English tests each sample member took when the survey was

for Education Statistics (2015). Population averages for Catholic vs non-Catholic private school enrollment in the year 2000 are from the Private School Universe Survey (National Center for Education Statistics, 2002).

[27] White is the omitted baseline race in Table 4.1. "Other race" is comprised of Asian individuals, Native American individuals, and individuals of more than one race.

first administered in 2002.[28] In the sample, approximately 80% of students attended public high schools, 10% of students attended Catholic schools, and 10% of students attended non- Catholic private schools.[29] Next, Table 4.2 provides summary statistics on the log hourly wages of sample members (w_{it}^{k}).[30] Individuals in professional occupations received the highest log hourly wages, on average, followed by individuals in the skilled other, skilled manual labor, skilled non-manual labor, and unskilled occupations, respectively.

Table 4.3 provides summary statistics about the high school vocational and academic opportunities at each student's school, the selection methods for school enrollment at each student's school, and the selection methods for high school course selection at each student's school (I_i and A_i).[31] Approximately three-fourths of students in the sample attended high schools that offered some type of vocational curriculum either on-site or at an area vocational school.[32] Approximately 10% of the students in the sample attended schools that conferred GED degrees on-site, and one-fourth of the students in the sample received free or reduced price lunches. Three-fourths of the students in the sample attended schools that admitted students principally based on the geographic location of

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[28] The range of the test scores was readjusted, originally from 20 to 80, to have a mean of zero and a standard deviation of one, in order to make the estimates easier to directly compare to the estimates for the other individual characteristics. The range of SES was also slightly readjusted, originally from -2 to 2, to have a mean of zero and a standard deviation of one.

[29] Public is the omitted baseline school type in Table 4.1.

[30] Each observation is a student-year log hourly wage. Log hourly wages are constructed by first converting all wages that were recorded over the length of the survey into real 2002 dollars. Wages are then converted into hourly wages and any hourly wages below 5 dollars an hour and above 100 dollars an hour are dropped. Nine percent of hourly wages are dropped because they were below $5 an hour, and one half of one percent of hourly wages are dropped because they were above $100 an hour. Finally, hourly wages are transformed into log hourly wages. Most wages in ELS:2002 were collected as hourly wages, although for a subset of student-year observations weekly, monthly, or yearly income was collected instead. These incomes are first converted to hourly wages based on the number of hours each individual worked per week and the number of months they worked throughout the year. For further details on hourly wage construction see Appendix D.1.

[31] ELS:2002 includes a substantial number of variables about each high school's vocational offerings, academic offerings, and selection methods. I choose the particular subset of variables depicted in Table 4.3 to be indicative of the full set of high school-related variables available in ELS:2002. Changing the subset of chosen variables does not affect the 2SLS parameter estimates in Section 6.1 or their statistical significance.

[32] An area vocational school is an off-grounds location where high school vocational courses are taught. Students who enroll in courses at an area vocational school bus between the area vocational school and their primary high school multiple times each week.

Table 4.2: Log Hourly Wages

Variable	Mean	Std Dev	# Obs
(ln) Professional Hr Wage	2.666	0.493	6,310
(ln) Skilled Manual Labor Hr Wage	2.430	0.437	5,870
(ln) Skilled Non-Manual Labor Hr Wage	2.299	0.414	7,120
(ln) Skilled Other Hr Wage	2.502	0.460	1,140
(ln) Unskilled Hr Wage	2.073	0.357	2,290

Notes:
1) Sample sizes are rounded to the nearest ten to comply with secure data disclosure requirements.

their parents' homes. Next, the influence students had on their own course selection varied widely throughout the sample, though on average students had a large influence on their own course selection.[33] Nearly every student's high school offered academic counseling. Finally, the average student attended a high school where, in regards to the previous year's graduating class, a large percent had enrolled in a four-year college, a relatively small percent had enrolled in a two-year college, and a relatively small percent had entered the labor market.[34]

Table 4.4 provides summary statistics about the local labor market characteristics, in 2002, in the county in which the student's high school was located (M_i). Data on average wages and industry employment percentages by county is from the Bureau of Economic Analysis's (BEA) regional data on Local Area Personal Income & Employment.[35] Data on county unemployment rates is from the Bureau of Labor Statistics' (BLS) Local Area Unemployment Statistics.[36] The average unemployment rate across counties was 4.2%

[33] "Student Infl on Course Selection" is a discrete variable that takes the values of none (0), a little (1), moderate (2), and a lot (3).

[34] "% Prev Students Attend 4yr College", "% Prev Students Attend 2yr College", and "% Prev Students Enter Labor Market" are discrete variables that take the values of none (0), 1-10% (1), 11-24% (2), 25-49% (3), 50-74% (4), and 75-100% (5).

[35] Employment percentages across industries are used because employment percentages across occupations are not available at the county level. However, industry employment percentages closely match occupation employment percentages at the national level and at the MSA level (See Appendix C.2 for a detailed discussion). As such, industry employment percentages are a good approximation for occupation employment percentages.

[36] Average wages are constructed as the total sum of wage and salary income in the county divided by the total amount of wage and salary employment in the county, converted from an average yearly salary into an

Table 4.3: Instruments

Variable	Mean	Std Dev	# Obs
1. High School Curricula Instruments			
Voc Taught in High School	0.349	0.477	15,450
Voc Taught in Area School	0.068	0.252	15,450
Voc Taught in Both HS & Area Sch	0.312	0.463	15,450
Marketing Courses Taught On-Site	0.580	0.494	10,310
Marketing Courses Taught at Area Sch	0.116	0.320	10,310
Precisions Courses Taught On-Site	0.614	0.487	10,150
Precisions Courses Taught at Area Sch	0.221	0.415	10,150
# Vocational Teachers per 100 Students	0.522	0.593	12,370
Career Pathways Prog Available	0.740	0.439	11,010
% Students Free / Reduced Price Lunch	0.240	0.250	15,690
Admission Based on Geography	0.737	0.440	11,790
Student Infl on Course Selection (0-3 Scale)	2.517	0.709	11,090
% Students Take Academic Courses	0.645	0.313	10,260
% Students Take Vocational Courses	0.174	0.186	7,460
% Prev Students Enter Labor Market (0-5 Scale)	1.542	0.917	11,360
GED Confered by High School	0.118	0.322	11,650
2. High School PSE Enrollment Instruments			
Academic Counseling Available	0.958	0.200	13,680
% Students Attend College Fairs	0.148	0.142	10,940
% Students in College App Prog (0-5 Scale)	3.572	1.580	11,030
% Prev Students Attend 4yr College (0-5 Scale)	3.590	1.157	11,490
% Prev Students Attend 2yr College (0-5 Scale)	2.326	0.982	11,400

Notes:

1) Baseline options are as follows: Vocational Courses - Not Taught.

2) A subset of percentage variables (e.g. Prev Students Enter Labor Market) were recorded in discrete bins with ranges of 0-3 and 0-5.

3) Sample sizes are rounded to the nearest ten to comply with secure data disclosure requirements.

average hourly wage and logged. The four industry categories of professional, manual labor, non-manual labor, and other are constructed by aggregating the 21 industry categories provided in the BEA Employment by Industry data file, which provides the percentage of employees in each county working in each North American Industry Classification System (NAICS) two-digit industry category in 2002. The manual labor category includes industries such as construction and manufacturing, and the non-manual labor category includes industries such as retail trade and real estate. Industry types that do not fit into the professional, manual labor, or non-manual labor categories, such as farm employment and educational services, are included in the other category, which is the omitted category. Additional details about the local labor market variable construction rules can be found in Appendix C.1.

Table 4.4: Local Labor Market Characteristics

Variable	Mean	Std Dev	# Obs
Unemployment Rate	0.042	0.017	16,200
(ln) Average Hr Wage	2.928	0.245	16,200
% Professional Industry	0.067	0.032	16,200
% Manual Labor Industry	0.228	0.074	16,200
% Non-Manual Labor Industry	0.244	0.041	16,200

Notes:
1) Baseline options are as follows: Industry - Other.
2) Sample sizes are rounded to the nearest ten to comply with secure data disclosure requirements.

with a fairly large variance across counties. The percent of employees working in each type of industry varied widely across counties, however, more employees worked in non-manual labor and other industries, on average, than in professional and manual labor industries.

4.2 Choice Construction

Each student's yearly high school field choices are constructed using her high school transcript data. First, each course the student took is coded into one of five field types (academic, general education, trade vocational, business vocational, or other) based on the Classification of Secondary School Courses (CSSC) code for that class.[37] Academic courses include all honors, Advanced Placement (AP), and International Baccalaureate (IB) courses, while general education courses include all non-honors math, science, English, and foreign language courses. Trade vocational courses include all CTE courses that prepare students for a specific manual trade, such as construction, mechanics, industrial arts, and personal services (e.g., barber / beautician training). Business vocational courses include all CTE courses that teach students general business skills which can be used across a variety of careers, such as office management, marketing, communications, and computer

[37] CSSC codes are six digit codes associated with each secondary school course taught in the United States. Codes are assigned based on the content of each course (National Center for Education Statistics, 2000).

sciences. Other courses include all courses that do not fit into any of these categories, such as agriculture, home economics, art, music, health, and physical education.[38] This mapping roughly follows the mapping used by Meer (2007), with the exception that I have added a fifth category, "other", which Meer instead spread across the general education, trade vocational, and business vocational fields.[39]

After each individual course is mapped to a specific field, a single overall field concentration is constructed for each year of high school. Specifically, yearly field concentration is chosen as the field in which the student took a plurality of courses.[40] The tiebreaking rule favors labeling a yearly concentration as vocational as opposed to non-vocational, though very few ties occur.[41] After yearly concentrations are constructed, overall high school curriculum is determined as defined in Section 3.1.[42] Summary statistics on overall high school curricula are presented in Table 4.5. In the sample, 33% of students completed a general education curriculum, 21% of students completed an academic curriculum, and 5%, 5%, and 13% of students completed a business vocational curriculum, trade vocational curriculum, and other curriculum, respectively. Just under 7% of students in the sample did not graduate from high school by age 19. Unfortunately, this 7% number is around half the national average for high school dropouts by age 19 in 2005 (National Center for Education Statistics, 2015). Even under the strong assumption that all 300 sample members who are missing high school graduation information had not graduated high school prior to age 19, and correcting for the study's oversampling of

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[38] The complete mapping of CSSC codes to curriculum types is provided in Appendix A.1.

[39] I separate "other" courses to restrict them from impacting the parameter estimates associated with general education, trade vocational, and business vocational high school curricula.

[40] In practice the yearly curriculum construction rule is slightly more complicated than this with regard to the other and general education fields: students are considered other and general education yearly concentrators only if they took twice as many courses in the other or general education fields as courses in any academic or vocational field. The reason for this complexity is that students who are considered academic and vocational concentrators in the U.S. high school education system generally still take a few general education and alternative (art, health, physical education, etc.) courses each year in addition to their academic and vocational courses. This specification is similar to that of Meer (2007).

[41] The tiebreaking order is trade vocational, business vocational, academic, other, and general education. Note that only 0.2% of student-year curricula observations had ties. Using alternative tiebreaking rules does not affect the estimation results.

[42] The high school curricula outcomes I construct are very similar to outcomes constructed using alternative curriculum construction rules. For a detailed comparison of high school curricula outcomes under three alternative construction rules, see Appendix A.3.

Table 4.5: High School Curricula (By Age 19)

HS Curriculum	# Obs	% Sample
Academic	3,370	21%
General Education	5,320	33%
Business Vocational	870	5%
Trade Vocational	720	5%
Other	2,130	13%
HS Graduate, Curr Unknown	1,960	12%
GED	470	3%
No HS Degree	1,070	7%

Notes:

1) Total # observations is 15,900. HS graduation is unknown for remaining 300 sample members.

2) Table refers to HS graduation attainment through the '04-'05 academic year, 5 years after sample members began high school.

3) Sample sizes are rounded to the nearest ten to comply with secure data disclosure requirements.

private school students, this percentage is notably lower than the population average.[43] Thus, it appears that the ELS:2002 survey under-sampled students who were at risk of dropping out of high school, which means that my sample estimates regarding the effects of different high school curricula on high school dropout propensity may not be indicative of population estimates.

Next, ELS:2002 includes yearly information about post-secondary education enrollment and completion. See Table 4.6 for the aggregate PSE attainment rates in the

[43] Note that the ELS:2002 data set provides sample weights for each wave of the survey based on which sample members' information was missing for that wave. However, the entire sample of 16,200 individuals (comprised of 16020 individuals in the baseline wave and 180 individuals retroactively added to the sample in the first follow-up wave) was meant to be nationally representative across a variety of demographic measures, with the exception of school control. As I use the entire nationally representative sample of 16,200 individuals in my analysis I do not use these sample weights. With the exception of the dropout rate percentage and school control, summary statistics in the data closely match population moments. Also, note that applying the ELS:2002 survey weights for any / each of the sample waves causes no more than a 0.5% increase in the dropout rate percentage in the sample, likely due to the fact that the weights did not include the high school dropout rate in the list of population moments used to create the weights. I am currently following up with the Department of Education to gain more insight into why the dropout rate percentage in ELS:2002 is notably lower than the population average.

Table 4.6: Educational Attainment (By Age 26)

PSE Attainment	# Obs	% Sample	2012 CPS 25-34 Yr Olds
No HS Graduation	450	3%	11%
HS Graduation Only	5,420	40%	45%
1-yr Trade School	1,230	9%	--
2-yr Community College	1,050	8%	10%
4-yr University	5,100	38%	34%

Notes:
1) Total # observations is 13,250. Educational attainment is unknown for 2,340 sample members.
2) The CPS does not collect vocational certificate information.
3) Sample sizes are rounded to the nearest ten to comply with secure data disclosure requirements.

sample for each type of PSE institution at the time the study concluded in 2012. Slightly more than one-third of the students in the sample had graduated from a four-year university, while 9% and 8% of students in the sample had graduated from at most a trade school or community college, respectively. As shown in Table 4.6, these numbers are relatively similar to national college attendance and graduation rates during the sample period (Current Population Survey, 2012), with the exception that high school dropouts were under-sampled (see the discussion in the preceding paragraph). Table 4.7 displays PSE degree attainment conditional on high school curriculum choice. Overall, 73% of individuals who took academic courses completed four-year university degrees, and 59% of individuals who took trade vocational courses, 49% of individuals who took business vocational courses, and 93% of individuals who had not graduated high school by age 19 had not graduated from any type of PSE institution by the time the study concluded in 2012.

Next, I construct occupation type by reassigning the 17 occupation codes provided in ELS:2002 to one of the five occupation types (professional, skilled manual labor, skilled non-manual labor, skilled other, and unskilled). These occupation categories are similar to the categories used in the previous literature, such as Aram and Shavit (1995), which in general follows the occupation schema created by Erikson, Goldthorpe, and Portocarero (1979). Professional occupations include professional and managerial occupations, and

Table 4.7: PSE Attainment (Age 26) by HS Curriculum

HS Curriculum	No PSE % Sample	1-yr Trade School % Sample	2-yr Community College % Sample	4-yr University % Sample	# Obs
Academic	19%	4%	4%	73%	3,050
Gen Ed	41%	10%	10%	38%	4,310
Bus Voc	49%	10%	11%	30%	710
Trade Voc	59%	13%	12%	17%	570
Other	53%	14%	10%	22%	1,690
GED (By Age 19)	74%	15%	5%	5%	390
No HS Degree (By Age 19)	93%	5%	2%	0%	870

Notes:
1) Percentages aggregate left to right.
2) Total # observations is 12,580. Observations missing HS Curriculum or PSE attainment were dropped.
3) Sample sizes are rounded to the nearest ten to comply with secure data disclosure requirements.

skilled manual labor occupations include craftspersons, operatives, protective service occupations, and skilled laborers. Skilled non-manual labor occupations include clerical, sales, and skilled service occupations, and skilled other occupations include farmers, military occupations, and teachers. Note that, while the other 15 occupation codes provided in ELS:2002 fit directly into one of my five employment categories, the laborer and service occupations do not as they aggregate both skilled and unskilled workers together. As such, to construct the unskilled occupation, I further split these employment categories between the skilled manual labor, skilled non-manual labor, and unskilled occupations based on the 6-digit O*NET occupation code provided in the data set for each occupation. Unskilled occupations include low-skill and minimum wage jobs such as fast food workers, bartenders, waiters, janitors, cleaners, attendants (service stations, ticket takers, etc.) and cashiers.[44] Table 4.8 displays 2012 employment outcomes conditional on high school curriculum. Overall, academic concentrators were the most likely to later work in professional occupations (49%), trade vocational concentrators were the most likely to later work in skilled manual labor occupations (45%), and business vocational concentrators were the most likely to later work in skilled non-manual labor occupations (35%).

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[44] Additional occupation mapping details can be found in Appendix B.

Table 4.8: Employment Outcomes (Age 26) by HS Curriculum

HS Curriculum	Professional *% Sample*	Sk. Manual Labor *% Sample*	Sk. Non-Manual Labor *% Sample*	Sk. Other *% Sample*	Unskilled *% Sample*	Not Employed *% Sample*	# Obs
Academic	49%	13%	21%	7%	4%	5%	2,690
Gen Ed	29%	20%	30%	5%	7%	9%	3,880
Bus Voc	27%	19%	35%	2%	7%	9%	650
Trade Voc	18%	45%	20%	3%	7%	8%	520
Other	20%	23%	30%	5%	9%	12%	1,500
GED (By Age 19)	18%	24%	28%	2%	11%	16%	340
No HS Degree (By Age 19)	11%	28%	22%	1%	13%	26%	760

Notes:

1) Percentages aggregate left to right.

2) Employment type is during the final year of the survey (2012).

3) Total # observations is 10,330. Observations missing HS Curriculum or 2012 employment were dropped.

4) Sample sizes are rounded to the nearest ten to comply with secure data disclosure requirements.

When constructing individual-year choices, I treat an individual who worked part-time while attending high school full-time or college full-time as having attended school and not as having worked. This simplification is made to greatly reduce the number of choices in the model and is used in previous dynamic structural models such as Keane and Wolpin (1997). However, it implies that an individual receives no utility or occupation-specific human capital from part-time work, which may slightly bias the estimation results. Additionally, I code an individual as attending high school or a post-secondary institution in a given year if she took and passed at least half the average course load of credit hours at her school that year. If an individual failed her high school or post-secondary education coursework, she is considered not to have attended school / college during that year.[45] Failing is treated as the active choice of an individual not to work hard enough to pass her classes in a given year. An individual who chose to nominally attend school and failed in a given year is coded the same as an individual who chose not to attend school in the first place.[46] Similarly, an individual who took five years of attendance in high school to graduate is coded as having failed her coursework during the year in which she passed the least number of credits.

Using the construction rules discussed above, I assign each individual an education or labor market choice during each year of the sample period. Table 4.9 includes the aggregate percentage breakdown of individual choices between 2000 and 2012. The majority of individuals attended high school between 2000 and 2003, and those who attended PSE institutions mostly did so between 2004 and 2008.[47] Note that I do not observe high school transcripts after 2003: all high school attendance between 2004 and 2007 is coded as "HS Unknown Type." Finally, the study asked very few job market questions about the period between 2006-2010. While some of these values are imputed

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[45] If she was working part-time during the year she failed her coursework, she is coded as working. If she was not working part-time during the year she failed her coursework, she is coded as not employed.

[46] This assumption is implied in previous structural models such as Eckstein and Wolpin (1999) and is analogous to the assumption in labor market literature that treats individuals who are fired from their job the same as individuals who quit their job.

[47] Approximately 480 individuals in the sample attended a PSE masters, professional, or doctoral program. As I do not include this choice in the model, these individuals are currently treated as "missing information" during years when they attended these programs.

Table 4.9: ELS:2002 Choices By Year

Choices by year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
HS Academic	5%	11%	18%	19%	-	-	-	-	-	-	-	-	-
HS Gen Ed	75%	67%	51%	34%	-	-	-	-	-	-	-	-	-
HS Business Voc	1%	2%	3%	5%	-	-	-	-	-	-	-	-	-
HS Trade Voc	1%	2%	4%	4%	-	-	-	-	-	-	-	-	-
HS Other	5%	5%	7%	12%	-	-	-	-	-	-	-	-	-
GED	-	0%	1%	1%	1%	1%	0%	0%	0%	0%	0%	0%	0%
HS UNKNOWN TYPE	10%	9%	11%	10%	2%	0%	0%	0%	-	-	-	-	-
WORK Professional	-	-	-	0%	1%	2%	3%	2%	5%	7%	10%	15%	22%
WORK Skilled Manual Labor	-	0%	0%	1%	4%	6%	9%	4%	5%	6%	8%	11%	15%
WORK Skilled Non-Manual Labor	-	0%	0%	1%	4%	6%	9%	4%	6%	8%	10%	14%	20%
WORK Skilled Other	-	-	-	0%	1%	1%	1%	0%	1%	2%	2%	3%	4%
WORK Unskilled	-	0%	0%	1%	4%	4%	5%	1%	2%	2%	3%	3%	5%
WORK UNKNOWN TYPE	0%	2%	0%	3%	2%	3%	0%	0%	0%	25%	20%	11%	2%
UNEMPLOYED	-	-	0%	4%	5%	3%	3%	1%	1%	7%	6%	6%	7%
PSE 1YR Trade School	-	-	-	0%	1%	1%	1%	1%	1%	1%	1%	1%	0%
PSE 2YR Community College	-	-	0%	0%	17%	10%	3%	2%	2%	2%	2%	2%	1%
PSE 4YR University	-	-	-	0%	42%	40%	27%	20%	14%	8%	6%	5%	1%
PSE UNKNOWN TYPE	-	-	-	-	0%	0%	0%	0%	0%	0%	0%	0%	0%
PSE HIGHER DEGREE	-	-	-	-	-	0%	-	0%	1%	1%	1%	1%	2%
MISSING	2%	1%	4%	4%	16%	23%	38%	63%	62%	31%	29%	29%	21%

Notes:

1) Percentages are over the entire sample of 16,200.

2) Percentages used to calcuate sample sizes are rounded to the nearest ten to comply with secure data disclosure requirements.

based on job start and end dates, many of them are coded as missing or "Work Unknown Type" during these years.[48]

5. Estimation Methodology

5.1 Unobserved Heterogeneity

In order to estimate the model, I restrict each individual's unobserved heterogeneity values ($\tilde{u}_i^k$ and u_i^k) to one of two possible sets in the population, u_1 (type one) and u_2 (type two), where

$$u_\tau = (\tilde{u}_\tau^{k_1}, \tilde{u}_\tau^{k_2}, \dots, \tilde{u}_\tau^{k_5}, u_\tau^{k_1}, u_\tau^{k_2}, \dots, u_\tau^{k_{15}}) \quad , \quad \tau = 1, 2 \quad .$$

Define ζ as the proportion of individuals in the population with type-one unobserved heterogeneity values. The elements of u_1 are standardized to zero, and the elements of u_2 and the value of ζ are estimated in the model. This approach is similar to the treatment of unobserved heterogeneity used in the previous literature (e.g., Keane and Wolpin, 1997, and Chan, 2013).

5.2 Likelihood Function

The parameters in the model are estimated using maximum simulated likelihood estimation. The likelihood function is constructed as described below. First, define an individual's realized log-wage offer in occupation k in period t as $\widehat{w}_{it}^k$, define d_{wit}^k as a binary variable equal to one if $\widehat{w}_{it}^k$ is observed in the data set, and define $\omega_{it} = (\widehat{w}_{it}^1, d_{wit}^1, \widehat{w}_{it}^2, d_{wit}^2, \dots, \widehat{w}_{it}^5, d_{wit}^5)$. Note that each ω_{it} contains at most one non-zero d_{wit}^k as I observe at most one log-wage offer in the data set for an individual each period.

Recall from Section 3.4 that each pre-period state $\bar{S}_{it}$ includes the personal characteristics of the individual (X_i), the unobserved heterogeneity type of the individual (u_i), the previous high school and post-secondary education experience of the individual

[48] Additional details about the imputation rules are provided in Appendix D.2. In addition to the observed choices described in Table 4.9, I observe information about whether some individuals never graduate from high school, never attain a GED, or never graduate from a particular kind of PSE institution. This information is used when calculating the likelihood functions of individuals with missing information as described in Sections 5.2 and 5.3 below.

$(F_{it}, H_{it}, N_{it}, P_{it})$, and the previous human capital accumulation of the individual (O_{it}). Also, recall that each state vector S_{it} includes $\bar{S}_{it}$ as well as the period *t* utility and log-wage error terms $\tilde{\varepsilon}_{it}$ and ε_{it}. Define the expected value of log wages in occupation *k* in period *t* as

$$E\left[w_{it}^{k}(\bar{S}_{it})\right] = w_{it}^{k}(S_{it}) - \tilde{\varepsilon}_{it}^{k}$$

and define an individual's residual log-wage error term associated with realized log-wage offer $\widehat{w}_{it}^{k}$ as

$$\hat{\tilde{\varepsilon}}_{it}^{k} = \widehat{w}_{it}^{k} - E\left[w_{it}^{k}(\bar{S}_{it})\right] \quad . \tag{5}$$

Finally, define $f\left(\tilde{\varepsilon}_{it} \backslash \tilde{\varepsilon}_{it}^{k} \mid \hat{\tilde{\varepsilon}}_{it}^{k}\right)$ as the joint density function of the log-wage error terms for every occupation except occupation *k*, conditional on the realized residual log-wage error term for occupation *k*. As each $\tilde{\varepsilon}_{it}^{k}$ is assumed to be *iid*, the joint density of the unobserved $\tilde{\varepsilon}_{it}^{k}$'s does not depend on the value of the realized residual $\hat{\tilde{\varepsilon}}_{it}^{k}$. That is, $\tilde{\varepsilon}_{it} \backslash \tilde{\varepsilon}_{it}^{k} \mid \hat{\tilde{\varepsilon}}_{it}^{k} \sim N(0, \sigma_{\tilde{\varepsilon}}^{2} I)$, where I is a four-by-four identity matrix corresponding to the four occupations with unobserved wages in period *t*.

Recall that $\bar{V}_{it}^{k}(S_{it})$ is a function of $w_{it}^{k}(S_{it})$ which is a function of $\tilde{\varepsilon}_{it}^{k}$ as defined in Section 3.4. Because the non-pecuniary error terms for each choice (ε_{it}^{k}) are distributed $iid\ EV(0{,}1)$, the conditional likelihood that individual *i*, with pre-period state $\bar{S}_{it}$, chose choice *k* in period *t* is

$$L_{cit}^{k}(\bar{S}_{it}, \omega_{it}) = \int \frac{\exp\left\{\bar{V}_{it}^{k}(S_{it})\right\}}{\sum_{j} \exp\left\{\bar{V}_{it}^{j}(S_{it})\right\}} f\left(\tilde{\varepsilon}_{it} \backslash \tilde{\varepsilon}_{it}^{k} \mid \hat{\tilde{\varepsilon}}_{it}^{k}\right) d\tilde{\varepsilon}_{it} \backslash \tilde{\varepsilon}_{it}^{k} \qquad if \quad d_{wit}^{k} = 1\,, \tag{6}$$

$$L_{cit}^{k}(\bar{S}_{it}, \omega_{it}) = \int \frac{\exp\left\{\bar{V}_{it}^{k}(S_{it})\right\}}{\sum_{j} \exp\left\{\bar{V}_{it}^{j}(S_{it})\right\}} f(\tilde{\varepsilon}_{it}) d\tilde{\varepsilon}_{it} \qquad if \quad d_{wit}^{k} = 0\,,$$

where $$\tilde{\varepsilon}_{it}^{k} = \hat{\tilde{\varepsilon}}_{it}^{k} \quad \text{iff} \quad d_{wit}^{k} = 1 \quad .$$

Note that ω_{it} has two effects on the likelihood function. First, when a wage is observed $(d_{wit}^{k} = 1)$, the corresponding residual log-wage error term $(\hat{\tilde{\varepsilon}}_{it}^{k})$ is directly inserted into the likelihood function. Second, when a wage is observed $(d_{wit}^{k} = 1)$, the corresponding residual log-wage error term affects the conditional joint distribution of the remaining unobserved error terms ($f\left(\tilde{\varepsilon}_{it} \backslash \tilde{\varepsilon}_{it}^{k} \mid \hat{\tilde{\varepsilon}}_{it}^{k}\right)$), which is integrated over to calculate the likelihood function.[49] Also, note that, as the pre-period state $\bar{S}_{it}$ includes a particular unobserved heterogeneity type u_i, the likelihood function $L_{cit}^{k}(\bar{S}_{it}, \omega_{it})$ is conditional on the specific unobserved heterogeneity type u_i in $\bar{S}_{it}$.

Every period that a log wage is observed a wage likelihood can be calculated. Because each log-wage error term is distributed $iid\ N(0, \sigma_{\tilde{\varepsilon}}^{2})$, the conditional likelihood that a particular log wage was offered in occupation *k* in period *t*, given pre-period state $\bar{S}_{it}$, is

$$L_{wit}^{k}(\bar{S}_{it}, \omega_{it}) = \left(\frac{1}{\sigma_{\tilde{\varepsilon}}}\right) \phi\left(\frac{\hat{\tilde{\varepsilon}}_{it}^{k}}{\sigma_{\tilde{\varepsilon}}}\right) \qquad \text{iff} \quad d_{wit}^{k} = 1 \ .$$

Thus, the total conditional likelihood contribution for individual *i* in period *t*, given a particular pre-period state $\bar{S}_{it}$ and observed wage vector ω_{it}, is

$$L_{it}^{k}(\bar{S}_{it}, \omega_{it}) = L_{cit}^{k}(\bar{S}_{it}, \omega_{it}) L_{wit}^{k}(\bar{S}_{it}, \omega_{it}) \quad \text{if} \ \ d_{wit}^{k} = 1 \,, \qquad (7)$$

$$L_{it}^{k}(\bar{S}_{it}, \omega_{it}) = L_{cit}^{k}(\bar{S}_{it}, \omega_{it}) \qquad \text{if} \ \ d_{wit}^{k} = 0 \,.$$

Define the path of choices over the individual's lifetime as $K_{pi} = \{k_{i1}, k_{i2}, \dots, k_{iT}\}$, the associated pre-period state path over the individual's lifetime as $\bar{S}_{pi} = \{\bar{S}_{i1}, \bar{S}_{i2}, \dots, \bar{S}_{iT}\}$, and the path of observed wages over the individual's lifetime as $\omega_{pi} = \{\omega_{i1}, \omega_{i2}, \dots, \omega_{iT}\}$.[50] The conditional lifetime likelihood function for individual *i* is a function of the path of choices over her lifetime (K_{pi}), the associated pre-period states over her lifetime ($\bar{S}_{pi}$), and the observed wage information over her lifetime (ω_{pi}):

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[49] Note that observed wage bias is taken into account in Equation 7.

[50] Note that a choice path (K_{pi}) can be mapped to multiple state vector paths ($\bar{S}_{pi}$), and that a state vector path ($\bar{S}_{pi}$) can be mapped to multiple choice paths (K_{pi}). For example, while choosing to attend a four-year university in period *t* (k_{it} = *Four-Year University*) deterministically affects state vector $\bar{S}_{it+1}$ ($N_{it}^{4yr} = N_{it}^{4yr} + 1$), choosing to work in a professional occupation in period *t* (k_{it} = *Professional*) can have two possible effects on $\bar{S}_{it+1}$ depending on whether or not occupation-specific human capital (O_{it}) is gained (see Equation 3). Conversely, the state space transition of $\bar{S}_{it} = \bar{S}_{it+1}$ can be caused by multiple choices of k_{it}, e.g., choosing not to be employed (k_{it} = *Not Employed*) or choosing to work in the professional field and not gaining occupation-specific human capital (k_{it} = *Professional*, $\psi_{it} = 0$).

$$L_{li}\left(K_{pi}, \bar{S}_{pi}, \omega_{pi}\right) = \prod_{t=1}^{T} L_{it}^{k_{it}}(\bar{S}_{it}, \omega_{it}) \quad .$$

However, I do not always observe K_{pi} and $\bar{S}_{pi}$ because I do not observe the choices an individual makes during periods where information is missing in the data set (when k_{it} is unknown) and do not observe when an individual gains occupation-specific human capital. Define the path of occupation-specific human capital over an individual's lifetime as $O_{pi} = \{O_{i1}, O_{i2}, \dots, O_{iT}\}$, and note that $O_{pi} \in \bar{S}_{pi}$. Define d_{it}^{o} as a binary variable equal to one if the individual's choice in period *t* (k_{it}) is observed in the data set, T_i as the set of all time periods for which d_{it}^{o} = 1 for individual *i*, and K_{pi}^{o} as the set of all k_{it}'s for which d_{it}^{o} = 1 for individual *i*. Note that, for every possible choice path (K_{pi}) and every possible occupation-specific human capital accumulation path (O_{pi}), I can calculate the individual's associated lifetime likelihood ($L_{li}\left(K_{pi}, \bar{S}_{pi}, \omega_{pi}\right)$). The conditional lifetime likelihood contribution of an individual with missing information can be calculated as a weighted sum of the conditional lifetime likelihood functions for each possible path of education and employment that could have taken place for the individual:

$$L_{ui}\left(u_i, X_i, K_{pi}^{o}, \omega_{pi}\right) = \sum_{\bar{S}_{pi}} P\left(\bar{S}_{pi} \middle| K_{pi}^{o}\right) \prod_{T_i} L_{it}^{k_{it}}(\bar{S}_{it}, \omega_{it})$$

where the summation is over all possible $\bar{S}_{pi}$ such that u_i,$X_i \in \bar{S}_{pi}$, and $P\left(\bar{S}_{pi} \middle| K_{pi}^{o}\right)$ is the probability that pre-period state path $\bar{S}_{pi}$ occurred given observable choices K_{pi}^{o}.

Next, note that the probability that the individual chose choice *k* in period *t* when k_{it} is unobserved ($d_{it}^{o} = 0$) is also $L_{it}^{k}(\bar{S}_{it}, \omega_{it})$ and that the probability the individual accumulated human capital in period *t* if she worked and had education level *e* is θ_e. As such, the conditional lifetime likelihood contribution for individual *i* with unobserved heterogeneity type u_i and personal characteristics X_i can be rewritten as

$$L_{ui}\left(u_i, X_i, K_{pi}^{o}, \omega_{pi}\right) = \sum_{\bar{S}_{pi}} \sum_{K_{pi}} P\left(\bar{S}_{pi} \middle| K_{pi}\right) L_{li}\left(K_{pi}, \bar{S}_{pi}, \omega_{pi}\right)$$

where the second summation is over all K_{pi} such that $K_{pi}^{o} \in K_{pi}$. Note that $P\left(\bar{S}_{pi} \middle| K_{pi}\right)$ is comprised entirely of a product of θ_e's and $[1-\theta_e]$'s based on whether O_{pi} increased each period the individual worked along choice path K_{pi}.[51] Also, note that $L_{li}\left(K_{pi}, \bar{S}_{pi}, \omega_{pi}\right)$ is a product of the conditional period likelihood contributions ($L_{it}^{k}(\bar{S}_{it}, \omega_{it})$) for individual *i* for every period $t = 1,2,\ldots,T$. This includes the likelihood contributions for periods where choice $k_{it} \in K_{pi}$ is observed (d_{kit} = 1) as well as the likelihood contributions for periods when choice $k_{it} \in K_{pi}$ is unobserved (d_{kit} = 0).

Finally, note that $L_{ui}\left(u_i, X_i, K_{pi}^{o}, \omega_{pi}\right)$ is the lifetime likelihood contribution for an individual with unobserved heterogeneity type u_i. Since I do not observe whether the person is a type-one or type-two individual, the individual's overall lifetime likelihood function is the weighted sum of her type-one and type-two conditional lifetime likelihood functions, where the weights are the percentages of each type of individual in the population:

$$L_i\left(X_i, K_{pi}^{o}, \omega_{pi}\right) = \zeta L_{ui}\left(u_1, X_i, K_{pi}^{o}, \omega_{pi}\right) + (1-\zeta) L_{ui}\left(u_2, X_i, K_{pi}^{o}, \omega_{pi}\right) \quad .$$

The sample likelihood function (L) is the product of each sample member's individual likelihood contribution:

$$L = \prod_i L_i\left(X_i, K_{pi}^{o}, \omega_{pi}\right) \quad .$$

Values of the parameters in the model are chosen iteratively to maximize the sample likelihood function.[52] The covariance matrix of maximum simulated likelihood estimates is standard.[53]

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[51]For example, if an individual never graduated from high school and worked in a skilled manual labor job in every period *t* = 1,2,…,*T*, the probability that pre-period state path $\bar{S}_{pi}$ occurred in which no occupation-specific human capital was accumulated is $P\left(\bar{S}_{pi} \middle| K_{pi}\right) = [1-\theta_{nohs}]^{T}$.

[52] Parameter values are chosen following the Berndt, Hall, Hall, and Hausman (1974) (BHHH) optimization algorithm.

[53] Estimation code is available upon request. Due to secure data disclosure requirements, all parameter values are estimated on a stand-alone secure data computer.

5.3 Simulation

Integrating over the distribution of each unknown wage error term $\tilde{\varepsilon}_{it}^{k}$ to calculate each $V_{it}^{*}(\bar{S}_{it})$ and $L_{cit}^{k}(\bar{S}_{it}, \omega_{it})$ function, as described in Equations 4 and 6, respectively, is computationally burdensome. In addition, calculating the lifetime likelihood function for individual *i* for every possible choice path K_{pi} such that $K_{pi}^{o} \in K_{pi}$ and every pre-period state path $\bar{S}_{pi}$ such that $u_i, X_i \in \bar{S}_{pi}$ is computationally burdensome. To simplify these calculations, simulation methods are used. First, 10 independent values for each wage error term ($\tilde{\varepsilon}_{it}^{k}$) are simulated using antithetic acceleration.[54] Define each simulated value of $\tilde{\varepsilon}_{it}^{k}$ as $\epsilon_{\xi it}^{vk}$, where the ξ subscript refers to the simulation number (ξ = 1,2,…,10) and the v superscript denotes that the value is used when simulating the value function ($V_{it}^{*}(\bar{S}_{it})$). Define a set of simulated values across all occupations *k* in period *t* as $\epsilon_{\xi it}^{v}$. The value of the integral in Equation 4 is approximated as

$$V_{it}^{*}(\bar{S}_{it}) \approx V_{\xi it}^{*}\left(\bar{S}_{it}, \epsilon_{\xi it}^{v}\right) = \left(\frac{1}{10}\right) \sum_{\xi=1}^{10} \left[ln\left(\sum_j \exp\left\{ \bar{V}_{it}^{j}(S_{it}) \right\} \right) \mid \tilde{\varepsilon}_{it} = \epsilon_{\xi it}^{v} \right] \quad .$$

Next, 10 independent values of each ε_{it}^{k} and $\tilde{\varepsilon}_{it}^{k}$ are simulated for each available choice each period using antithetic acceleration. In addition, 10 independent values of ψ_{it}, related to human capital accumulation, are simulated each period using antithetic acceleration. Define these simulated values as $\epsilon_{\xi it}^{\varepsilon k}$, $\epsilon_{\xi it}^{\tilde{\varepsilon} k}$, and $\epsilon_{\xi it}^{\psi}$, respectively, and collectively define a set of these simulated values across all occupations *k* in period *t* as $\epsilon_{\xi it}$. First, the value of L_{cit}^{k} in Equation 6, given pre-period state $\bar{S}_{it}$, is simulated as

$$L_{\xi cit}^{k}\left(\bar{S}_{it}, \omega_{it}, \epsilon_{\xi it}\right) = \frac{\exp\left\{\bar{V}_{it}^{k}(S_{it})\right\}}{\sum_j \exp\left\{\bar{V}_{it}^{j}(S_{it})\right\}} \quad ,$$

$$\text{where} \quad \tilde{\varepsilon}_{it}^{k} = \hat{\tilde{\varepsilon}}_{it}^{k} \quad \text{if} \quad d_{wit}^{k} = 1 \quad ,$$

$$\tilde{\varepsilon}_{it}^{k} = \epsilon_{\xi it}^{\tilde{\varepsilon} k} \quad \text{if} \quad d_{wit}^{k} = 0 \quad .$$

[54] Borsch-Supan and Hajivassiliou (1993) showed that 20 simulations without antithetic acceleration is a large enough number of simulations to produce consistent estimates. Geweke (1988) showed that antithetic acceleration reduces the sample size required to produce consistent estimates for an initial sample of 20 by at least a factor of four. As such, 10 simulations is a large enough number of simulations to construct consistent estimates of V_{it}^{*} and L_{ui}.

Following Equation 7, the simulated value of L_{it}^{k} is constructed as

$$L_{\xi it}^{k}\left(\bar{S}_{it}, \omega_{it}, \epsilon_{\xi it}\right) = L_{\xi cit}^{k}\left(\bar{S}_{it}, \omega_{it}, \epsilon_{\xi it}\right) L_{wit}^{k}(\bar{S}_{it}, \omega_{it}) \quad if \quad d_{wit}^{k} = 1 \,,$$

$$L_{\xi it}^{k}\left(\bar{S}_{it}, \omega_{it}, \epsilon_{\xi it}\right) = L_{\xi cit}^{k}\left(\bar{S}_{it}, \omega_{it}, \epsilon_{\xi it}\right) \qquad\qquad if \quad d_{wit}^{k} = 0 \,.$$

Second, when $d_{it}^{o} = 0$ the value of k_{it}, given pre-period state $\bar{S}_{it}$, is simulated as

$$k_{\xi it}(\bar{S}_{it}, \epsilon_{\xi it}) = \text{argmax}_{k}\left\{V_{it}^{k}(S_{it}) \mid \varepsilon_{it} = \epsilon_{\xi it}^{\varepsilon} \,, \tilde{\varepsilon}_{it} = \epsilon_{\xi it}^{\tilde{\varepsilon}}\right\} \quad .$$

Finally, human capital accumulation (O_{it}), given pre-period state $\bar{S}_{it}$, is simulated each period as

$$O_{\xi it+1}^{k}(\bar{S}_{it}, \epsilon_{\xi it}) = O_{it}^{k} + \epsilon_{\xi it}^{\psi} \quad \text{iff} \quad d_{it}^{k} = 1 \quad \& \quad \underset{j}{sum}(O_{it}^{j}) \leq 2 \,,$$

$$O_{\xi it+1}^{k} = O_{it}^{k} \qquad\qquad \text{otherwise.}$$

Define $K_{\xi pi}$ as the simulated choice path that includes K_{opi} and a simulated $k_{\xi it}(\bar{S}_{\xi it}, \epsilon_{\xi it})$ in each period that choice k_{it} is unobserved, such that $\bar{S}_{\xi it} \in \bar{S}_{\xi pi}$, where $\bar{S}_{\xi pi} = \{\bar{S}_{\xi i1}, \bar{S}_{\xi i2}, \ldots, \bar{S}_{\xi iT}\}$ is the associated simulated pre-period state path and each $\bar{S}_{\xi it}$ is constructed iteratively, starting from period one, based on $\bar{S}_{\xi it-1}$, $k_{it-1} \in K_{\xi pi}$, and $\epsilon_{\xi it-1}^{\psi}$ as defined in Equation 3. The conditional lifetime likelihood for a particular simulated choice path $K_{\xi pi}$, along pre-period state path $\bar{S}_{\xi pi}$, is

$$L_{\xi ui}\left(u_i, X_i, K_{opi}, \omega_{pi}, K_{\xi pi}, \bar{S}_{\xi pi}\right) = \prod_{T_i} L_{\xi it}^{k_{it}}\left(\bar{S}_{\xi it}, \omega_{it}, \epsilon_{\xi it}\right) \quad .$$

Recall that T_i is the set of all time periods for which the individual's choice was observed in the data set (i.e., all periods for which $d_{it}^{o} = 1$). The conditional lifetime likelihood function for individual *i* is approximated as the average of 10 simulated conditional lifetime likelihoods, using antithetic acceleration:

$$L_{ui}\left(u_i, X_i, K_{pi}^{o}, \omega_{pi}\right) \approx \left(\frac{1}{10}\right) \sum_{\xi=1}^{10} L_{\xi ui}\left(u_i, X_i, K_{opi}, \omega_{pi}, K_{\xi pi}, \bar{S}_{\xi pi}\right) \quad .$$

5.4 Model Parameters

The number of parameters to estimate in the model, though sizable, is small enough to facilitate estimation. Specifically, there are 479 total parameters to estimate in the model. 153 of the parameters are related to the wage utility equations (equation 1) for the five occupations. For each of the five occupations there are 13 parameters associated with personal characteristics (C_i), five parameters associated with local labor market conditions (M_i), six parameters associated with high school graduation curriculum (H_{it}), three parameters associated with PSE graduation (P_{it}), one parameter associated with unobserved heterogeneity, and one constant. Next, there are also four parameters associated with interaction terms between high school graduation curriculum and PSE trade degree graduation ($P_{it}^{1yr} H_{it}$) and four parameters associated with work experience in each of the work occupations that accrue work experience.

319 of the parameters in the model are related to the non-pecuniary (see equation 2) of each of the 14 choices that derive utility (recall that the utility of the Not Employed choice is standardized to zero). First, for each choice there are 13 parameters associated with personal characteristics (C_i), one parameter associated with unobserved heterogeneity, and one constant. Next, there are 76 total parameters that affect the utility of high school fields which are associated with characteristics about the individual's high school related to curriculum selection (I_i). There are 18 total parameters that affect the utility of PSE institutions which are associated with characteristics about the individual's high school related to college attendance (A_i), and 15 total parameters that affect the utility of PSE institutions which are associated with previous high school education choices (H_{it}). Finally, there are seven parameters that do not directly affect wages or non-pecuniary utility. These remaining parameters include a parameter for the relationship between wage and non-pecuniary utility (φ), a parameter for the variance of the normal wage error terms ($\sigma_{\tilde{\varepsilon}}^2$), a parameter for the percentage of the population with type one unobserved heterogeneity (ζ), and four parameters for the probability of gaining work experience given different levels of educational attainment (θ_e).

5.5 Identification

Two types of identification issues merit discussion. First, I address the issue of what moments in the data identify each of the parameters in the model. Second, I address the issue of how the exogenous variation of the instruments (presented in Table 4.3) and estimation of unobserved heterogeneity deal with the bias caused by high school curriculum self-selection.

First, variation across individuals over time allows me to identify each of the parameters in the model. Each parameter in the wage equation ($\tilde{\alpha}^k, \tilde{\beta}_C^k, \tilde{\beta}_L^k, \tilde{\beta}_H^k, \tilde{\beta}_P^k, \tilde{\beta}_{HP}^k, \tilde{\beta}_O^k$), Equation 1, is identified. For example, the effect of gender on wages in occupation k ($\tilde{\beta}_{C_{MALE}}^k$) is identified by the co-variation between gender and wages (i.e., the difference in wages between individuals of different genders) in occupation k among individuals with otherwise equivalent pre-period states in the periods the wages are observed. The effect of occupation-specific human capital in occupation k on wages in occupation k ($\tilde{\beta}_{O_j}^k$) is identified by the co-variation in simulated occupation-specific human capital and wages in occupation k among individuals with otherwise equivalent pre-period states in the periods the wages are observed.

Each parameter in the non-pecuniary utility equation ($\varphi, \alpha^k, \beta_C^k,\ \beta_I^k, \beta_A^k, \beta_H^k$), Equation 2, is also identified. For example, the utility effects of a business vocational high school curriculum on attending two-year community college ($\beta_{H_{BUS}}^{CC}$) is identified by the co-variation in two-year community college attendance between individuals who completed a business vocational high school curriculum and individuals who completed a general education high school curriculum among individuals that attended high schools with different vocational and PSE opportunities (I_i and A_i) but otherwise had equivalent characteristics in their pre-period states. The total amount of additional utility (both pecuniary and non-pecuniary) males receive in occupation k ($\tilde{\beta}_{C_{MALE}}^k + \beta_{C_{MALE}}^k$) is identified by the co-variation in occupation choice and gender among individuals with otherwise equivalent pre-period states. As the pecuniary portion of this utility ($\tilde{\beta}_{C_{MALE}}^k$) is identified from observed wages, as discussed in the preceding paragraph, the non-pecuniary portion of this utility ($\beta_{C_{MALE}}^k$) is identified as the difference between "$\tilde{\beta}_{C_{MALE}}^k + \beta_{C_{MALE}}^k$" and $\tilde{\beta}_{C_{MALE}}^k$.

Next, the distribution of unobserved heterogeneity values in the population ($\tilde{u}_2^k$, u_2^k, ζ) is identified by variation across and persistence in individual choice paths and wages. For example, the magnitude of wage-related unobserved heterogeneity in the population in occupation *k* for type-two individuals ($\tilde{u}_2^k$) is identified by the number of individuals across the sample with persistently higher and lower observed wages than average in occupation *k* over time, and the extent to which their wages are higher and lower than average, among individuals with otherwise equivalent pre-period states. The distribution of non-pecuniary-utility-related unobserved heterogeneity in the population in occupation *k* (u_2^k) is identified by the number of individuals across the sample who persistently choose occupation *k* more than average, and the extent of that persistence, among individuals with otherwise equivalent pre-period states and observed wages.

The variance of the normal wage error terms (σ_{ε}^2) is identified by the variation in residual log-wage error terms (see Equation 5) throughout the sample. The parameter relating wage utility to non-pecuniary utility (φ) is identified because wages are observed and the distribution of the non-pecuniary utility error terms is assumed to be $EV(0,1)$. As wage and non-pecuniary utility parameters are identified as discussed in the preceding paragraphs, the extent to which co-variation in wages and non-pecuniary utility across options affect individuals' choices each period identifies how wage utility relates to non-pecuniary utility. Finally, the probabilities that individuals with different educational attainment levels accrue occupation-specific human capital from working ($\theta_{noHS}, \theta_{HS}, \theta_{1yr}, \theta_{CC}, \theta_{4yr}$) are identified by the rates at which wages discretely jump across periods for individuals with each level of educational attainment.

Next, I deal with the problem of endogenous high school curriculum selection in two ways. First, I explicitly estimate unobserved heterogeneity. Differences in individuals' choice paths and wages given observable personal characteristics provide additional information about the unobserved heterogeneity within the population that drives selection, such as motivation and ability. Second, I use the CTE programs and opportunities available at a student's high school (I_i) as instruments for her high school curriculum choices. CTE opportunities are correlated with a student's high school curriculum choice (as they influence the courses the student chooses to take) but are uncorrelated with the student's unobserved heterogeneity (such as ability and passion) that influences the student's later labor market outcomes.

These instruments include whether each individual's high school offers CTE curricula, whether it is offered within the school or at an area vocational school, the number of CTE–related opportunities in the individual's high school / community, and the number of CTE teachers per student in the individual's high school. These variables indicate options and opportunities that are exogenously available to some students in the sample and are not available to others. Observing otherwise identical individuals making different choices when they have access to expanded curriculum offerings and curriculum-related opportunities identifies the effects of those curriculum offerings separately from the unobserved heterogeneity that may be influencing both student curricula choices and labor market outcomes. In addition, I include the PSE-related programs and opportunities available at a student's high school (A_i) as instruments for her PSE choices. These instruments include whether each student's high school offers college application programs, whether each student's high school offers academic counseling, and the percent of the previous year's class that attend two-year and four-year PSE institutions.[55]

CTE programs and opportunities at each student's school are determined by a combination of state requirements and local school board choices. To deal with the concern that local school board choices about vocational offerings may be correlated with local labor market conditions (e.g., local school boards in areas with more CTE labor market job opportunities may choose to offer more CTE programs in their high schools), I add controls for the local labor market characteristics in the county where each school is located. After controlling for the local labor market characteristics around each school, the remaining difference in CTE opportunities across schools is fully accounted for by state requirement differences and local randomness that is uncorrelated with local labor market conditions

[55] A potential extension to this research involves constructing PSE instruments for the distance from an individual's high school to the nearest post-secondary trade school, community college, and four-year university following Card (1995). While these instruments were considered, they were not constructed due to the time and effort it would take to construct them for each of the 750 high schools in the sample.

(e.g., historic curriculum offerings at that school, a CTE teacher happening to live in the area, school board superintendent preferences, etc.).

Another potential endogeneity concern is that a family may choose where to live based on the location of the school that the family wants its child to attend. However, for a lower income family whose child is more likely to take general education and vocational education classes, the family's housing choice is much more likely to be motivated by the parents' job and housing situation than by the vocational programs available in the area school system, as discussed in Lareau (2011). A final concern is that, conditional on housing location, parents sometimes have an endogenous choice between multiple nearby high schools for their child to attend. I deal with this concern by including indicators for the type of each student's high school (public, non-Catholic private, Catholic) as well as an indicator for whether the high school admits students primarily based on geographic area, which is the case for 74% of the students in the sample.[56]

5.6 Structural vs. Non-Structural Estimates

In Section 6 below, I estimate the parameters of various non-structural models in addition to the parameters of the structural model described in Section 3. While both types of estimation results provide insight into the educational attainment and labor market effects of career and technical education, the structural estimation strategy has a variety of advantages over the non-structural estimation strategy.

First, by estimating a structural model, I am able to separately identify the intertemporal benefits of different choices and how those choices affect present and future utility separately. A less structural model is unable to separately identify whether the benefit of making a particular choice in the current period is driven by increased utility in the current period or by increased utility flows in future periods and is unable to separately identify the specific mechanisms that cause current and future utility flows to increase. For example, by estimating a structural model, I can identify whether a student takes high

[56]Further, conditional on housing location, a student in a rural area is less likely to have a choice between multiple high schools than a student in an urban area. As such, estimates for rural students in particular should not be subject to this potential school selection bias.

school vocational education because of the current period utility she derives, because of its effects on her future PSE institution utility, or because of its effects on her future wages in each occupation, as discussed in Section 5.5. Due to this identification, the parameter estimates of the dynamic discrete choice model provide more detail about the relationship between the explanatory and dependent variables and more context about what drives individual decision making. Second, the structural model enables me to estimate effects that pertain to several research questions jointly in a fairly straightforward way (e.g., by estimating a structural model, I can jointly estimate the effects of high school vocational education on wages in each occupation, the likelihood of being employed in a skilled occupation, the likelihood of graduating from high school, and the likelihood of graduating from a PSE institution).

Third, I can use the structural model to conduct the policy simulations discussed in Section 7. It is worth noting that some policy simulations can be conducted using non-structural models. For example, the effects of increasing vocational high school opportunities nationwide could be simulated by adding vocational high school opportunities into the first stage of a 2SLS regression for every individual in the data set and seeing how the addition of these opportunities, for the subset of the sample that did not previously have access to them, would affect predicted values for aggregate wages and employment outcomes. For this simulation, the main benefit of the structural estimation approach is improved sample fit caused by accounting for forward-looking behavior and applying structure to the model (for examples of the general model fit and out-of-sample fit benefits provided by structural models, see Todd & Wolpin's (2006) model of Progressa, Duflo, Hanna & Ryan's (2008) model of teacher attendance decisions in India, and Kaboski & Townsend's (2011) model of microfinance programs in Thailand).

However, many policy simulations cannot be conducted without a structural model of forward-looking behavior. This class of simulations includes policy simulations that force individuals down alternative choice paths, those that change the structure of the model in a substantive ways, and those that change the intertemporal effects of different choices (which cannot be identified in a less structural model, such as how decreasing the cost of community college will effect an individual's high school decisions). Estimating a structural model allows me to simulate the effects of these types of policies and predict how they would affect an individual's decisions throughout her lifetime.

6. Estimation Results

6.1 Two-Stage Least Squares Estimates

First, I estimate linear models of later-life wages and employment using two-stage least squares estimation. The 2SLS regressions use data on each student's HS curriculum, PSE attainment, and wage and occupation information at the time the final survey wave was conducted in 2012.

The first-stage regression, used to construct high school curriculum predicted probabilities, is a multinomial logit regression of high school curriculum on personal characteristics (X_i), local labor market characteristics (M_i), and high school vocational instruments (I_i). The estimates from the first-stage regression are displayed in Table 6.1; note that all estimates are relative to graduating high school in a general education curriculum. Overall, men are more likely to concentrate in a trade vocational field then women. Specifically, men receive 1.43 more utils than women from concentrating in the trade vocational curriculum relative to concentrating in the general education curriculum. Next, Caucasian individuals are more likely than black, Hispanic, and other race individuals to concentrate in a trade vocational, business vocational, or other curriculum, and individuals who attend Catholic or non-Catholic private high schools are very likely to take general education courses as opposed to academic or vocational courses and are also very unlikely to drop out of high school. Local labor market characteristics have little effect on curriculum take-up, although there are a few exceptions. For example, as the hourly wage increases in the county where the school is located, the number of individuals who concentrate in other curricula decreases, and as the percent of manual labor employment increases in the county where the school is located, the number of individuals who concentrate in a trade vocational curriculum increases.

Each instrument has a significant effect on the utility associated with at least one high school curriculum relative to graduating in the general education field, with the

Table 6.1a: Selected First Stage Estimates

Variable	Academic Estimate	Academic *SE*	Business Voc Estimate	Business Voc *SE*	Trade Voc Estimate	Trade Voc *SE*	Other Estimate	Other *SE*	GED Estimate	GED *SE*	Dropping Out Estimate	Dropping Out *SE*
1. Personal Characteristics												
Male	**-0.36** ***	*0.06*	-0.05	*0.08*	**1.43** ***	*0.11*	**-0.18** ***	*0.05*	**0.62** ***	*0.11*	**0.42** ***	*0.08*
Black	0.02	*0.12*	-0.15	*0.15*	**-0.83** ***	*0.17*	**-0.37** ***	*0.10*	**-0.62** ***	*0.19*	-0.22	*0.15*
Hispanic	-0.14	*0.10*	**-0.56** ***	*0.18*	**-0.83** ***	*0.18*	**-0.36** ***	*0.10*	-0.23	*0.20*	0.21	*0.13*
Other Race	**0.60** ***	*0.08*	-0.06	*0.14*	**-0.39** ***	*0.15*	**-0.36** ***	*0.11*	-0.04	*0.18*	0.19	*0.14*
Socio-Economic Status	**0.24** ***	*0.03*	**-0.11** **	*0.05*	**-0.16** ***	*0.06*	-0.04	*0.03*	**-0.18** ***	*0.06*	**-0.39** ***	*0.05*
Test Score	**1.34** ***	*0.04*	-0.07	*0.05*	**-0.36** ***	*0.05*	**-0.29** ***	*0.04*	**-0.14** **	*0.07*	**-0.66** ***	*0.05*
Midwest	**-0.43** ***	*0.13*	-0.22	*0.19*	**-0.41** **	*0.19*	**0.27** *	*0.15*	-0.24	*0.26*	**-0.43** **	*0.19*
South	0.08	*0.13*	-0.03	*0.18*	**-0.56** ***	*0.20*	0.03	*0.15*	0.16	*0.25*	**-0.39** **	*0.19*
West	**-0.65** ***	*0.14*	**-1.29** ***	*0.25*	**-0.85** ***	*0.26*	-0.03	*0.19*	**-0.63** **	*0.28*	**-0.84** ***	*0.23*
Suburban	**-0.33** ***	*0.10*	-0.06	*0.15*	0.24	*0.16*	0.11	*0.11*	-0.12	*0.16*	-0.20	*0.13*
Rural	**-0.46** ***	*0.14*	-0.06	*0.18*	-0.10	*0.21*	0.12	*0.14*	-0.16	*0.24*	-0.01	*0.20*
Catholic School	**-0.83** ***	*0.19*	0.18	*0.29*	**-0.85** **	*0.36*	**-1.44** ***	*0.27*	**-1.33** ***	*0.41*	**-1.74** ***	*0.32*
Non-Catholic Private School	**-1.07** ***	*0.21*	**-0.78** **	*0.32*	**-1.32** ***	*0.41*	**-1.46** ***	*0.27*	**-0.83** **	*0.39*	**-1.01** ***	*0.28*
2. Local Labor Market Characteristics												
Unemployment Rate	-0.60	*3.12*	4.83	*4.06*	-1.57	*5.04*	-1.01	*2.80*	-0.83	*4.26*	-3.58	*3.01*
(ln) Average Hourly Wage	0.08	*0.28*	-0.08	*0.41*	-0.27	*0.45*	**-0.74** **	*0.32*	-0.39	*0.49*	-0.32	*0.37*
% Professional Employment	0.40	*2.09*	0.81	*2.73*	-0.65	*3.59*	0.89	*2.31*	-5.16	*3.54*	-3.11	*2.99*
% Manual Labor Employment	-0.32	*0.70*	0.54	*0.90*	**2.25** **	*1.10*	**-1.27** *	*0.67*	-1.21	*0.99*	-1.10	*0.93*
% Non-Manual Labor Employment	-0.10	*1.22*	1.87	*1.74*	0.17	*2.05*	-1.31	*1.21*	-1.43	*1.85*	0.64	*1.63*

Notes:

1) Multinomial Logit regression. Estimates are relative to graduating high school in the general education field.

2)*,**,*** denote 90%, 95%, and 99% statistical significance respectively.

3) Standard Errors (SE) are clustered at the school level.

4) Total # Observations is 15,890.

Table 6.1b: Selected First Stage Estimates

Variable	Academic Estimate	Academic *SE*	Business Voc Estimate	Business Voc *SE*	Trade Voc Estimate	Trade Voc *SE*	Other Estimate	Other *SE*	GED Estimate	GED *SE*	Dropping Out Estimate	Dropping Out *SE*
3. Vocational Instruments												
Voc Taught in High School	-0.05	*0.16*	0.37	*0.31*	0.43	*0.30*	0.13	*0.16*	-0.24	*0.36*	0.26	*0.25*
Voc Taught in Area School	**-0.29** **	*0.14*	0.21	*0.35*	0.16	*0.28*	0.03	*0.17*	-0.29	*0.43*	**0.45** *	*0.26*
Voc Taught in Both HS & Area Sch	-0.14	*0.16*	0.33	*0.32*	0.22	*0.30*	0.14	*0.17*	-0.15	*0.38*	0.30	*0.25*
Marketing Courses Taught On-Site	-0.03	*0.12*	**0.61** ***	*0.17*	0.15	*0.17*	**0.20** *	*0.11*	**0.36** **	*0.18*	0.06	*0.14*
Marketing Courses Taught at Area Sch	**-0.31** *	*0.18*	0.08	*0.25*	0.04	*0.27*	0.09	*0.16*	-0.01	*0.28*	-0.24	*0.24*
Precisions Courses Taught On-Site	0.15	*0.14*	-0.16	*0.20*	**0.42** **	*0.20*	-0.06	*0.14*	-0.02	*0.23*	0.18	*0.19*
Precisions Courses Taught at Area Sch	-0.03	*0.16*	-0.13	*0.22*	**0.41** *	*0.24*	-0.14	*0.17*	-0.03	*0.26*	0.16	*0.21*
# Vocational Teachers per 100 Students	**-0.26** **	*0.11*	0.07	*0.13*	**0.16** *	*0.09*	0.06	*0.08*	-0.10	*0.13*	0.03	*0.11*
Career Pathways Prog Available	0.14	*0.10*	**0.31** *	*0.17*	0.26	*0.19*	-0.02	*0.11*	-0.09	*0.45*	0.03	*0.21*
% Students Free/Reduced Price Lunch	0.12	*0.22*	-0.10	*0.32*	0.31	*0.31*	-0.07	*0.21*	0.08	*0.35*	**0.46** *	*0.25*
% Students Take Academic Courses	-0.06	*0.20*	**-0.55** **	*0.27*	-0.20	*0.31*	**-0.62** ***	*0.17*	**-1.88** ***	*0.70*	0.16	*0.35*
% Students Take Vocational Courses	0.45	*0.45*	**1.00** ***	*0.37*	**1.88** ***	*0.43*	**1.19** ***	*0.34*	**1.92** **	*0.90*	0.42	*0.53*
% Prev Students Enter Labor Market (0-5)	-0.04	*0.07*	0.12	*0.09*	0.10	*0.10*	0.06	*0.06*	**-0.41** *	*0.24*	**-0.22** **	*0.11*
Admission Based on Geography	0.04	*0.13*	0.06	*0.19*	0.13	*0.23*	-0.04	*0.13*	0.60	*0.59*	**-0.53** **	*0.24*
Student Infl on Course Selection (0-3)	0.01	*0.06*	**0.17** *	*0.10*	0.15	*0.11*	0.08	*0.07*	-0.25	*0.21*	0.10	*0.15*
GED Confered by High School	-0.03	*0.14*	-0.12	*0.17*	-0.08	*0.19*	**-0.34** ***	*0.11*	**0.90** **	*0.35*	**0.48** **	*0.21*
Constant	-0.20	*0.91*	**-2.87** **	*1.43*	**-4.15** ***	*1.39*	**1.67** *	*1.00*	-2.12	*2.07*	-1.23	*1.29*

Notes:

1) Multinomial Logit regression. Estimates are relative to graduating high school in the general education field.

2)*,**,*** denote 90%, 95%, and 99% statistical significance respectively.

3) Standard Errors (SE) are clustered at the school level.

4) Total # Observations is 15,890.

exception of whether most vocational courses are taught in the high school, at an area vocational school, or both (this variable has a positive but statistically insignificant effect on concentrating in a trade or business vocational curriculum).[57] As the number of individuals in the previous year's graduating class who took vocational courses increases, the probability that an individual concentrates in a trade vocational curriculum or a business vocational curriculum increases. Next, when business courses such as marketing are taught on-site, individuals are more likely to concentrate in business vocational fields. When trade courses such as precisions are taught on-site, individuals are more likely to concentrate in trade vocational fields. Offering career pathways programs to students increases their likelihood of taking business vocational courses, while increasing the number of vocational teachers per student at a school increases the likelihood of taking trade vocational courses. As well, students who attend schools that confer GEDs on-site are more likely to pursue GEDs and are also slightly more likely to drop out of high school. Whether schools admit students based on geographic location has little effect on curriculum choice, with the exception that students are less likely to pursue GEDs or dropout. Finally, as students' influence on course selection increases, students are more likely to take business vocational courses relative to general education courses and are less likely to pursue GEDs.

Table 6.2 presents the estimates from a second-stage OLS regression of log hourly wages on personal characteristics (X_i), local labor market characteristics (M_i), high school curriculum (H_i), and post-secondary education attainment (P_i), under four different specifications. Specification 1 includes no instruments and does not account for post-secondary education attainment. Specification 2 replaces high school curriculum with high school curriculum predicted probabilities $\widehat{H}_i$, from the first-stage regression described in the preceding paragraph, but still does not account for post-secondary education attainment. Specification 3 also includes predicted probabilities for high school curriculum but first

[57] The first-stage estimates for vocational course location are significant for many alternative specifications of the instrument subset. As discussed in Section 4.1, changing the instrument subset has little effect on the estimates in the second-stage regressions. The instrument subset presented here was chosen to be indicative of the full set of variables available in ELS:2002.

Table 6.2: HS Curricula on Log Hourly Wages (Age 26)

Variable	(1) Estimate		SE	(2) Estimate		SE	(3) Estimate		SE	(4) Estimate		SE
Prob Academic	**0.13**	***	(.01)	**0.14**	**	(.05)	0.01		(.07)	-0.02		(.07)
Prob Business Vocational	**0.06**	***	(.02)	**-0.41**	**	(.21)	-0.26		(.23)	**-0.45**	**	(.21)
Prob Trade Vocational	**0.06**	**	(.02)	**0.32**	***	(.11)	**0.34**	**	(.14)	**0.34**	***	(.12)
Prob Other Curriculum	-0.01		(.02)	-0.04		(.11)	0.13		(.13)	0.01		(.11)
Prob GED	**-0.08**	***	(.02)	-0.13		(.19)	0.24		(.22)	0.12		(.20)
Prob HS Dropout	**-0.17**	***	(.02)	**-0.18**	**	(.08)	**-0.18**	**	(.09)	**-0.23**	***	(.08)
Prob 1-yr Trade School	-		-	-		-	-		-	**-0.45**	*	(.23)
Prob 2-yr Community College	-		-	-		-	-		-	0.00		(.21)
Prob 4-yr University	-		-	-		-	-		-	**0.32**	***	(.09)
Male	**0.08**	***	(.01)	**0.06**	***	(.01)	**0.12**	***	(.02)	**0.06**	***	(.01)
Black	**-0.08**	***	(.01)	**-0.08**	***	(.02)	**-0.07**	***	(.02)	**-0.07**	***	(.02)
Hispanic	-0.01		(.01)	-0.02		(.02)	0.02		(.02)	-0.01		(.02)
Other Race	0.02		(.01)	0.02		(.02)	0.01		(.02)	0.01		(.02)
Socio-Economic Status	**0.04**	***	(.01)	**0.04**	***	(.01)	**0.02**	***	(.01)	0.01		(.01)
Test score	**0.07**	***	(.01)	**0.07**	***	(.01)	**0.05**	***	(.01)	**0.03**	**	(.01)
Midwest	**-0.07**	***	(.02)	**-0.07**	***	(.02)	**-0.06**	***	(.02)	**-0.06**	***	(.02)
South	**-0.08**	***	(.02)	**-0.08**	***	(.02)	**-0.08**	***	(.02)	**-0.06**	***	(.02)
West	-0.03		(.02)	**-0.04**	*	(.02)	-0.01		(.03)	-0.02		(.02)
Suburban	**0.03**	**	(.01)	**0.03**	**	(.01)	**0.02**	*	(.01)	**0.03**	**	(.01)
Rural	**0.03**	*	(.02)	**0.03**	*	(.02)	**0.04**	**	(.02)	**0.03**	*	(.02)
Catholic School	**0.08**	***	(.02)	**0.08**	***	(.02)	**0.10**	***	(.03)	**0.05**	**	(.02)
Non-Catholic Private School	**0.07**	***	(.02)	**0.05**	**	(.02)	0.04		(.03)	0.02		(.02)
Unemployment Rate	0.22		(.34)	0.36		(.35)	-0.09		(.38)	0.16		(.36)
(ln) Average Hourly Wage	**0.07**	*	(.04)	**0.06**	*	(.04)	0.07		(.05)	**0.08**	**	(.04)
% Professional Employment	**0.61**	**	(.28)	**0.62**	**	(.28)	**0.78**	**	(.34)	0.37		(.29)
% Manual Labor Employment	0.09		(.09)	0.10		(.09)	0.09		(.11)	0.12		(.10)
% Non-Manual Labor Employment	0.02		(.14)	0.08		(.14)	0.12		(.19)	0.06		(.14)
Constant	**2.17**	***	(.11)	**2.19**	***	(.12)	**2.02**	***	(.16)	**2.12**	***	(.12)

Notes:
1) Ordinary Least Squares regressions. Specification 1 includes no instruments. Specifications 2-4 use high school predicted probabilities from the first stage regression (See Table 6.1). Specification 3 drops all individuals who graduated from CC or 4yr university. Specification 4 includes predicted probabilities from a separate first stage instrumental variables multinomial logit regression of PSE completion on PSE instruments (See Table 4.2 section 5).
2) HS predicted probabilities are relative to graduating high school in the general education field.
3)*,**,*** denote 90%, 95%, and 99% statistical significance respectively.
4) Standard Errors are clustered at the school level.
5) Total # observations is 10,020 for regressions 1, 2, and 4. Total # observations is 5,010 for regression 3.

drops any individual who graduated from community college or a four-year university. Finally, Specification 4 includes predicted probabilities for high school curriculum in addition to predicted probabilities for post-secondary education attainment ($\hat{P}_i$) from a separate first-stage multinomial logit regression of post-secondary education attainment on personal characteristics (X_i), labor market characteristics (L_i), and the post-secondary education instruments (A_i) presented in Table 4.3, Section 2.[58]

Specification 1 shows that, without accounting for selection, individuals who concentrate in vocational education courses unambiguously receive higher later-life wages than individual who concentrate in general education courses. For example, the estimate on the variable "Prob Trade Vocational" in Column 1 suggests that, as the probability of graduating with a trade vocational curriculum goes from zero to one (relative to graduating with a general education curriculum), an individual's log hourly wages increase by 0.06. However, Specifications 2, 3, and 4 show that selection is driving much of this result. After instrumenting for high school curriculum selection, the results in Specifications 2, 3, and 4 show that trade vocational education increases later-life wages (by .32, .34, and .34 log dollars an hour, respectively) and business vocational education decreases later-life wages (by -.41, -.26, and -.45 log dollars an hour, respectively) relative to general education courses. Specification 4 shows similar results to Specification 2, except that the returns to an academic high school curriculum disappear after accounting for post-secondary education attainment. In addition, Specification 4 shows that the returns to wages from graduating from a four-year university are quite high (.32 log dollars an hour).[59] Regarding personal characteristics, non-black men receive higher wages than other demographic groups. Students who have higher test scores and graduate from Catholic high schools also receive higher wages. Individuals from urban communities receive lower wages than individuals from suburban or rural communities, and wages tend to be higher in the west and northeast than in the south or Midwest. Finally, as average wages in a student's high school county increase, her later-life wages increase.

Table 6.3 presents the estimates from two different second-stage logit regressions. In the first, I regress whether or not an individual is employed at age 26, and, in the second, I regress whether or not an individual is employed in a skilled occupation at age 26 (relative to being employed in an unskilled occupation) conditional on being employed. These two

[58] The estimates from this separate first-stage regression are presented in Appendix E.
[59] Note that each of these results is robust to choosing different subsets of instruments in the first-stage regression, with the exception of the estimate for business vocational curricula (which is always negative but whose statistical significance varies across regressions as I choose different subsets of instruments).

Table 6.3: HS Curricula on Employment (Age 26)

Variable	Employed Estimate	Employed SE	Skilled Occupation Estimate	Skilled Occupation SE
Prob Academic	-0.81	*(.55)*	0.12	*(.56)*
Prob Business Vocational	0.74	*(1.38)*	1.29	*(1.78)*
Prob Trade Vocational	0.77	*(.83)*	**3.03** ***	*(1.04)*
Prob Other Curriculum	**-2.55** ***	*(.69)*	-0.45	*(.86)*
Prob GED	-0.40	*(1.28)*	-0.19	*(1.35)*
Prob HS Dropout	**-1.92** ***	*(.55)*	-0.52	*(.68)*
Prob 1-yr Trade School	2.51	*(1.64)*	-0.88	*(1.94)*
Prob 2-yr Community College	2.28	*(1.42)*	**-3.57** **	*(1.74)*
Prob 4-yr University	**2.33** ***	*(.69)*	1.26	*(.81)*
Male	**0.91** ***	*(.12)*	0.18	*(.14)*
Black	0.15	*(.12)*	0.15	*(.14)*
Hispanic	**0.24** **	*(.12)*	0.18	*(.13)*
Other Race	**-0.18** *	*(.11)*	-0.18	*(.13)*
Socio-Economic Status	-0.01	*(.06)*	-0.08	*(.07)*
Testscore	0.09	*(.09)*	0.10	*(.11)*
Midwest	**0.33** **	*(.13)*	-0.05	*(.15)*
South	0.08	*(.11)*	-0.17	*(.14)*
West	-0.03	*(.14)*	-0.01	*(.16)*
Suburban	0.07	*(.08)*	0.03	*(.10)*
Rural	0.09	*(.11)*	0.23	*(.15)*
Catholic School	-0.14	*(.19)*	0.09	*(.20)*
Non-Catholic Private School	**-0.81** ***	*(.17)*	**0.52** **	*(.23)*
Unemployment Rate	-1.60	*(2.63)*	0.86	*(2.46)*
(ln) Average Hourly Wage	**-0.49** **	*(.24)*	0.24	*(.28)*
% Professional Employment	**3.78** *	*(2.11)*	-0.10	*(2.04)*
% Manual Labor Employment	**-1.72** ***	*(.62)*	**1.26** *	*(.73)*
% Non-Manual Labor Employment	0.17	*(1.02)*	**2.07** *	*(1.21)*
Constant	**2.77** ***	*(.83)*	0.65	*(1.01)*

Notes:

1) Logit regressions. *Employed*: Employed (1) vs Not Employed (0). *Skilled Occupation: Employed in Skilled Occupation (1) vs Employed in Unskilled Occupation (0), conditional on working.*

2) HS predicted probabilities are relative to graduating high school in the general education field.

3)*,**,*** denote 90%, 95%, and 99% statistical significance respectively.

4) Standard Errors are clustered at the school level.

5) Total # observations is 12,100 for Employed regression and 10,590 for Skilled Occupation regression.

binary variables are regressed on personal characteristics (X_i), local labor market characteristics (M_i), high school curriculum predicted probabilities ($\widehat{H}_i$) from the regression in Table 6.1, and post-secondary education attainment predicted probabilities

($\hat{P}_i$) from a separate first-stage regression using the instruments presented in Table 4.3, Section 2. The estimates in Table 6.3, Column 1, suggest that concentrating in a business or trade vocational curriculum causes a positive but statistically insignificant increase in the chance of being employed relative to concentrating in a general education curriculum. E.g., the estimate on "Prob Business Vocational" in the "Employed" column indicates that, as the probability of graduating in a business vocational curriculum goes from zero to one (relative to graduating in a general education curriculum), the utility an individual receives from being employed increases by .74 utils. Column 1 also shows that concentrating in the other curriculum decreases the chances of being employed at age 26 and that dropping out of high school decreases the chances of being employed at age 26.

Next, the results in Table 6.3, Column 2, suggest that taking trade vocational courses increase the chances of being employed in a skilled occupation (relative to an unskilled occupation) conditional on being employed by 3.03 utils. The results also suggest that an academic high school curriculum has little effect on employment relative to a general education high school curriculum. Graduating from a four-year university greatly increases the chances of being employed later in life (by 2.33 utils), and individuals who graduate from community college are much more likely to be employed in unskilled occupations than those who do not graduate from community college.[60] Finally, individuals who attend schools in counties with high percentages of professional labor employment have higher chances than average of being employed at age 26, while individuals who attend schools in counties with high percentages of manual labor employment have lower chances than average of being employed at age 26.

6.2 Structural Estimates

Structural estimates are presented in Tables 6.4-6.7.[61] Selected structural wage and

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[60] Note that each of the results in Table 6.3 is robust to choosing different subsets of instruments in the first-stage regression with two exceptions: the skilled occupation parameter estimates for community college and four-year university graduation vary in significance as I run the regressions on different subsets of instruments (though the estimate on community college always has a negative sign and the estimate on four-year university always has a positive sign).

[61] The remaining structural parameters are presented in Appendix F.

utility parameters related to occupation choices are presented in Table 6.4. Looking vertically at each column in Section 1 provides a comparison of how each type of high school curriculum and PSE degree affects log wages in a particular occupation. First, graduation from high school in any field improves wages in four of the five occupations relative to dropping out. As expected, a business vocational curriculum has the greatest effect on log hourly wages in the skilled non-manual labor occupation (.29), while a trade vocational curriculum has the greatest effect on log hourly wages in the skilled manual labor occupation (.11), relative to any other high school curricula (for comparison, the effect of a general education curriculum on log hourly wages in the skilled manual labor occupation is .04). The large log hourly wage parameters associated with the skilled other occupation (ranging from 2.15 to 2.39), combined with the small log hourly wage constant for the skilled other occupation (-.59 relative to log hourly wage constants for the other occupations ranging from 1.30 to 1.89), imply that high school dropouts receive very low wages in the skilled other occupation relative to individuals who graduate from high school. Finally, the negative log hourly wage parameters for high school graduation associated with the professional occupation (ranging from -.26 to -.14) imply that individuals who drop out of high school receive higher wages than individuals with only a high school degree in the professional occupation. This result is driven by the fact that few individuals in the data set work in the professional occupation without having earned a bachelor's degree and that, of those individuals, high school dropouts had slightly higher wages than individuals with any type of high school degree. The parameter estimates imply that the education wage premium in the professional occupation is almost entirely concentrated in four-year university graduation (an increase of .46 log hourly wages) as opposed to being concentrated in high school graduation.

The 2SLS regression result that a business vocational curriculum has little effect on wages relative to a general education curriculum, discussed in Section 6.1, does not appear in the structural estimates. Interestingly, the structural estimates show that this 2SLS result was driven by two factors. First, the structural estimates break up wages by occupation type. Once wages are allowed to vary across occupations, the estimates suggest that a business vocational curriculum improves log hourly wages in the skilled non-manual labor

Table 6.4: Selected Structural Occupation Parameters

Variable	Professional Estimate		Professional SE	Skilled Manual Labor Estimate		Skilled Manual Labor SE	Skilled Non-Manual Labor Estimate		Skilled Non-Manual Labor SE	Skilled Other Estimate		Skilled Other SE	Unskilled Estimate		Unskilled SE
1. Previous Education (Log-Wage Utility)															
Academic	-0.26	***	*(.027)*	0.04	**	*(.015)*	0.17	***	*(.016)*	2.16	***	*(.068)*	0.16	***	*(.024)*
General Education	-0.21	***	*(.026)*	0.04	***	*(.012)*	0.20	***	*(.014)*	2.25	***	*(.068)*	0.23	***	*(.016)*
Business Vocational	-0.14	***	*(.028)*	0.09	***	*(.015)*	0.29	***	*(.017)*	2.15	***	*(.071)*	0.19	***	*(.026)*
Trade Vocational	-0.16	***	*(.029)*	0.11	***	*(.013)*	0.22	***	*(.018)*	2.39	***	*(.074)*	0.13	***	*(.025)*
Other Curriculum	-0.16	***	*(.027)*	0.08	***	*(.013)*	0.24	***	*(.015)*	2.38	***	*(.068)*	0.27	***	*(.017)*
GED	-0.23	***	*(.028)*	-0.02		*(.015)*	0.27	***	*(.017)*	2.27	***	*(.065)*	0.13	***	*(.024)*
1-yr Trade School	0.22	***	*(.014)*	0.15	***	*(.011)*	0.15	***	*(.010)*	-0.08		*(.049)*	-0.11	***	*(.023)*
2-yr Community College	0.02	***	*(.006)*	-0.05	***	*(.006)*	-0.02	***	*(.005)*	-0.01		*(.021)*	-0.10	***	*(.022)*
4-yr University	0.46	***	*(.008)*	0.25	***	*(.009)*	0.25	***	*(.008)*	0.46	***	*(.018)*	0.12	***	*(.022)*
2. Personal Characteristics (Log-Wage Utility)															
Male	0.05	***	*(.011)*	0.22	***	*(.013)*	-0.04	***	*(.011)*	0.09	***	*(.024)*	0.07	***	*(.018)*
Black	-0.09	***	*(.022)*	-0.03		*(.018)*	0.01		*(.018)*	0.16	***	*(.039)*	-0.07	**	*(.029)*
Hispanic	-0.06	***	*(.019)*	-0.04	*	*(.018)*	0.04	*	*(.018)*	0.10	***	*(.039)*	0.01		*(.026)*
Other Race	0.05	***	*(.016)*	-0.06	***	*(.018)*	0.05	***	*(.018)*	0.15	***	*(.037)*	0.08	***	*(.027)*
Socio-Economic Status	0.03	***	*(.006)*	0.00		*(.007)*	-0.01		*(.007)*	0.00		*(.014)*	0.03	**	*(.011)*
Testscore	0.06	***	*(.007)*	0.03	***	*(.007)*	0.02	***	*(.007)*	0.04	***	*(.014)*	-0.01		*(.011)*
Constant	1.89	***	*(.080)*	1.62	***	*(.056)*	1.30	***	*(.065)*	-0.59	***	*(.156)*	1.62	***	*(.102)*
3. Personal Characteristics (Non-Pecuniary Utility)															
Male	0.07	***	*(.020)*	0.91	***	*(.021)*	-0.08	***	*(.018)*	-0.18	***	*(.036)*	-0.15	***	*(.031)*
Black	0.00		*(.036)*	-0.33	***	*(.029)*	0.05		*(.029)*	-0.16	***	*(.061)*	-0.01		*(.047)*
Hispanic	0.02		*(.031)*	-0.30	***	*(.027)*	-0.07	**	*(.027)*	-0.22	***	*(.064)*	-0.26	***	*(.043)*
Other Race	-0.27	***	*(.029)*	-0.41	***	*(.028)*	-0.22	***	*(.027)*	-0.55	***	*(.062)*	-0.45	***	*(.045)*
Socio-Economic Status	0.48	***	*(.011)*	0.16	***	*(.011)*	0.31	***	*(.011)*	0.51	***	*(.021)*	0.13	***	*(.018)*
Testscore	0.81	***	*(.012)*	0.40	***	*(.011)*	0.5	***	*(.011)*	0.83	***	*(.021)*	0.32	***	*(.017)*
Constant	-1.05	***	*(.040)*	-2.21	***	*(.039)*	-0.93	***	*(.038)*	-1.31	***	*(.066)*	-2.62	***	*(.060)*
4. Occupation-Specific Human Capital (Wage Utility)															
Occ-Specific Human Capit	0.83	***	*(.012)*	0.71	***	*(.011)*	0.71	***	*(.011)*	0.78	***	*(.022)*	-		-

Notes:

1) The parameter on log hourly wages (relating wage utility to non-pecuniary utility) is 1.37, with SE of *(.002)*.

2) The variance of the normal wage error terms is estimated to be 0.16, with a SE of *(.001)*.

3) The estimates for work experience accumulation probabilities with educational attainment HS Degree, 1-yr Trade, 2-yr CC, and 4-yr University are 9%, 14%, 14%, and 11% respectively, with SEs of *(.000)*, *(.001)*, *(.001)*, and *(.000)* respectively.

4)*,**,*** denote 90%, 95%, and 99% statistical significance respectively.

5) Total # Observations is 16,200.

6) Standard errors (SE) are calculated using the covariance of the parameter estimate scores, following Train (2003).

occupation (.29) more than any other high school curriculum improves log hourly wages in the skilled non-manual labor occupation. Since the skilled non-manual labor occupation has the lowest average wages of any occupation type, and a larger proportion of individuals who graduate high school in the business vocational field choose that occupation relative to individuals who graduate high school in other fields (such as general education), business vocational curriculum completers receive lower wages on average across occupations.

Second, the structural estimates answer the question of why business vocational completers choose skilled non-manual labor occupations (which provide lower average wages) more than other individuals, after controlling for observables. This choice is driven by the higher total utility (wage plus non-pecuniary utility) business vocational completers receive from the skilled non-manual labor occupation relative to other occupations. Though wages are lower on average across the sample in the skilled non-manual labor occupation relative to other occupations, non-pecuniary utility is higher on average across the sample in the skilled non-manual labor occupation relative to other occupations (as seen by comparing the non-pecuniary utility constants in Table 6.1). Since an individual with a general education high school curriculum is more or less indifferent between different occupations after taking into account both the wage and non-pecuniary utility she receives, an individual with a business vocational high school curriculum is more likely to choose a skilled non-manual labor occupation, due to the relative increase in wages she receives in that occupation. Thus, a business vocational concentrator chooses the skilled non-manual labor occupation because of the non-pecuniary utility the occupation provides in addition to the wage premium she receives in the occupation from graduating high school with a business vocational curriculum, despite the fact that the job provides lower total wages than other occupations available to her. Similar incentives cause individuals who take trade vocational high school curricula to work in skilled manual labor occupations, individuals who take other (alternative) high school curricula to work in skilled other occupations, and individuals who take academic high school curricula to work in the professional, skilled non-manual labor, and skilled other occupations.

Next, recall that an individual's choice of whether to work in the model is driven by three factors: the wage offer she receives in each occupation in the current period, the non-pecuniary utility of each occupation in the current period, and the increase in future wages she will receive if she gains occupation-specific human capital from working in the current period. As an individual receives a wage offer in every occupation each period with 100% certainty, the effects of high school curriculum on employment and skilled employment are driven exclusively by the wage premium of each type of high school graduation curriculum in each occupation. Note that business vocational and trade vocational curricula provide higher wage returns than a general education curriculum in the professional, skilled manual labor, and skilled non-manual labor occupations. Also, note that, in the skilled other occupation, a trade vocational curriculum provides higher returns than a general education curriculum which provides higher returns than a business vocational curriculum. Finally, note that, in the unskilled occupation, a general education curriculum provides higher wage returns than either a business vocational or trade vocational curricula. Thus, by providing higher wage returns across all skilled occupations, a trade vocational curriculum conclusively increases an individual's likelihood to be employed in a skilled occupation, which confirms the 2SLS result in Table 6.3. As a business vocational curriculum, relative to a general education curriculum, decreases an individual's likelihood of being employed in both unskilled occupations and skilled other occupations, the estimates are ambiguous regarding the effects of a business vocational curriculum on skilled employment. Additionally, as a general education curriculum, relative to a trade or business vocational curriculum, increases the likelihood of being employed in an unskilled occupation, the results are ambiguous regarding the effects of trade vocational and business vocational curricula on the overall chances of being employed. This result also confirms the 2SLS results in Table 6.3.

Finally, graduating from a four-year university provides very high log hourly wage returns to all occupations but provides particularly high returns to the professional occupation (.46). Community college and one-year trade schools provide much smaller returns overall, with community college graduation providing slightly negative returns in the skilled manual labor, skilled non-manual labor, and unskilled occupations. Men receive higher wages than women in every occupation except the skilled non-manual labor occupation, and wages tend to increase on average as an individual's socio-economic status and test score each increase. In addition, the non-pecuniary utility of each occupation, relative to choosing not to work, also increases as an individual's socio-economic status and test score increase. Finally, gaining occupation-specific human capital in each occupation adds a large premium to log hourly wages (ranging from .71 to .83), though occupation-specific human capital gains occur infrequently over an individual's lifetime (9%-14% chance each year based on educational attainment).

Selected structural estimates regarding PSE choices are presented in Table 6.5. Note that all estimates in Table 6.5, Section 1, are relative to concentrating in a general education curriculum in high school. The estimates show that concentrating in an academic curriculum in high school greatly increases the utility of attending a four-year university (recall that the model is agnostic about whether this is caused by an increase in the enjoyment of attending a four-year university, a decrease in the monetary cost of attending a four-year university, or an increase in the number and quality of four-year universities that accept the student). This result further explains the relationship between academic high school curriculum, four-year university graduation, and the professional occupation depicted in Tables 6.2 and 6.4: individuals choose an academic high school curriculum to increase their chances of attending a four-year university, which in turn improves wages in the professional occupation. Concentrating in business vocational courses has a negative effect on four-year university enrollment (-.09 utils), while concentrating in trade vocational courses has a negative effect on enrollment in one-year trade schools (-1.31 utils). Thus, both types of vocational curricula slightly decrease the propensity to attend PSE institutions relative to a general education curriculum. Obtaining a GED has a negative effect on the utility an individual later receive from attending a two-year community college or a four-year university. Finally, non-white women and individuals with high socio-economic statuses and test scores receive higher utility from attending four-year universities than other demographic groups.

Selected structural estimates regarding HS choices are presented in Table 6.6. Increased vocational offerings and opportunities, controlling for local labor market conditions, nearly all increase the utility of taking a vocational curriculum in high school. For example, schools that offer marketing courses in high school increase the non-pecuniary utility of concentrating in the business vocational field each year by .50 utils. Additionally, as the percent of students in the previous year's class who took academic classes increases, the non-pecuniary utility of concentrating in an academic curriculum increases by .82 utils. As well, schools that confer GEDs on-site increase the non-

Table 6.5: Selected PSE Structural Parameters

	1-yr Trade School		2-yr CC		4-yr University	
Variable	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
1. Previous Education						
Academic	-0.43 ***	*(.119)*	-0.66 ***	*(.042)*	0.43 ***	*(.034)*
Business Vocational	-0.12	*(.315)*	0.14 **	*(.058)*	-0.09 *	*(.042)*
Trade Vocational	-1.31 ***	*(.542)*	0.14 *	*(.068)*	-0.09 *	*(.048)*
Other Curriculum	0.20 **	*(.098)*	0.03	*(.043)*	0.06 *	*(.030)*
GED	0.19	*(.157)*	-0.20 **	*(.089)*	-0.58 ***	*(.064)*
2. Personal Characteristics						
Male	-0.82 ***	*(.106)*	0.08 **	*(.037)*	-1.09 ***	*(.041)*
Black	0.54 ***	*(.104)*	0.09 *	*(.054)*	2.12 ***	*(.051)*
Hispanic	-0.03	*(.103)*	-0.04	*(.049)*	0.61 ***	*(.050)*
Other Race	-0.01	*(.104)*	-0.09 *	*(.046)*	1.94 ***	*(.052)*
Socio-Economic Status	0.17 ***	*(.045)*	0.45 ***	*(.019)*	2.15 ***	*(.022)*
Testscore	0.13 **	*(.055)*	0.64 ***	*(.021)*	3.31 ***	*(.024)*
Constant	-2.67 ***	*(.304)*	2.00 ***	*(.105)*	4.64 ***	*(.107)*

Notes:
1) Estimates are relative to graduating high school in the general education field.
2) *,**,*** denote 90%, 95%, and 99% statistical significance respectively.
3) Total # Observations is 16,200.
4) Standard errors (SE) are calculated using the covariance of the parameter estimate scores, following Train (2003).

pecuniary utility of completing a GED degree by 2.15 utils. These estimates imply that, as the vocational and academic opportunities in high school increase, the high school drop-out rate decreases, as each vocational and academic opportunity increases the utility of concentrating in a vocational or academic curriculum relative to dropping out of high school to pursue occupation choices or the not employed choice. Different vocational and academic opportunities increase the utility of concentrating in different types of high school curricula, which differentially decrease the dropout propensity for each at-risk student based on the high school curriculum they each would be most likely to concentrate in if they do not drop out of high school. Finally, women receive higher utility than men in the academic, general education, business vocational, and other high school fields. In

Table 6.6: Selected HS Education Structural Parameters

	Academic		General Ed		Business Voc		Trade Voc		Other		GED	
Variable	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
1. HS Education Instruments												
Marketing HS	-	-	-	-	0.50 ***	*(.067)*	-	-	-	-	-	-
Marketing Area	-	-	-	-	0.16	*(.114)*	-	-	-	-	-	-
Precisions HS	-	-	-	-	-	-	0.29 ***	*(.075)*	-	-	-	-
Precisions Area	-	-	-	-	-	-	0.43 ***	*(.089)*	-	-	-	-
Voc Taught HS	-	-	-	-	0.22 *	*(.113)*	0.18	*(.126)*	0.00	*(.071)*	-	-
Voc Taught Area	-	-	-	-	0.16	*(.111)*	-0.12	*(.132)*	-0.12	*(.074)*	-	-
Voc Taught Both	-	-	-	-	0.28 ***	*(.115)*	0.01	*(.129)*	-0.01	*(.073)*	-	-
Career Pathways	-	-	-	-	0.27 ***	*(.082)*	0.34 ***	*(.086)*	-0.17 ***	*(.054)*	-	-
Percent Vocational	-	-	-	-	1.20 ***	*(.162)*	2.02 ***	*(.138)*	1.29 ***	*(.120)*	-	-
Percent Academic	0.82 ***	*(.078)*	0.42 ***	*(.062)*	-	-	-	-	-	-	-	-
GED Offered	-	-	-	-	-	-	-	-	-	-	2.15 ***	*(.210)*
2. Personal Characteristics												
Male	-0.81 ***	*(.065)*	-0.48 ***	*(.057)*	-0.53 ***	*(.087)*	0.90 ***	*(.092)*	-0.47 ***	*(.068)*	1.27 ***	*(.111)*
Black	0.40 ***	*(.101)*	0.43 ***	*(.085)*	0.27 **	*(.119)*	-0.31 **	*(.123)*	-0.04	*(.097)*	-0.76 ***	*(.145)*
Hispanic	-0.07	*(.098)*	-0.12	*(.083)*	-0.67 ***	*(.125)*	-0.80 ***	*(.119)*	-0.47 ***	*(.096)*	-0.59 ***	*(.135)*
Other Race	0.46 ***	*(.087)*	-0.12	*(.077)*	-0.23 *	*(.117)*	-0.53 ***	*(.111)*	-0.51 ***	*(.092)*	-0.55 ***	*(.132)*
Socio-Economic Status	1.10 ***	*(.038)*	0.91 ***	*(.034)*	0.79 ***	*(.048)*	0.71 ***	*(.049)*	0.78 ***	*(.039)*	0.69 ***	*(.059)*
Testscore	2.34 ***	*(.042)*	1.23 ***	*(.035)*	1.15 ***	*(.051)*	0.75 ***	*(.048)*	0.75 ***	*(.039)*	0.87 ***	*(.064)*
Constant	26.2 ***	*(.589)*	27.1 ***	*(.582)*	23.3 ***	*(.621)*	23.2 ***	*(.626)*	25.1 ***	*(.595)*	24.0 ***	*(.768)*

Notes:

1)*,**,*** denote 90%, 95%, and 99% statistical significance respectively.

2) Total # Observations is 16,200.

3) Standard errors (SE) are calculated using the covariance of the parameter estimate scores, following Train (2003).

addition, individuals with a higher socio-economic status and higher test scores receive higher non-pecuniary utility from attending each high school field relative to dropping out of high school.

Lastly, Table 6.7 presents the estimates for unobserved heterogeneity. Recall that the unobserved heterogeneity parameters for the first type of individual in the population are standardized to zero. Table 6.7 presents the unobserved heterogeneity parameters for the second type of individual in the population, which is estimated to comprise 34.3% of the population. In order to evaluate individuals with the second type of unobserved heterogeneity, the estimates in Table 6.7 must be added to the constants in Tables 6.4-6.6. Note that the constants for high school curricula in the bottom row of Table 6.5 are quite large (23.2 to 27.1 utils). These large high school curriculum constants imply that anyone who has the first type of unobserved heterogeneity (65.7% of the population) will never drop out of high school. The non-pecuniary utility of attending high school for these individuals is so high that they will always choose to attend high school for four years, no matter their other demographic characteristics. Next, note that the high school curriculum unobserved heterogeneity parameters for the second type of individual in the population, presented in Table 6.7, are negative and of a similar magnitude (-33.71 to -32.0 utils) to the constants for high school curricula. These estimates imply that, for an individual who has the second type of unobserved heterogeneity, not graduating from high school is a distinct possibility, which is driven by how the individual's other demographic characteristics affect the utility she derives from attending high school. Individuals with the second type of unobserved heterogeneity also receive lower non-pecuniary utility from working and from attending PSE institutions and are much more likely to choose to be neither working nor attending school than individuals with the first type of unobserved heterogeneity.

6.3 Model Fit

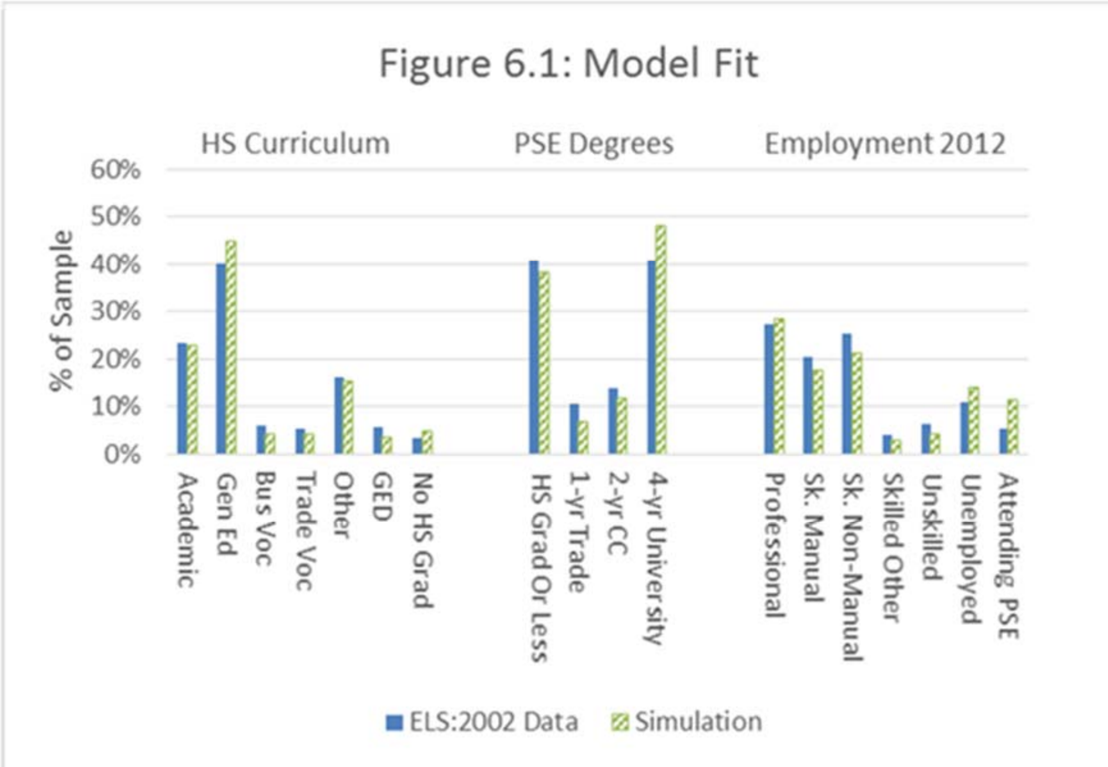
Figure 6.1 compares ELS:2002 student outcomes with simulated student outcomes, given the initial conditions of each student in the data set at age 16 and the parameter

Table 6.7: Unobserved Heterogeneity Parameters

Variable	Non-Pecuniary Utility Estimate		*SE*	Wages Estimate		*SE*
1. Employment						
Professional	-4.38	***	*(0.04)*	-0.12	***	*(0.03)*
Skilled Manual Labor	-2.27	***	*(0.03)*	0.03		*(0.01)*
Skilled Non-Manual Labor	-2.56	***	*(0.03)*	0.03	*	*(0.01)*
Skilled Other	-5.57	***	*(0.13)*	0.34	***	*(0.07)*
Unskilled	-1.65	***	*(0.04)*	-0.03		*(0.02)*
2. High School Education						
Academic	-33.71	***	*(0.56)*	-		-
General Education	-32.69	***	*(0.56)*	-		-
Business Vocational	-32.51	***	*(0.57)*	-		-
Trade Vocational	-32.00	***	*(0.56)*	-		-
Other Curriculum	-32.04	***	*(0.56)*	-		-
GED	-32.73	***	*(0.61)*	-		-
3. Post-Secondary Education						
1-yr Trade School	-0.67	***	*(0.16)*	-		-
2-yr Community College	-2.93	***	*(0.06)*	-		-
4-yr University	-8.71	***	*(0.07)*	-		-

Notes:
1) The estimate for the percentage of the population with type-two unobserved heterogeneity is 34.3%.
2)*,**,*** denote 90%, 95%, and 99% confidence respectively.
3) Total # Observations is 16,200.
4) Standard errors (SE) are calculated using the covariance of the parameter estimate scores, following Train (2003).

estimates discussed in Section 6.2. The aggregate simulated student outcomes closely reflect the aggregate student outcomes observed in the data. However, the structural model slightly over-predicts the number of individuals who graduate from high school in a general education curriculum, at the expense of graduating from each of the other four high school curricula. In addition, the model under-predicts the number of individuals who earn GED degrees, instead simulating that they will never graduate from high school. It also under-predicts the number of individuals who work in unskilled occupations, instead simulating



that they will be unemployed. Next, it under-predicts the number of individuals who obtain one-year PSE trade degrees and over-predicts the number of individuals who obtain four-year university degrees. Finally, the model largely over-predicts the number of individuals who are still attending PSE institutions in 2012. This over-prediction, related to PSE attendance, is driven by the assumption in the model that the non-pecuniary utility from attending a PSE institution does not change over time. In reality, the non-pecuniary utility from attending a PSE institution likely decreases over time as an individual become older than their potential peers at each PSE institution. Since the non-pecuniary utility from attending college in the model remains constant as an individual ages, the model over-predicts the number of individuals that choose to attend college both during and after turning 26.

7 Policy Analysis

I use the structural estimates discussed in Section 6.2 to conduct four policy simulations. The results of each policy simulation are presented in Tables 7.1 and Table 7.2 relative to the results of the simulation under current policy settings presented in Section 6.3.[62] The simulated wage differences in Table 7.2 are averaged across all individuals who choose to work at age 26 in both the baseline simulation and policy simulation and whose simulated wages at age 26 differ between the baseline simulation and the policy simulation. The simulated early-life utility (i.e., realized utility between ages 16-26) and later-life utility (i.e., expected utility from ages 27+) differences in Table 7.2 are averaged across all individuals whose simulated early-life and later-life utility differed between the baseline simulation and the policy simulation.

7.1 Federal Vocational Offering Requirements

The structural estimates suggest that both business high school vocational education and trade high school vocational education are beneficial for the later-life outcomes of a subset of non-college bound students. The first policy simulation I conduct investigates ways to incentivize more students to concentrate in vocational high school curricula. Specifically, this policy simulation investigates the extent to which vocational curriculum take-up rates would increase if we increased the number and access of vocational opportunities in high school nationally.

I simulate the effects of a federal mandate requiring vocational education to be taught on-site in every high school nationwide. The results of this simulation are shown in Column 2 of Tables 7.1 and 7.2. This policy increases the percent of individuals who take high school vocational curricula by 4.8% and decreases the percent of individuals who take other types of high school curricula. This change in high school curricula choice, in turn, causes a few additional individuals to complete two-year community college degrees and a few less individuals to be working in unskilled labor occupations. Overall, however, this policy has little long-term effect on individuals' overall PSE attainment, occupation

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[62] Note that general equilibrium labor market effects are not taken into account in these policy simulations. The model assumes that the wages and utility for each occupation remain constant as students in the population change their labor supply decisions. This assumption may slightly bias the results, which is worth noting when drawing conclusions from these simulations.

Table 7.1: Policy Simulation Choice Outcomes

Variable	Simulation No Policies	Voc In Every Sch	No Voc Offered	HS Voc Certificate	HS Tracking	Free CC
HS Graduation Curriculum						
Academic	22.8%	-0.9%	0.4%	-0.9%	8.2%	-1.6%
Gen Ed	44.9%	-2.2%	1.1%	-1.1%	-14.6%	1.1%
Bus Voc	4.1%	3.9%	-2.1%	-0.2%	2.9%	0.5%
Trade Voc	4.3%	0.9%	-1.1%	3.1%	9.0%	0.2%
Other	15.4%	-1.6%	1.5%	-0.7%	-15.4%	0.2%
GED	3.5%	-0.2%	0.2%	-0.2%	9.5%	0.3%
Never Graduate	4.9%	0.0%	0.0%	0.0%	0.3%	-0.7%
PSE Degrees						
HS Grad Or Less	38.2%	0.1%	-0.1%	-0.9%	-9.6%	-5.0%
1-yr Trade	6.8%	-0.3%	0.2%	8.6%	18.3%	-1.9%
2-yr Community College	11.7%	0.3%	-0.2%	-2.6%	-2.7%	15.3%
4-yr University	48.2%	-0.2%	0.0%	-1.1%	-0.4%	-3.4%
Employment 2012						
Professional	28.5%	0.0%	0.0%	0.3%	-0.1%	-0.4%
Skilled Manual Labor	17.7%	0.0%	0.0%	0.5%	0.4%	-0.5%
Skilled Non-Manual Labor	21.3%	0.0%	0.0%	0.4%	1.1%	-0.6%
Skilled Other	3.0%	0.0%	0.0%	-0.4%	-0.2%	-0.1%
Unskilled	4.2%	-0.1%	0.1%	-0.3%	-0.5%	-0.2%
Unemployed	13.9%	0.0%	0.0%	-0.3%	0.0%	-0.2%
Attending PSE	11.3%	0.1%	0.0%	-0.3%	-0.7%	2.0%

Notes:
1) Column (1) displays simulated outcomes given the model, structural parameters, and initial conditions in the ELS:2002 data set. Columns (2-6) display the difference between the baseline simulation in column (1) and the simulated outcomes for the five policy simulations discussed in sections 7.1, 7.2, 7.3, 7.4, and 7.5 respectively.
2) PSE degrees are cummulative: An individal in the sample can have multiple types of PSE credentials. Hence the total number of PSE degrees for each simulation can be higher than the number of individuals in the sample.
3) Total # Observations is 16,200.

choices, and employment chances. Table 7.2 shows that this policy slightly increases the average wages of individuals who switch their high school curricula to vocational high school curricula and increases average lifetime utility for these individuals.

7.2 Removal of Vocational Offerings

Next, I simulate the effects of removing vocational course offerings from high schools and area vocational schools nationwide, while keeping other high school course offerings and extracurricular offerings the same. Specifically, I simulate the effects of having every high school nationwide no longer offer vocational classes, marketing classes,

Table 7.2: Policy Simulation Wage and Utility Outcomes

Variable	Simulation No Policies	Voc In Every Sch	No Voc Offered	HS Voc Certificate	HS Tracking	Free CC
Wages 2012						
Average (ln) Hourly Wage	2.419	0.042	-0.041	0.220	0.058	-0.089
Lifetime Utility						
Realized Utility Ages 16-26	104.7	0.118	-0.059	-0.446	-2.918	0.990
Expected Utility Ages 27+	45.3	0.907	-0.623	3.818	1.005	0.177
# Changed Observations						
# Observations Average (ln) Hourly Wage		630	440	2,560	6,530	2,150
# Observations Realized Utility Ages 16-26		4,350	4,180	4,480	11,770	10,480
# Observations Expected Utility Ages 27+		890	630	3,850	9,140	9,120

Notes:
1) Column (1) displays simulated outcomes given the model, structural parameters, and initial conditions in the ELS:2002 data set. Columns (2-6) display the average difference between the baseline simulation in column (1) and the simulated outcomes for the four policy simulations discussed in sections 7.1, 7.2, 7.3, 7.4, and 7.5 respectively, conditional on the value changing for the individual between the baseline outcome and simulated outcome, and in the case of wages on an occupation being chosen in 2012 in both simulations. "# Changed Observations" denotes the number of individuals who meet these conditions.
2) Total # Observations is 16,200. # Changed Observations are rounded to the nearest ten to comply with secure data disclosure requirements.

or precisions classes on site or at an area vocational school. Note that this does not imply that vocational courses are strictly unavailable to students (students can still go out of their way to take other vocational courses or bus to other nearby locations that may offer vocational course credit); it instead implies that vocational courses are much more difficult to pursue.

The results of this simulation are shown in column 3 of tables 7.1 and 7.2. As expected, removing vocational offerings largely decreases the number of individuals who pursue high school vocational curricula. However, similar to the simulation discussed in section 7.1, this policy has little effect on individuals' PSE attainment and employment outcomes. Finally, individuals who changed their high school curricula due to the removal of vocational course offerings had lower average wages and lower average lifetime utility. While this simulation predicts that this policy would decrease average student welfare, in order to perform a full cost-benefit analysis the decrease in average student welfare would have to be compared with the cost savings of removing vocational course offerings across schools.

7.3 Vocational Certificates in High School

The second policy simulation investigates the effects of allowing individuals to receive a vocational certification in high school when they concentrate in a vocational curricula. Historically, vocational high school education in the United States has not included industry certification exams or certificate conferral: students have had to take relevant certification exams after graduating from high school, by attending one-year PSE trade schools or taking the exams independently, in order to become certified. Over recent decades, however, the number of high school vocational programs that confer vocational certifications has begun to increase (Castellano et al., 2005) and, over the last decade, has dramatically increased following the re-authorization of the Carl D. Perkins Career and Technical Education Act of 2006 (U.S. Department of Education, 2013). This policy simulation investigates how an increase in the returns of high school vocational education, caused by incorporating industry certification directly into each high school vocational curriculum, would affect students' high school education, PSE attainment, and labor market outcomes.

To run this simulation, I update the model so that an individual who completes a high school trade or business vocational curriculum immediately receives a one-year PSE trade school degree. Additionally, an individual who completes high school with a trade or business vocational curriculum also receives the non-pecuniary utility associated with attending a one-year PSE trade school during her fourth year of high school, in addition to the non-pecuniary utility she receives associated with her high school field choice that year.[63] The results of this policy simulation are presented in Column 3 of Tables 7.1 and 7.2. This policy incentivizes many additional students to concentrate in a trade vocational curriculum in high school (2.9% of U.S. high school students), as it allows them to receive

[63] Note that I am assuming that the returns to high school vocational education and one-year PSE trade degrees are driven by the knowledge a student learns and the degrees that are conferred at graduation as opposed to any signaling value the student receives from choosing to pursue each degree separately. To the extent that the latter is true, the results of this policy simulation are upwardly biased.

both a high school diploma and an industry certification concurrently. Fewer individuals graduate from a community college or a four-year university, however, because fewer individuals take academic and general education courses in high school. Finally, this policy leads to more individuals working in the skilled non-manual labor and skilled manual labor occupations and decreases the number of individuals working in the unskilled occupation or choosing not to work. Individuals' average wages increase as does their expected lifetime utility after the age of 26. Overall, the simulation predicts that incorporating vocational certifications into high school vocational curricula will have large positive effects on students' labor market outcomes.

7.4 German-Style High School Tracking

Next, I simulate the effects of the United States instituting a high school tracking system similar to the tracking system used in Germany. In Germany, students are split into three separate tracks when they enter secondary school: a vocational track (Hauptschule) which prepares students for career and technical occupations, a general education track (Realschule) which teaches students general education math, science, and English content, and an academic track (Gymnasium) which teaches students rigorous academic content and prepares them for a university education. Tracks are chosen for each student based on their abilities and grades throughout primary school and to a lesser extent student and parent preferences. By comparison, relatively little tracking occurs in the United States: most students retain a large amount of control over the high school course they take throughout their high school experiences. This policy simulation investigates how restricting U.S. students' ability to select their own high school curriculum, and pushing students onto particular tracks when they begin high school, would impact student's education and labor market outcomes.

To evaluate this hypothetical policy, I split all students in the sample into three tracks in 9th grade: an academic track, a general education track, and a vocational track. Students are split based on the test score they received when the ELS:2002 survey was first administered in 2002. Following the approximate proportion of German students in each type of high school, I assign the students with the lowest 33% of test scores to the vocational track, students with test scores in the 33-66th percentile to the general education track, and students with the highest 33% of test scores to the academic track. In high school, students on the academic track can take only academic courses, students on the general education track can take only general education courses, and students on the vocational track can take only business vocational or trade vocational courses. No students have access to other curricula, but students may still drop out of high school starting in 11th grade. Due to the rigorous nature of Germany's vocational track, students on the vocational track receive a vocational certificate at the time of high school graduation.[64]

The results of this simulation are presented in Column 4 of Tables 7.1 and 7.2. By forcing students onto particular tracks, many more students graduate in academic (8.2%) and vocational curricula (11.9%) who otherwise would have chosen a general education curriculum. However, due to the restricted high school options, many more students also decide not to finish four years of high school and instead pursue GEDs (9.5%). The additional academic high school concentrators are each more likely to graduate from four-year universities while the additional GED completers are each less likely to graduate from four-year universities, leading to an overall slight decrease in the number of individuals who attain bachelor's degrees. The additional vocational concentrators each receive a vocational certificate at high school graduation, which contributes to decreasing the number of individuals in the population without any PSE credentials and causes more individuals to be employed in the skilled manual labor and skilled non-manual labor occupations. Overall, the individuals who are forced onto academic and vocational tracks, who otherwise would have concentrated in the general education field, realize better labor market outcomes as long as they finishing high school. For these students, improved labor market outcomes come at the expense of non-pecuniary utility in high school as the students would have preferred to take a general education curriculum if it had been

[64] In the simulation, I allow students on any of the three tracks to attend all types of PSE institution following high school graduation. In the German system, it is more difficult for students who graduate from Realschule and Hauptschule to attend four-year universities (though not impossible) than for students who graduate from Gymnasium. A question of future work is whether to incorporate this difficulty into the policy simulation by calibrating the β_H^k variables to reflect the ease / difficulty of attending college after graduating from each type of German high school.

available. However, many students who are forced onto the academic and vocational tracks choose not to finish high school and instead complete GEDs, which leads to worse education and labor market outcomes for this subset of students. Cumulatively, across the population, this leads to slightly higher average labor market wages, labor market utility, and skilled employment opportunities, though benefits are concentrated among non-GED high school graduates.

7.5 Free Community College

Finally, the forth policy simulation investigates the effects of a policy that makes community college free for all United States high school graduates. In January 2015, President Barack Obama proposed a plan to make two years of community college free for all students in the United States (Obama, 2015), which has since been incorporated into the policy platform of 2016 presidential candidates Bernie Sanders and Hillary Clinton.[65] As the model takes into account education choices, labor market choices, and forward-looking behavior, an interesting question is what the model predicts the effects of this policy would be on students' high school education, PSE attainment, and labor market outcomes.

I evaluate this policy by decreasing the cost of community college for individuals in the sample. The extent of this decrease in cost is chosen to accurately reflect the monetary cost of attending community college. In the U.S., the average cost of community college in 2004 was $2,700. Since the model estimates the relationship between pecuniary wage utility and non-pecuniary utility (φ), I can convert hourly wages to non-pecuniary utility in the model. First, I convert the average cost of community college to a log hourly wage for an individual who works 40 hours a week, in 2002 dollars. Then, I multiply this value by my estimate for φ (1.37), the number of non-pecuniary utils that are equivalent to a log hourly wage of one dollar. This value is the average non-pecuniary utility cost of one year of community college tuition and fees.

[65] Both Bernie Sanders and Hillary Clinton have proposed plans that, in addition to providing free tuition to community colleges, also provide free tuition to certain four-year colleges and universities and include additional debt relief (Sanders, 2016; Clinton, 2016). This policy simulation does not include these additions and focuses on the effects of the central plan to provide free tuition to community colleges for all U.S. high school graduates.

While the monetary cost of community college is the same for all individuals, I assume that the non-pecuniary utility associated with this monetary cost is higher for poorer students than for richer students, due to diminishing marginal utility of wealth. As such, I allow the reduction in the non-pecuniary cost of community college to vary across individuals based on their socio-economic statuses. Specifically, I assume that the individual with the highest socio-economic status in the sample receives no non-pecuniary utility reduction in the cost of community college due to this policy, and I assume that the individual with the lowest socio-economic status in the sample receives double the average non-pecuniary utility reduction in the cost of community college due to this policy.[66]

The results of this policy simulation are presented in Column 5 of Tables 7.1 and 7.2. Decreasing the cost of community college causes many more individuals to attend community college (15.3% of U.S. high school students) as well as more individuals to concentrate in general education courses in high school (1.1% of U.S. high school students) (as high school general education courses improve the non-pecuniary utility of attending community college) at the expense of taking academic courses in high school. In addition, fewer individuals drop out of high school (-0.7%) as high school graduation is required to attend community college. Next, the policy predicts that fewer individuals will graduate from four-year universities by the age of 26 (3.4%) but more individuals will be attending four-year universities at the age of 26 (2.0%). Recall that my model does not allow community college credit to transfer to four-year universities, when in reality approximately 50% of community college credit is transferable (Monaghan and Attewell, 2014) and approximately 20% of individuals who enroll in a two-year community college eventually transfer to a four-year university (Hossler et al., 2012). Under the weak assumption that this policy would not increase the 20% transfer rate, the model predicts that 20% of new community college graduates (who do not obtain four-year university degrees by age 26 in the simulation) would transfer to and graduate from four-year

[66] In reality a subset of low socio-economic status individuals currently receive Pell Grants that decrease the cost of community college to close to zero. A question of future work is whether to incorporate these Pell Grants into the simulation by holding the cost of community college fixed for the subset of students in the population who are eligible to receive these grants.

universities (2.1% of U.S. high school students). Combining these individuals with the individuals who later graduate from a four-year university after age 26, this policy simulation predicts that the more total individuals (0.7%) would eventually graduate with a four-year university degree.

As more individuals concentrate in high school general education and obtain community college degrees, lifetime expected utility increases. Under the assumption that no individuals transfer from community colleges to four-year universities, the simulation predicts that average wages will slightly decrease. Under the assumption that 20% of community college attendees transfer to four-year universities, the simulation predicts that average wages will slightly increase. Overall, this simulation predicts that there would be various positive education and labor market consequences from a free community college policy. Note, however, that this policy would be fairly costly. Under the assumption that low socio-economic status students receive a utility benefit worth twice the monetary cost of community college every year they attend community college, the simulation predicts that this policy would increase social welfare under either community college transfer assumption. However, under more conservative welfare assumptions, such as an assumption that all students receive a utility benefit equal to the monetary cost of community college each year they attend community college, the simulation predicts that this policy would decrease social welfare under either community college transfer assumption.

8. Conclusion

In conclusion, I have found that a high school trade vocational curriculum is very beneficial to a student's later labor market wages and chances of being employed in a skilled occupation relative to a general education curriculum. I have also found that a high school business vocational curriculum is only beneficial, relative to a general education curriculum, in skilled non-manual labor occupations, which provide higher non-pecuniary utility and lower wages relative to other occupations. In addition, I have found that concentrating in a vocational high school curricula modestly decreases a student's propensity to attend PSE institutions. I have also found that additional high school vocational and academic opportunities decrease a student's high school dropout propensity but decrease it differentially for different types of students. Finally, policy simulations predict that improving high school vocational education on the intensive margin (i.e, improving the value of vocational education courses by incorporating vocational certification into vocational high school curricula) will provide greater labor market benefits than improving high school vocational education on the extensive margin (i.e., increasing the number and availability of vocational opportunities). Policy simulations also predict that a German-style tracking system, that pushes more individuals to take academic and vocational courses, will improve the labor market outcomes of high school completers at the expense of their non-pecuniary utility in high school but that it will also increase the high school drop-out rate. Finally, policy simulations predict that free community college for all U.S. high school graduates will increase the number of students graduating from community college, slightly increase the number of students graduating from four-year universities, slightly increase average wages and lifetime utility, but increase utility by less than the cost of the policy (under conservative welfare assumptions).

Pertinent areas of future research include updating the model to allow students to transfer from community college to four-year universities and adding distance-to-college instruments to the model following Card (1995). Additional future research involves estimating model parameters using data from the three panel data sets conducted by the National Center for Education Studies prior to ELS:2002: the National Education Longitudinal Study of 1988 (NELS:88), High School and Beyond (HS&B), and the National Longitudinal Study of the High School Class of 1972 (NLS-72). Estimating the model with these historic data sets would provide context on whether the returns to high school vocational education have changed over time in the United States and allow me to evaluate the robustness of my parameter estimates over time. It would also allow me to test the out-of-sample fit of my model by constructing predicted outcomes for the ELS:2002 data set using the model estimates from the three historic data sets. Additionally, estimating trends in the effects of high school CTE over the last four decades will allow me to better predict how the effects of high school CTE will change in the future.

Appendices

Appendix A. High School Curricula Construction Rules

A.1 High School Course Mapping

The transcript courses in ELS:2002 are coded using the Classification of Secondary School Courses (CSSC), a coding system based on the High School Transcript Studies conducted by the NCES (National Center for Education Statistics, 2000). All U.S. high school courses are coded with a six digit code, organized by course type. The first two digits, which denote the main program area, range from 01 – 56. See Table A.1 for how these codes are mapped to the five high school fields in my model (*Academic*, *General Education, Business Vocational, Trade Vocational, and Other Curriculum*).

Table A.1: CSSC Code Mapping

Course Content	CSSC Code
Academic Courses	
Area and Ethnic Studies (Honors)	050105, 050116, 050120, 050126
Computer and Information Sciences (Honors/AP/IB)	110132-44, 110212, 110213
Engineering	14****
Foreign Languages (Honors/AP/IB/CEEB Prep)	160517, 160544, 160545, 160556, 160907, 160917, 160937, 160943-52
Letters/English (Honors/AP/IB)	230102, 230105, 230108, 230111, 230114, 230117, 230165-71
Liberal/General Studies (Gifted / College Level)	240141, 240151
Life Sciences (Honors/AP/IB)	260141-46
Mathematics (Honors/AP/IB/Advanced)	270410, 270414, 270415, 270417-20, 270424, 270429-35, 270532
Multi/Interdisciplinary Studies (IB/Advanced)	300112-21, 300623
Philosophy and Religion (IB)	380142
Physical Sciences (Honors/AP/IB/ Advanced)	400300, 400521-41, 400622, 400821-31
Psychology (AP/IB)	420114, 420115
Social Sciences (Honors/AP/IB)	450613-16, 450711, 450803, 450806, 450808, 450836, 450850, 450853, 450856, 450870-74, 450921, 451013, 451015, 451018, 451034-37, 451171-81
General Education Courses	
Area and Ethnic Studies (non-honors)	05****
Foreign Languages (non-honors)	16****
Letters/English (non-honors)	23****
Liberal/General Studies (non-honors)	24****

Life Sciences (non-honors)	26****
Mathematics (non-honors)	27****
Multi/Interdisciplinary Studies (non-honors)	30****
Philosophy and Religion (non-honors)	38****
Physical Sciences (non-honors)	40****
Science Technologies	41****
Psychology (non-honors)	42****
Public Affairs	44****
Social Sciences (non-honors)	45****
Business Vocational Courses	
Business and Management	06****
Business and Office	07****
Marketing and Distribution	08****
Communications (except Journalism and Special languages)	09****
Computer and Information Sciences (non-honors)	11****
CTE Business and Office	552***
Trade Vocational Courses	
Communications Technologies	10****
Consumer, Personal, and Miscellaneous Services	12****
Engineering and Engineering-related Technologies	15****
Industrial Arts	21****
Protective Services	43****
Construction Trades	46****
Mechanics and Repairers	47****
Precision Production	48****
Transportation and Material Moving	49****
CTE Industrial Arts, CTE Precision Production, CTE Trades & Industrial Construction, CTE Mechanics & Repairers, Service Occupations	555***, 557***, 558***, 559***
Other Curriculum Courses	
Architecture and Environmental Design	04****
Communications (Journalism and Special languages)	0904**, 0908**
Education	13****
Home Economics	19****
Vocational Home Economics	20****
Law	22****
Summer Abroad, Independent Study, Other Liberal/General Studies	240121, 2401131, 240100
Library and Archival Sciences	25****
Military Sciences	28****
Military Technologies	29****
Parks and Recreation	31****
Citizenship/Activities	33****
Health Related Activities	34****
Interpersonal Skills	35****
Leisure and Recreational Activities	36****
Personal Awareness	37****
Theology	39****

Visual and Performing Arts	50****
Executive Internship	51****
General EMH (Including Pre-vocational Programs)	52****
Special Education	54****
Vocational Career Prep / Exploration, CTE Home Economics	550***, 554***
Special Education – Resource Curriculum	56****
Agribusiness and Agricultural Production	01****
Agricultural Sciences	02****
Renewable Natural Resources	03****
CTE Agriculture	551***
Allied Health	17****
Health Sciences	18****
CTE Health Occupations	553***
Basic Skills	32****

Notes:
1) "*" Indicates that all courses within the program area, not listed elsewhere, fall within the stated course content.

A.2 Yearly Curriculum Construction Rule Details

I assign a yearly field concentration to each year of high school based on the credit hours and field types of the classes the individual passed during the year. Each individual takes six credit hours of classes in a given year.[67] I assign yearly field concentration as described below. This specification is similar to other specifications used in the literature, such as Meer (2007).

- The year is coded as a Trade Vocational yearly field concentration if the individual took more Trade Vocational credits than either Business Vocational credits or Academic credits *AND* took 1.25 or more Trade Vocational credits.
- The year is coded as a Business Vocational yearly field concentration if the individual took more Business Vocational credits than either Trade Vocational credits or Academic credits *AND* took 1.25 or more Business Vocational credits.
- The year is coded as an Academic yearly field concentration if the individual took more Academic credits than either Trade Vocational credits or Business Vocational credits *AND* took 1.25 or more Academic credits.

[67] Credit hours from schools that assign a different number of credit hours in a year (e.g. 12 credit hours per year) are first adjusted so that the average number of credit hours taken by a full time student at that school each year is six.

- The year is coded as a General Education yearly field concentration if the individual took 1.25 or more General Education credits *AND* took less than 1.25 Trade Vocational credits, took less than 1.25 Business Vocational credits, took less than 1.25 Academic credits, and took less than 2 Other Curriculum credits.
- The year is coded as an Other Curriculum yearly field concentration if the individual took 2 or more Other Curriculum credits *AND* took less than 1.25 Trade Vocational credits, took less than 1.25 Business Vocational credits, and took less than 1.25 Academic credits.
- The year is coded as an Other Curriculum yearly field concentration if an individual took less than 1.25 credits in each of the other four fields.
- In the event of ties, the tiebreaking order is Trade Vocational, Business Vocational, Academic.[68]

A.3 Alternative Curriculum Construction Rules

I investigated three alternative curriculum construction rules. The first rule defines an individual's overall curriculum as the yearly field concentration (constructed as described above) taken during her senior year. The second rule aggregates a student's classes and credit hours across all four years of high school and then chooses an overall concentration based on aggregate credit hours in each field.[69] Finally, the third rule defines an individual's overall curriculum as the value of the pre-constructed variable in the ELS:2002 data set that assigned high school graduates to either an academic, occupational, academic & occupational, or other curriculum.

See Table A.2 for a comparison of how aggregate outcomes change with each of the four construction rules. The table shows that curriculum outcomes are very similar

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[68] 0.2% of student-year curricula observations had ties. Using alternative tiebreaking orders does not affect the estimation results.

[69]For this alternative construction rule I followed the yearly field concentration rules as defined above, except with slightly different credit assignment ratios (taking the place of 1.25 out of 6 and 2 out of 6): 3 out of 24 for trade vocational, business vocational, and academic, 6 out of 24 for general education, and 8 out of 24 for other curricula. These ratio's were chosen to take into account the large number of general education and other curricula courses that individual's take during their first and second years of high school, and to roughly follow the construction rules used in the previous literate (e.g. Meer, 2007).

across all four construction rules.

Table A.2: Curriculum Construction Rule Comparison

HS Curriculum	Constructed Outcomes	Alternative 1: Senior Year Classes	Alternative 2: All Classes	Alternative 3: ELS Concentrations	
Academic	28.1%	25.2%	30.6%	*Academic*	24.6%
Gen Ed	43.6%	46.0%	44.3%	*Occupational*	12.6%
Bus Voc	6.7%	6.7%	5.8%	*Acad & Occ*	2.3%
Trade Voc	5.5%	5.2%	5.8%	*Other*	60.4%
Other	16.3%	16.8%	13.5%		

Notes:
1) Total # of classifiable observations varies across construction rules based on available data, from 11,880 to 14,810.
2) Sample sizes are rounded to the nearest ten to comply with secure data disclosure requirements.

Appendix B. Employment Construction Rules

An ELS:2002 survey participant denoted her occupations between the years of 2002 and 2012 using six-digit O*NET occupation codes. ELS:2002 survey staff then mapped these six-digit O*NET occupation codes to one of 14 constructed occupations (Ingels et al., 2014). See Table B.1 for how these 14 occupations are mapped into the five occupation choices in my model (*Professional, Skilled Manuel Labor, Skilled Non-manual Labor, Skilled Other, and Unskilled*).

Table B.1: 2002-2012 Occupation Code Mapping

Coded Occupation	ELS:2002 Occupation
Professional	
	Manager, Administrator
	Professional A
	Professional B
Skilled Manual Labor	
	Craftsperson
	Operative
	Technical
	Protective Service
	Laborer (skilled, see notes)
Skilled Non-Manual Labor	
	Clerical
	Sales
	Service (skilled, see notes)
Skilled Other	
	Farmer, Farm Manager
	Military
	School Teacher
Unskilled	
	Laborer (unskilled, see notes)
	Service (unskilled, see notes)

Notes:
1) Based on six-digit O*NET codes, the following Laborer and Service occupations were coded as Unskilled Occupations: Merchandise Displayers and Window Trimmers; Lifeguards, ski patrol, and other recreational protective service workers; cooks – fast food; food prep, bartenders, counter attendants, waiters, hosts, dishwashers; janitors and cleaners; Attendants (service stations, ticket takers, etc); bellhops; and cashiers. All other Laborer and Service occupations were coded as Skilled Manual Labor and Skilled Non-Manual Labor occupations, respectively.

An ELS:2002 survey participant denoted her occupations prior to 2002 by selecting one of 15 occupation types. The 15 occupation types available were chosen by ELS:2002 survey staff. See table B.2 for how these 15 occupations are mapped into the five occupation choices in the model (*Professional, Skilled Manuel Labor, Skilled Non-manual Labor, Skilled Other, and Unskilled*).

Table B.2: 2000-2001 Occupation Code Mapping

Coded Occupation	ELS:2002 Occupation
Professional	
	No Codes
Skilled Manual Labor	
	Construction work
	Beautician, hair stylist, barber
Skilled Non-Manual Labor	
	Salesperson, customer service
	Computer related job
	General office or clerical worker
Skilled Other	
	Farm worker
	Hospital or health worker
Unskilled	
	Food service/server/host/dishwasher
	Babysitter or child care
	Cashier, grocery clerk/bagger
	Lawn work or odd jobs
	Camp counselor/lifeguard/coach
	Warehouse worker
	House cleaning or janitorial work
Unknown Occupation	
	Other

Appendix C. Local Labor Market Characteristic Construction Rules

C.1 Local Labor Market Industry Mapping

Bureau of Economic Analysis Local Area Personal Income & Employment data (U.S. Bureau of Economic Analysis, 2002) contains county-level employment percentages for each two-digit NAICS industry. See Table C.1 for how each two-digit NAICS industries is mapped into one of four constructed industries (*Professional Industries, Skilled Manuel Labor Industries, Skilled Non-manual Labor Industries, and Other Industries*).

Table C.1: Local Labor Market Industry Mapping

Industry	NAICS Industry Code
Professional	
Professional, Scientific, and Technical Services	54
Management of Companies and Enterprises	55
Skilled Manual Labor	
Mining	21
Utilities	22
Construction	23
Manufacturing	31-33
Transportation and Warehousing	48-49
Waste Management	562
Other Services (Repair and Maintenance)	811
Skilled Non-Manual Labor	
Wholesale Trade	42
Retail Trade	44-45
Information	51
Finance and Insurance	52
Real Estate and Rental and Leasing	53
Other	
Farm Employment	NA
Agriculture, Forestry, Fishing, and Hunting	11
Administration	561
Educational Services	61
Health Care and Social Assistance	62
Arts, Entertainment, and Recreation	71
Accommodation and Food Services	72
Other Services (Everything except Repair and Maintenance)	812,813,814
Public Administration	92

C.2 Industry / Occupation Comparison

As discussed in Section 4.1, local labor market industry variables are used because local labor market occupation data is not available at the county level. However, occupation data is only available at the national level and for each metropolitan statistical area in the United States. This occupation data is available from the Bureau of Labor Statistics' Occupational Employment Statistics (OES) program (U.S. Bureau of Labor Statistics, 2002). In order to compare industry percentages and occupation percentages at the national and MSA level, I first map each Standard Occupation Classification (SOC) System occupation code into one of four constructed occupations (*Professional Occupations, Skilled Manuel Labor Occupations, Skilled Non-manual Labor Occupations, and Other Occupations*) as described in Table C.2.

Table C.2: Local Labor Market Occupation Mapping

Occupation	SOC Code
Professional	
Management Occupations	11
Computer and Mathematical Occupations	15
Architecture and Engineering Occupations	17
Life, Physical, and Social Science Occupations	19
Legal Occupations	23
Healthcare Practitioners and Technical Occupations	29
Skilled Manual Labor	
Construction Trades and Extraction Workers	47
Installation, Maintenance, and Repair Workers	49
Production Occupations	51
Transportation and Material Moving Occupations	53
Skilled Non-Manual Labor	
Business Operations and Financial Specialists	13
Sales Occupations	41
Office and Administrative Support Occupations	43
Other	
Community and Social Science Occupations	21
Education, Training, and Library Occupations	25
Arts, Design, Entertainment, Sports, and Media Occupations	27
Healthcare Support Occupations	31
Protective Service Occupations	33
Food Preparation and Serving Occupations	35
Building and Ground Cleaning and Maintenance Occupations	37
Personal Care and Service Occupations	39
Farming, Fishing, and Forestry Occupations	45
Military Specific Occupations	55

Table C.3 presents a comparison of national occupation percentages and industry percentages using my constructed occupations and industries. Table C.4 provides the average difference across MSAs between occupation percentages and industry percentages. Finally, Table C.5 provides a more detailed crosswalk between national occupation percentages, broken down by OCCSOC codes, and national industry percentages, broken down by two-digit NAICS industry codes. Tables C.3, C.4, and C.5 show that the industry mapping used to create my local labor market characteristic variables reasonably reflect OCC occupation mappings at the national level and within MSAs. As such, my local labor market industry percentages are likely a good proxy for local labor market occupation percentages at the county level.

Table C.3: National Constructed Industy / Occupation Crosswalk

Occupations	*Industries*			
	Professional	Sk. Manual Labor	Sk. Non-Manual Labor	Other
Professional	**47.5%**	10.1%	11.6%	16.8%
Sk. Manual Labor	5.8%	**71.7%**	16.0%	8.7%
Sk. Non-Manual Labor	38.8%	16.0%	**65.0%**	20.7%
Other	7.8%	1.9%	6.7%	**53.7%**

Notes:
1) Constructed occupations are on the y-axis, and constructed industries are on the x-axis.
2) Data is from 2002.

Table C.4: Constructed Industy / Occupation Variable Difference Across MSAs

	Professional	Sk. Manual Labor	Sk. Non-Manual Labor	Other
Mean	-9%	-1%	-8%	17%
Std Dev	3%	5%	3%	6%

Notes:
1) Percentages are industry percentages minus occupation percentages.
2) Data is from a comparison of 295 MSAs in 2002.

Table C.5: Detailed National Crosswalk

SOC Occupations	*NAICS Industries* Professional		Sk. Manual Labor										Sk. Non-Manual Labor						Other							
	54 - Professional Services	55 - Management	21 - Mining	22 - Utilities	23 - Construction	31 - Manufacturing A	32 - Manufacturing B	33 - Manufacturing C	48 - Transportation A	49 - Transportation B	562 - Waste Management	811 - Repair	42 - Wholesale Trade	44 - Retail Trade A	45 - Retail Trade B	51 - Information	52 - Finance & Insurance	53 - Real Estate & Leasing	11 - Agriculture & Forestry	561 - Administration	61 - Education	62 - Health Care	71 - Arts	72 - Lodging & Food	812-4 - Other Services	92 - Public Administration
Professional																										
11 - Management	9%	16%	6%	6%	6%	4%	6%	6%	4%	4%	6%	4%	7%	4%	3%	8%	9%	11%	3%	3%	5%	4%	5%	4%	8%	6%
15 - Computer / Mathematical	11%	9%	1%	3%	0%	0%	1%	2%	0%	1%	0%	0%	3%	1%	0%	10%	5%	1%	0%	1%	1%	0%	0%	0%	1%	2%
17 - Architecture / Engineering	16%	3%	4%	8%	1%	1%	2%	8%	0%	1%	2%	0%	1%	0%	0%	2%	0%	0%	0%	1%	0%	0%	0%	0%	0%	3%
19 - Sciences	5%	2%	3%	2%	0%	1%	3%	0%	0%	0%	1%	0%	0%	0%	0%	1%	0%	0%	1%	0%	1%	1%	0%	0%	0%	3%
23 - Legal	6%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	3%
29 - Health Technical	3%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	4%	0%	0%	0%	1%	0%	2%	2%	32%	1%	0%	0%	4%
Sk. Manual Labor																										
47 - Construction / Extraction	1%	1%	33%	7%	67%	0%	2%	2%	1%	0%	18%	1%	0%	0%	0%	0%	0%	2%	0%	2%	0%	0%	0%	0%	0%	5%
49 - Maintenance / Repair	1%	2%	9%	26%	8%	5%	6%	4%	8%	3%	6%	50%	7%	7%	2%	8%	0%	14%	2%	2%	1%	1%	3%	1%	1%	4%
51 - Production	2%	2%	10%	12%	1%	55%	49%	54%	1%	3%	3%	7%	7%	3%	1%	4%	0%	1%	4%	8%	0%	1%	0%	1%	9%	2%
53 - Transportation	1%	3%	17%	2%	3%	16%	13%	5%	56%	58%	44%	18%	20%	9%	6%	3%	0%	7%	13%	10%	3%	1%	2%	2%	5%	4%
Sk. Non-Manual Labor																										
13 - Business Ops / Financial	9%	14%	4%	7%	2%	1%	2%	3%	2%	2%	2%	1%	3%	1%	1%	4%	19%	3%	0%	2%	2%	1%	1%	0%	8%	8%
41 - Sales	4%	5%	1%	2%	2%	4%	3%	2%	2%	3%	2%	5%	25%	50%	56%	13%	13%	22%	1%	9%	0%	0%	8%	4%	6%	1%
43 - Office & Admin Support	24%	34%	10%	23%	9%	8%	11%	10%	19%	25%	12%	11%	24%	14%	20%	23%	50%	22%	5%	22%	11%	17%	10%	4%	17%	25%
Other																										
21 - Community / Social Sci	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	6%	0%	0%	4%	4%
25 - Education	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	58%	3%	2%	0%	3%	2%
27 - Arts	4%	1%	0%	1%	0%	0%	1%	0%	0%	0%	0%	0%	1%	0%	2%	16%	0%	1%	0%	0%	1%	0%	9%	0%	2%	1%
31 - Heath Support	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	1%	0%	19%	0%	0%	1%	2%
33 - Protective Service	0%	1%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%	2%	0%	13%	1%	0%	4%	1%	1%	18%
35 - Food Prep & Serving	0%	1%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	4%	1%	2%	0%	2%	0%	1%	4%	3%	18%	75%	4%	1%
37 - Building Maintenace	1%	1%	0%	1%	1%	1%	1%	1%	0%	1%	1%	1%	1%	1%	0%	1%	0%	10%	1%	21%	5%	3%	10%	6%	4%	2%
39 - Personal Care	1%	1%	0%	0%	0%	0%	0%	0%	5%	0%	0%	0%	0%	0%	0%	3%	0%	2%	1%	1%	2%	7%	26%	2%	24%	3%
45 - Farming & Forestry	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	68%	0%	0%	0%	0%	0%	0%	0%
55 - Military	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Notes:

1) Percentages aggregate vertically. They display the occupational breakdown of types of job in each industry nationwide.

2) Constructed occupations are on the y-axis, and constructed industries are on the x-axis.

3) Data is from 2002.

Appendix D. Variable Construction Details

D.1 ELS:2002 Raw Variables

This subsection provides additional information about the data elements available in ELS:2002 that are used to construct the variables used in this paper. See table D.1 for a list of the variables in the ELS:2002 raw data file that are used to create log-hourly wage, high school attendance, PSE attendance, and employment outcomes each year. The Stata do files that map this information into the variables discussed in Section 4 are available upon request.

D.2 Additional Imputation Rules

As discussed in Section 4.2, choice information is missing for many student-year observations in the data set. In addition, conflicting choice information is provided for a small number of student-year observations. See Table D.2 for details on how a subset of these missing student-year observations are imputed based on available data as well as how conflicting choice information is coded. The Stata do files that contain these rules are available upon request.

Table D:1: Raw Variables

Constructed Variable / Raw Variables
High School Attendance
High School Transcript data 2000-2003 (courses, credits, grades)
Year/month graduated from high school, and type of graduation (GED or diploma)
Year/month left high school (prior to 2006) and why (graduated, dropped out, or transferred)
High School grade attended in 2003
Enrolled in the spring of 2003 (Y/N)
Enrolled in the spring of 2004 (Y/N)
Working towards graduation (GED) in 2012 (Y/N)
Failed 9th or 10th grade (Y/N)
Failed 11th or 12th grade (Y/N)
Dropouts
Year/month first dropped out
Year/month first returned
Year/month second dropped out
Last grade attended before dropping out and whether passed/failed
Attended High School in 2002 (Y/N)
Post-Seconardry Education Attendance
Year/month first began attending a PSE intuition, and institution type
Year/month began attending most recent PSE intuition, and institution type
Year/month last attended most recent PSE intuition, and institution type
Year/month first received a PSE degree, and degree type
Year/month received highest PSE degree, anddegree type
Ever attended a PSE (asked in both 2006 and 2012) (Y/N)
Attended a PSE institution, and institution type, monthly from 2003 to 2005 (Y/N)
Attending a PSE institution in 2012 and institution type (Y/N)
Employment
Prior to Jun 2012: Occupation type and year/month began and ended most recent job
Prior to Jan 2006: Occupation type and year/month began and ended first job after high school
Occupation type and year/month began the job employed in during Jan 2006.
Prior to May 2002: Occupation type and year/month began and ended most recent job
Occupation and hours worked a week in 2001
Whether working in 2012
Number of weeks employed in 2011
Whether working for six or more months in 2010 and 2009
Whether employed each month from Jun 2002 to Jan 2006
Number of hours worked a week in 2001 and 2003
Whether working in 2003
Year/month began and ended most recent job (as of ’03), only for dropouts and early graduators
Log Hourly Wages
Wages current / most recent job as of 2012
Wages in 2011
Wages in 2005
Wages first job after school (prior to Jan 2006)
Wages current / most recent job (as of Jan 2006)
Wages current / most recent job (as of 2003), only for dropouts and early graduators

Table D.2: Additional Interpolation Rules (for Years with Missing Data)

Constructed Variable / Raw Variables
High School Attendance
On Time Graduates: Individuals that graduated on time (in 2003) are coded as attending in 2000, 2001, and 2002
Early Graduates: Individuals that graduated early (in 2002 or 2001) are coded as attending in 2000 and 2001, and are coded as already having finished 1-2 years of high school (respectively) prior to 2000
Late Graduates: Individuals that graduated after 2003 are coded as attending in the year of graduation
All years after graduation are coded as not attending
Dropouts: Every year after final dropout, including final dropout year, is coded as not attending. Every year before first dropout year is coded as attending. If dropped out twice, year of return is coded as attending and year of first dropout is coded as not attending
Post-Seconardry Education Attendance
Individuals that attended a PSE institution for at least six months in a year are coded as attending that year
Every year before began attending first PSE institution is coded as not attending
Every year after last began attending most recent PSE institution is coded as not attending
If the first year attended and most recent year attended are both at 4-yr institutions, and the years are four years apart, the two years between them are coded as attending 4-yr institutions
Employment
Code as working (type unknown) if worked more than six months each year
Code as working if worked more than 20 hours a week in 2001
Conflicting Data
When data on whether an individual attended HS / PSE full-time or part-time is missing, I code individuals as follows:
a. Individuals that attended school (credit amount unknown) and worked during any year between 2000 and 2008 are coded as attended school
b. Individuals that attended school (credit amount unknown) and worked during any year between 2009 and 2012 are coded as worked

Notes:

1) These interpolation rules are only used for student-years for which outcomes are unobserved in the data.

Appendix E. First Stage PSE Regression Estimates

Table E.1 provides the results of a first first-stage regression used to construct post-secondary education attainment predicted probabilities. The regression is a multinomial logit regression of PSE attainment on personal characteristics (X_i), local labor market characteristics (M_i), and high school instruments related to PSE attendance and PSE opportunities (A_i).

Table E.1: Selected PSE First Stage Estimates

	1-yr Trade School		2-yr CC		4-yr University	
Variable	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
1. Personal Characteristics						
Male	**-0.63** ***	*0.06*	**-0.47** ***	*0.07*	**-0.60** ***	*0.04*
Black	0.07	*0.10*	**-0.31** ***	*0.12*	0.05	*0.09*
Hispanic	**-0.21** **	*0.10*	-0.14	*0.11*	**-0.16** *	*0.09*
Other Race	-0.10	*0.11*	**-0.21** *	*0.11*	**0.37** ***	*0.07*
Socio-Economic Status	0.04	*0.04*	**0.12** ***	*0.04*	**0.51** ***	*0.03*
Test Score	**-0.08** **	*0.04*	**0.15** ***	*0.04*	**0.94** ***	*0.03*
Midwest	0.04	*0.10*	-0.01	*0.11*	**-0.26** ***	*0.08*
South	0.04	*0.10*	**-0.19** *	*0.11*	**-0.24** ***	*0.08*
West	0.10	*0.11*	-0.16	*0.14*	**-0.44** ***	*0.09*
Suburban	-0.02	*0.08*	0.04	*0.09*	**-0.17** ***	*0.06*
Rural	-0.02	*0.11*	0.11	*0.13*	**-0.18** **	*0.09*
Catholic School	**0.31** **	*0.15*	**0.29** *	*0.18*	**0.44** ***	*0.11*
Non-Catholic Private School	0.18	*0.15*	**0.42** **	*0.17*	**0.41** ***	*0.11*
2. Local Labor Market Characteristics						
Unemployment Rate	2.56	*2.20*	0.43	*2.58*	**7.44** ***	*2.10*
(ln) Average Hourly Wage	0.40	*0.21*	0.12	*0.28*	0.10	*0.19*
% Professional Employment	-1.95	*1.86*	0.86	*1.95*	**3.63** **	*1.46*
% Manual Labor Employment	1.34	*0.48*	0.70	*0.59*	0.56	*0.44*
% Non-Manual Labor Employment	0.02	*0.89*	0.86	*1.12*	0.35	*0.75*
3. High School PSE Instruments						
% Students Attend College Fairs	-0.03	*0.03*	0.00	*0.04*	0.03	*0.02*
% Students in College App Prog (0-5 Scale)	0.01	*0.03*	0.01	*0.03*	-0.02	*0.02*
% Prev Students Enter Labor Market (0-5 Scale)	0.00	*0.05*	-0.03	*0.06*	-0.05	*0.04*
% Prev Students Attend 2yr College (0-5 Scale)	**0.13** ***	*0.05*	**0.16** ***	*0.05*	0.03	*0.03*
% Prev Students Attend 4yr College (0-5 Scale)	0.02	*0.04*	-0.09	*0.06*	**0.12** ***	*0.04*
% Students Free/Reduced Price Lunch	-0.03	0.15	-0.09	0.18	**-0.29** *	0.16
% Students Take Academic Courses	-0.13	*0.16*	0.07	*0.20*	**-0.28** **	*0.14*
Admission Based on Geography	0.03	*0.13*	0.07	*0.13*	0.10	*0.08*
Student Infl on Course Selection (0-3)	-0.01	*0.06*	**0.11** *	*0.06*	0.07	*0.04*
Constant	**-2.80** ***	*0.68*	**-2.18** **	*0.91*	**-1.14** ***	*0.63*

Notes:

1) Multinomial Logit regression. Estimates are relative to no PSE attainment.

2)*,**,*** denote 90%, 95%, and 99% statistical significance respectively.

3) Standard Errors (SE) are clustered at the school level.

4) Total # Observations is 13,250.

Appendix F. Additional Structural Estimates

Tables F.1, F.2, and F.3 display the 216 structural parameter estimates not provided in section 6.2. Table F.1 displays the omitted parameters related to the five occupation choices in the model. Table F.2 displays the omitted parameters related to the three PSE institution choices in the model. Table F.3 displays the omitted parameters related to the five high school field choices and the GED choice in the model.

Table F.1: Additional Structural Occupation Parameters

	Professional		Skilled Manual Labor		Skilled Non-Manual Labor		Skilled Other		Unskilled	
Variable	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
1. HS Curriculum & 1-yr Trade School Complementarity (Log-Wage Utility)										
Business Voc & 1-yr PSE	-	-	-0.01	*(.028)*	-0.02	*(.025)*	-	-	-	-
Trade Voc & 1-yr PSE	-	-	0.05 *	*(.030)*	0.11 ***	*(.039)*	-	-	-	-
2. Local Labor Market Characteristics (Log-Wage Utility)										
Unemployment Rate	-0.12	*(.274)*	0.66 ***	*(.179)*	-0.62 ***	*(.212)*	1.35 ***	*(.472)*	-1.40 ***	*(.309)*
(ln) Average Hourly Wage	0.10 ***	*(.024)*	0.03 *	*(.017)*	0.13 ***	*(.020)*	-0.07	*(.044)*	0.11 ***	*(.032)*
% Professional Emp	0.90 ***	*(.197)*	0.59 ***	*(.141)*	-0.55 ***	*(.153)*	0.52	*(.342)*	-0.84 ***	*(.252)*
% Manual Labor Emp	0.22 ***	*(.060)*	0.25 ***	*(.044)*	-0.19 ***	*(.049)*	0.07	*(.100)*	-0.63 ***	*(.074)*
% Non-Manual Labor Emp	-0.07	*(.104)*	-0.08	*(.081)*	0.44 ***	*(.087)*	0.44 **	*(.195)*	0.11	*(.138)*
3. Personal Characteristics (Log-Wage Utility)										
Midwest	-0.10 ***	*(.016)*	-0.04 **	*(.018)*	-0.04 **	*(.017)*	-0.16 ***	*(.035)*	-0.03	*(.029)*
South	-0.09 ***	*(.016)*	-0.05 ***	*(.018)*	-0.02	*(.017)*	-0.10 ***	*(.033)*	-0.05 *	*(.027)*
West	-0.02	*(.017)*	0.04	*(.019)*	0.03	*(.019)*	-0.20 ***	*(.041)*	-0.07 **	*(.030)*
Suburban	0.02	*(.013)*	0.05 ***	*(.014)*	-0.01	*(.013)*	0.02	*(.028)*	0.01	*(.021)*
Rural	0.01	*(.017)*	0.02	*(.018)*	0.02	*(.018)*	-0.06	*(.034)*	-0.07 **	*(.027)*
Catholic School	0.07 ***	*(.016)*	0.11 ***	*(.024)*	0.06 ***	*(.021)*	-0.04	*(.038)*	-0.02	*(.038)*
Non-Catholic Private Sch	0.02	*(.018)*	0.03	*(.024)*	0.09 ***	*(.021)*	0.09 **	*(.037)*	0.07	*(.043)*
4. Personal Characteristics (Non-Pecuniary Utility)										
Midwest	-0.01	*(.028)*	0.13 ***	*(.027)*	0.06 *	*(.027)*	0.11 *	*(.054)*	0.10 **	*(.047)*
South	-0.18 ***	*(.027)*	-0.03	*(.026)*	-0.15 ***	*(.025)*	-0.07	*(.051)*	0.17 ***	*(.044)*
West	-0.22 ***	*(.031)*	-0.12 ***	*(.029)*	-0.13 ***	*(.029)*	0.03	*(.067)*	0.18 ***	*(.051)*
Suburban	0.05 *	*(.023)*	0.13 ***	*(.021)*	0.09 ***	*(.021)*	0.09 **	*(.044)*	0.14 ***	*(.034)*
Rural	-0.01	*(.029)*	0.14 ***	*(.028)*	-0.01	*(.027)*	0.16 ***	*(.056)*	0.11 **	*(.047)*
Catholic School	0.78 ***	*(.038)*	0.22 ***	*(.037)*	0.49 ***	*(.036)*	0.95 ***	*(.065)*	0.4 ***	*(.065)*
Non-Catholic Private Sch	-0.09 **	*(.037)*	-0.20 ***	*(.039)*	-0.24 ***	*(.035)*	-0.09	*(.060)*	-0.57 ***	*(.073)*

Notes:
1) The parameter on log hourly wages (relating wage utility to non-pecuniary utility) is 1.37, with SE of *(.002)*.
2) The variance of the normal wage error terms is estimated to be 0.16, with a SE of *(.001)*.
4)*,**,*** denote 90%, 95%, and 99% statistical significance respectively.
5) Total # Observations is 16,200.
6) Standard errors (SE) are calculated using the covariance of the parameter estimate scores, following Train (2003).

Table F.2: Additional PSE Education Structural Parameters

Variable	1-yr Trade School Estimate	SE	2-yr CC Estimate	SE	4-yr University Estimate	SE
1. PSE Instruments						
% Prev Students Enter Labor Market (0-5 Scale)	-0.01	*(.043)*	-0.04 *	*(.020)*	-0.18 ***	*(.021)*
% Prev Students Attend 2yr College (0-5 Scale)	0.10 ***	*(.038)*	0.18 ***	*(.018)*	-0.16 ***	*(.021)*
% Prev Students Attend 4yr College (0-5 Scale)	0.05	*(.032)*	-0.11 ***	*(.015)*	0.51 ***	*(.018)*
% Students Attend College Fairs	-0.04	*(.031)*	0.01	*(.014)*	0.03	*(.016)*
% Students in College App Prog (0-5 Scale)	0.01	*(.027)*	0.04 ***	*(.012)*	0.18 ***	*(.014)*
2. Personal Characteristics						
Midwest	0.11	*(.106)*	-0.09 *	*(.048)*	-0.90 ***	*(.054)*
South	0.11	*(.101)*	-0.17 ***	*(.046)*	-0.68 ***	*(.051)*
West	0.09	*(.114)*	-0.08	*(.052)*	-0.92 ***	*(.058)*
Suburban	-0.04	*(.077)*	0.10 ***	*(.037)*	-0.74 ***	*(.038)*
Rural	-0.07	*(.102)*	-0.01	*(.049)*	-0.91 ***	*(.049)*
Catholic School	0.26 *	*(.132)*	0.75 ***	*(.060)*	2.71 ***	*(.080)*
Non-Catholic Private School	0.01	*(.134)*	0.04	*(.060)*	1.29 ***	*(.082)*

Notes:

2) *,**,*** denote 90%, 95%, and 99% statistical significance respectively.

3) Total # Observations is 16,200.

4) Standard errors (SE) are calculated using the covariance of the parameter estimate scores, following Train (2003).

Table F.3: Additional HS Education Structural Parameters

Variable	Academic Estimate		Academic SE	General Ed Estimate		General Ed SE	Business Voc Estimate		Business Voc SE	Trade Voc Estimate		Trade Voc SE	Other Estimate		Other SE	GED Estimate		GED SE
1. HS Education Instruments																		
# Voc Teachers per 100 Students	-		-	-		-	-0.01		*(.144)*	-0.02		*(.144)*	-0.02		*(.094)*	-		-
% Stu Free / Reduced Price Lunch	0.12		*(.116)*	-0.28	***	*(.084)*	-0.01		*(.149)*	-0.02		*(.148)*	-0.23	**	*(.110)*	-0.44	***	*(.151)*
Admission Based on Geography	7.01	***	*(.110)*	6.86	***	*(.101)*	6.88	***	*(.129)*	6.76	***	*(.124)*	6.74	***	*(.110)*	8.09	***	*(.258)*
Stu Infl on Course Selection (0-3 Scale)	1.77	***	*(.053)*	1.8	***	*(.050)*	1.83	***	*(.060)*	1.80	***	*(.061)*	1.87	***	*(.053)*	1.81	***	*(.118)*
% Prev Stu Enter Labor Market (0-5 Scale)	2.75	***	*(.053)*	2.77	***	*(.050)*	2.90	***	*(.058)*	2.79	***	*(.057)*	2.77	***	*(.052)*	2.62	***	*(.119)*
% Prev Stu Attend 4yr Col (0-5 Scale)	-1.45	***	*(.055)*	-1.46	***	*(.053)*	-1.40	***	*(.061)*	-1.41	***	*(.059)*	-1.42	***	*(.055)*	-1.66	***	*(.124)*
% Prev Stu Attend 2yr Col (0-5 Scale)	4.35	***	*(.042)*	4.31	***	*(.040)*	4.33	***	*(.047)*	4.29	***	*(.046)*	4.30	***	*(.042)*	4.08	***	*(.092)*
2. Personal Characteristics																		
Midwest	-0.11		*(.092)*	0.29	***	*(.080)*	0.23	*	*(.117)*	0.06		*(.111)*	0.49	***	*(.096)*	0.35	**	*(.138)*
South	-0.17	*	*(.082)*	-0.27	***	*(.072)*	0.04		*(.111)*	-0.67	***	*(.104)*	-0.18	*	*(.090)*	-0.03		*(.126)*
West	0.47	***	*(.097)*	0.89	***	*(.084)*	0.13		*(.143)*	-0.02		*(.129)*	0.85	***	*(.102)*	0.57	***	*(.152)*
Suburban	0.05		*(.071)*	0.35	***	*(.062)*	0.54	***	*(.092)*	0.61	***	*(.093)*	0.52	***	*(.073)*	0.59	***	*(.105)*
Rural	-0.42	***	*(.100)*	-0.05		*(.088)*	0.19		*(.118)*	0.08		*(.121)*	0.24	**	*(.099)*	0.15		*(.140)*
Catholic School	14.81	***	*(.224)*	15.29	***	*(.218)*	15.64	***	*(.263)*	13.82	***	*(.294)*	13.48	***	*(.251)*	14.74	***	*(.454)*
Non-Catholic Private School	3.67	***	*(.111)*	4.65	***	*(.089)*	4.19	***	*(.197)*	2.95	***	*(.263)*	3.12	***	*(.151)*	5.27	***	*(.157)*

Notes:

1)*,**,*** denote 90%, 95%, and 99% statistical significance respectively.

2) Total # Observations is 16,200.

3) Standard errors (SE) are calculated using the covariance of the parameter estimate scores, following Train (2003).

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