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

Michael LaForest*

May 13, 2020

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 use 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 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 have little effect on average future wages but 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 decrease a high school graduate's likelihood to pursue a four-year 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, while increasing the high school dropout rate. 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. Relative to the costs of such a policy, social welfare implications depend on assumptions about relative social marginal welfare for high and low socio-economic status individuals.

JEL classification: I2, J2, C3
Keywords: Returns to Education, Human Capital, Occupation Choice, Dynamic Discrete Choice Models

---

*Pennsylvania State University; 404 Oswald Tower, University Park, PA 16802; mlaforest@psu.edu; 269-470-0958. I am grateful to Steven Stern, John Pepper, and William Johnson for their extensive guidance. I would like to thank Leora Friedberg, Sarah Turner, Benjamin Castleman, James Wycoff, Jens Ludwig, several anonymous referees, and participants at various seminars for helpful advice and comments. I would like to thank the Institute for Education Sciences for restricted-use data access and Sarah Turner for facilitating access. Finally, I would like to thank the Bankard Fund for Political Economy, the Radulovacki Summer Research Fund, and the UVA Quantitative Collaborate for financial support. All errors are my own.

1. Introduction

In 2018, 31% of U.S. high school seniors did not attend any post-secondary institutions following graduation (Bureau of Labor Statistics, 2019). 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 in general education courses.[1] 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 their ability to find well-paying jobs after graduation. Alternatively, these students may be better served by learning a wide range of non-honors English, math, and science courses in high school and waiting to learn job-specific skills in the labor market.

There is disagreement among researchers and policy makers about the merits of high school career and technical education.[2] Some see high school CTE as an alternative to college which helps students find well-paying careers, while others see it as a system that limits students' future post-secondary education (PSE) and labor market opportunities. Still others see it as a system that can prepare students to pursue PSE as well as prepare them for 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, little empirical research has been conducted on the benefits and drawbacks of high school CTE, and there remains general disagreement among researchers about its effects.

In addition, the percentage of students who drop out of high school in the U.S. is sizable as is the percentage of students who begin but never complete a post-secondary education degree. Specifically, 10% of the potential high school class of 2012 did not receive a high school diploma or General Educational Development (GED) certificate by age 21 (Flood et al., 2015). As well, only 29% of students who began PSE certificate / associate degree programs in 2009 completed them in three years or less, and only 59% of students who began PSE bachelor's degree programs in 2006 completed them in six years or less (National Center for Education Statistics, 2015). These

[1] The terms "Career and Technical Education" and "Vocational Education" are used synonymously by different sets of policy makers and researchers throughout the field.
[2] 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).

sizable attrition rates motivate three additional questions. First, how does the availability of high school CTE affect students' propensity to drop out of high school? Second, how does taking high school CTE affect students' propensity to complete PSE degrees? Finally, how does taking high school CTE affect the labor market outcomes of both high school dropouts and high school graduates who begin but never complete PSE degrees?

This work contributes to the literature by providing a thorough empirical analysis of the education and labor market effects of different types of high school education. 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. Relative to other structural models, it requires fewer assumptions by modeling a broader range of lifetime choices and is the first to use simulation to manage unobserved and partially observed data. Relative to prior reduced-form analyses, it accounts for high school curriculum self-selection with high school vocational and academic opportunity instruments at each student's school along with local labor market controls. In addition, it jointly estimates the effects of high school education choices on dropout propensity, PSE attainment, employment, and wages, separately identifies and estimates the present and future benefits that drive current education and labor market decisions, and allows for the evaluation of several policy-relevant simulations.

The model, described in Section 3, separates education and labor market decisions into 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), or "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 year to maximize her expected lifetime utility.

I estimate the model using data from the restricted-use version of the Educational Longitudinal Study of 2002 (ELS:2002), as discussed in Section 4. The data set follows 16,200 students from the beginning of high school 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, yearly occupation information, and wages.

I estimate the parameters of the 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 parameter in the model, and instrumental variable exogeneity assumptions. Section 6 presents and discusses the parameter estimates of the structural model and compares them to parameter estimates of linear models of later-life wages and employment estimated using two-stage least squares (2SLS) regression analysis.

The parameter estimates from 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. The structural model estimates confirm these findings but provide additional context. First, they suggest that the lower average wages associated with completing business vocational courses are driven by occupation selection. Specifically, taking a business vocational curriculum improves wages in low-wage / high-non-pecuniary utility (skilled non-manual labor) occupations incentivizing business vocational concentrators to choose those occupations. The structural parameters also suggest that the positive wage returns to trade vocational education are generally confined to skilled manual labor occupations, incentivizing trade vocational concentrators to choose those occupations. Additionally, the estimates suggest that a general education curriculum increases wages in unskilled occupations, incentivizing general education concentrators to choose them, which drives the result that a trade vocational curriculum increases the chance of being employed in a skilled occupation but not the overall chance of employment.

Next, structural estimates suggest that concentrating in a trade or business vocational field slightly decreases the propensity to pursue a four-year 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 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 third of the population 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. These result suggests that interventions to decrease the high school dropout rate should be tailored to this subgroup of students.

I conduct four policy simulations using the structural model and estimates, presented in Section 7. The first simulates a federal policy that makes high school CTE available at every high school nationwide. This simulation leads to an additional 4.9 percentage points of high school students concentrating in vocational curricula but has relatively minor long-term effects on PSE and labor market outcomes. The second simulates the effect of incorporating vocational certification directly into high school vocational curricula.[3] The simulation leads to an additional 2.9 percentage points of U.S. high school students taking vocational courses and an additional 8.6 percentage points receiving vocational certifications by age 26. This, in turn, leads to an increase in the number of individuals working in skilled manual labor and skilled non-manual labor occupations (0.9 percentage points), a decrease in the number of individuals working in unskilled occupations (-0.3 percentage points), and an increase in average wages (9.1%) and average welfare (2.2%) in the population among individuals who change their behavior.

Third, I simulate the effect of a German-style high school tracking system in the United States, that pushes students onto vocational, general education, or academic tracks at the time they enter secondary school based on standardized test scores.[4] This simulation leads to many more students completing academic and vocational curricula (8.2 and 11.9 percentage point increases, respectively) instead of general education curricula. However, it also predicts a doubling of the number of students who drop out of high school and instead pursue GEDs, due to the inability to select their own high school curricula. Among individuals who graduate from high school, the increase in academic and vocational concentrations lead to increased PSE attainment, average wages, and likelihood of being employed, though these gains come at the expense of non-pecuniary utility in high school. Students who drop out of high school experience worse PSE and labor market outcomes, leading to an overall decrease in average welfare (-1.3%) in the population among individuals who change their behavior.

Finally, I simulate the effects of free community college for all United States high school

[3] 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).

[4] Following the German system, students who graduate high school on the vocational track are awarded vocational certifications at the time they receive their high school degree.

graduates.[5] The simulation predicts that the number of individuals in the population who complete associate degrees would more than double. It also predicts that more individuals would pursue general education courses in high school, in preparation to attend community college, and that slightly more individuals would complete bachelor's degrees (0.7 percentage points), due to an increase in the number of community college to four-year university transfer students. Overall, the simulation predicts that average wages would slightly increase (by 0.5%), driven by the slight increase in bachelor's degree attainment, and that average welfare in the population would increase (by 0.8%). Whether these gains offset the costs of the policy depend on how costs are shared across the population and assumptions about relative social marginal welfare for high and low socio-economic status individuals, as discussed in Section 7.4.

2. Literature Review

To date, little evidence exists about the effects high school career and technical education on education and labor market outcomes. The studies that have been conducted in the past have reached differing conclusions and largely suffered from self-selection issues which bias their results. These self-selection issues are caused by students endogenously choosing their 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. 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 high school curriculum selection. Most of these studies have used data from the same three 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)) and have reached differing conclusions regarding the effects of high school CTE due to differences in

[5] Versions of this policy have recently been proposed by President Barack Obama, Senator Bernie Sanders, Senator Hillary Clinton, and Vice-President Joe Biden (Obama, 2015; Sanders, 2016; Clinton, 2016; Biden, 2020).

empirical specifications. For example, Meyer and Wise (1982), Stromback (2010), and Davis and Obenauf (2011) each found no significant effect of high school CTE on early labor market experiences, while Arum and Shavit (1995), Mane (1999), and Bishop and Mane (2004) each found statistically significant positive effects of high school CTE on wages and employment chances. Overall, there has been a lack of consensus about the effects of high school CTE throughout the literature as well as an absence of rigorous, empirical studies investigating it.

Several recent studies merit 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 minor positive effects of high school CTE on later-life earnings for a subset of the population but that a majority of individuals in that subset were already concentrating in high school vocational curricula.

Kreisman and Stange (2020) investigated the returns to high school vocational education using data from NLSY97 and focused on the marginal effect of each additional vocational course taken. They split up vocational courses between basic and advanced courses and estimated the effects of high school course choice on post-secondary education attendance and wages. To attempt to control for high school curricula self-selection, they included a small set of student ability and high school characteristic controls in their regression equations. Their findings suggest that each additional vocational course taken marginally decreases four-year college attendance and has no effect on high school graduation, but that each additional advanced vocational course improves later life wages. Finally, recent work by Daugherty (2018) found positive effects of CTE on on-time graduation using a regression discontinuity design around admissions into a CTE program in Connecticut.

While my research reaches several similar conclusions to this recent work, it goes beyond these studies in several dimensions – it uses education and employment data from every year available in the panel data set to estimate more precise results, includes a fuller set of high school curricula choice instruments and local labor market controls, and uses students' choice paths over time to infer additional information about unobserved heterogeneity. In addition, it jointly estimates the effects of CTE education on an individual's high school dropout propensity, PSE attainment, employment outcomes and wages, and separately identifies the present and future benefits that drive current education and labor market choices. Finally, by estimating a dynamic structural model I can conduct several policy-relevant 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 requires fewer assumptions as it models a broader range of lifetime choices (6-12 choices in any given period, 15 choices across an individual's lifetime) than previous models.[6] In addition, my estimation methodology is the first to use simulation to deal with unobserved and partially unobserved choice data for certain individuals in certain periods. Instead of dropping these individuals, I simulate their state vector in every period where choice data is observed by first simulating unobserved choices, as discussed in Sections 5.3 and 5.4.

3. Model

I model an individual's schooling and work decisions 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. An 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.

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 education, etc.);*

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

---

[6] As comparison, 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.

Skilled Manual Labor, Skilled Other, or Unskilled;

(C) Neither working nor attending school: *Not Employed.*[7]

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.[8] 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 she completed:

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

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.[9] 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 curriculum will affect her future wage offers and PSE choices (as discussed below).

The individual cannot drop out of high school prior to age 16 due to compulsory school attendance laws.[10] The individual cannot choose to attend high school after age 21 due to high

[7] Choice categories were chosen based on prior literature as discussed in Section 4.2.

[8] 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 to 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.

[9] In practice, the aggregate curriculum construction rule is slightly more complicated for the general education and "other" fields: students receive 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 follows specifications used in the previous literature (e.g., Meer, 2007).

[10] 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).

school attendance age requirements.[11] 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.*[12]

The individual can pursue any of these 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 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

$$\begin{aligned} P_{it}^{4y} &= 1 \quad \text{iff} \quad N_{it}^{4yr} = 4 \quad , \\ P_{it}^{CC} &= 1 \quad \text{iff} \quad N_{it}^{CC} = 2 \quad , \\ P_{it}^{cert} &= 1 \quad \text{iff} \quad N_{it}^{cert} = 1 \quad . \end{aligned}$$

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.[13] The student is aware of these PSE institution graduation rules when making her choice

[11] 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).

[12] 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.

[13] 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.

each year.[14] 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.[15]

Every year an individual works in an occupation, she has a chance to gain 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.[16] The probability an individual gains occupation-specific human capital, θ_e, varies based on 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_{cert}), 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. Note that an individual can accumulate only up to two levels of occupation-specific human capital across all occupations ($sum_j(O_{it}^{j}) \leq 2$) over her lifetime, which follows the results of previous studies that show that individuals rarely accrue high levels of occupation-specific human capital in multiple occupations (e.g., Topel and Ward, 1992, and Pavan, 2010).[17]

[14] 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 across institutions 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). I currently code community college transfers who attain bachelor's degrees as having attended four-year universities for four years. 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.

[15] 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 5.6.

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

[17] 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 decrease the size of the state space.

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 during the second half of their careers (e.g., Neal, 1999) and follows the treatment of future utility used in prior studies (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.

3.2 Utility Function

The individual receives utility each period from both her current wage, if working, and the non-pecuniary utility of her current choice. Each period, the individual receives a wage offer in each of the five occupations.[18] Specifically, the wage offer for person i in occupation k in period t is

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

The symbol "~" denotes wage parameters and wage error terms. The vector X_i is comprised of time-invariant characteristics of the individual, such as personal characteristics about the individual, characteristics about the individual's high school, and characteristics about the local labor market where the individual's high school was located. Vectors H_{it} and P_{it} are comprised of dummy variables for high school graduation curriculum and PSE institution graduation as defined above. Vector $P_{it}^{cert}H_{it}$ is comprised of dummy variables for whether the individual completed a particular high school track followed by a PSE trade school certification.[19] Vector O_{it} is comprised of the occupation-specific human capital the individual has gained in each of the five occupations. Error terms $\tilde{u}_i^k$ and $\tilde{\varepsilon}_{it}^k$ are discussed below.

Next, the individual receives non-pecuniary utility each period from her current choice. The total utility she receives in a period is 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

[18] I assume the individual receives a wage offer in every occupation every period with 100% certainty, an assumption 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 that period.

[19] 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 receiving a PSE trade school certification in addition to the benefits of completing each individually.

choice k at time t is

$$\begin{aligned} U_{it}^k &= X_i\beta_X^k + u_i^k + \varepsilon_{it}^k && \forall k \in HS\ Fields, \\ U_{it}^k &= X_i\beta_X^k + u_i^k + \varepsilon_{it}^k + H_{it}\beta_H^k && \forall k \in PSE\ Institution\ Types, \\ U_{it}^k &= X_i\beta_X^k + u_i^k + \varepsilon_{it}^k + \varphi w_{it}^k && \forall k \in Occupations. \end{aligned} \quad (2)$$

The coefficient φ represents the utility value of wages relative to non-pecuniary utility.[20] 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 succeed in college, giving her more incentive to attend. All of these effects cumulatively make up β_H^k.[21]

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 $iid\ EV(0,1)$.[22] The error terms $\tilde{u}_i^k$ and u_i^k vary across individuals and choices but are constant over time, and reflect individual unobserved heterogeneity.[23] 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 Expected Lifetime Utility

Define $\tilde{\varepsilon}_{it}$ and ε_{it} (without superscripts) as the vectors of wage time-specific error terms and non-pecuniary time-specific error terms, respectively, for all choices 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

---

[20] The characteristics that comprise X_i (personal characteristics, high school characteristics, and labor market characteristics) vary across choices. Personal characteristics affect wages and utility for each of the 15 choices in the model. Local labor market characteristics affect the wages of each occupation choice. Characteristics about the individual's high school related to curriculum availability and curriculum selection affect the utility of each high school field and GED choice. Finally, characteristics about the individual's high school related to PSE attendance and PSE opportunities affect the utility of each PSE institution choice.

[21] 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.

[22] 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.

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

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+}^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. H_{it+} , P_{it+1}, and O_{it+1} change, as defined in Section 3.1, when the individual graduates from high school, graduates from each type of PSE institution, and works in a particular field and gains occupation-specific human capital.[24]

Denote individual *i*'s choice in period *t* as k_{it}. I define the transition of the state vector described in the preceding paragraph 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 $\tau = t+1, t+2, \ldots, T$. These increased stock values affect the value of utility for each choice in every future period $\tau = t+1, t+2, \ldots, T$.

An individual chooses between her education and employment options in each period *t* to maximize her expected lifetime utility between the current period and retirement at age 65 $(t = T)$. The individual's expected lifetime utility (i.e., value function) at the start of period *t* can be written as

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

where δ is the discount factor, $U_{it}^k(S_{it})$ is the current period utility from choosing option *k* given state vector S_{it}, and S_{it} follows the transition of the state vector noted 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 $\tau = t+1, t+2, \ldots, T$.

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

[24] There are 3,360 possible states of occupation-specific human capital and educational attainment in the model, comprised of 15 states of occupation-specific human capital and 224 states of education experience. The states of education experience are comprised of 56 states of high school education experience prior to high school graduation, 144 states of HS degree and PSE experience after high school graduation but prior to four-year university graduation, and 24 different states of HS degree and PSE degree attainment after four-year university graduation.

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

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

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 $\tau = t, t+1, t+2, \ldots, T$. Thus, 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 noted 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 the following closed-form solution:

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

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

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.[25]

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). The 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.[26] The study collected data from August 2000, when the respondents began high school, until May 2012, eight years after the majority of the

[25] The construction of the value function is similar to the derivation used in other dynamic discrete choice models such as Keane and Wolpin (1997) and Chan (2013).

[26] As shown below, the ELS:2002 study sample is nationally representative of U.S. high school sophomores in 2002 with two exceptions – it oversampled individuals attending private schools and undersampled eventual high school dropouts.

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, it collected supplementary information from each student's parents, teachers, high school administrators, high school librarians, and high school counselors. It also collected high school transcripts and post-secondary education transcripts for nearly all students.

Summary statistics about the personal characteristics of the students are displayed in Table 4.1. Among surveyed students, 50% of the sample was male, 56% of the sample was white, 13% of the sample was black, and 15% of the sample was Hispanic. 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. Approximately 80% of students attended public high schools, 10% of students attended Catholic schools, and 10% of students attended non-Catholic private schools.

Table 4.2 provides school-level summary statistics, including 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. 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.[27] Approximately 10% of students in the sample attended schools that conferred GED degrees on-site, and three-fourths of the students in the sample attended schools that admitted students principally based on the geographic location of their parents' homes. Next, the influence students had on their own course selection, as reported by high school counselors, varied widely throughout the sample, though on average students had a large influence on their course selection. 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 (~60%), a relatively small percent had enrolled in a two-year college (~25%), and a relatively small percent had entered the labor market (~15%).

Table 4.3 provides summary statistics about the local labor market characteristics, in 2002, in the county in which each student's high school was located. Data on average wages and industry employment percentages by county comes from the Bureau of Economic Analysis's (BEA)

[27] 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.

regional data on Local Area Personal Income & Employment.[28] Data on county unemployment rates comes from the Bureau of Labor Statistics' (BLS) Local Area Unemployment Statistics. The average unemployment rate was 4.2% 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 manual (23%) and non-manual labor (24%) industries, on average, than in professional industries (7%).

Finally, Table 4.4 provides summary statistics on the log hourly wages of individuals in the sample.[29] Individuals in professional occupations received the highest average log hourly wages (2.6, which corresponds to an hourly wage of $13.5), followed by individuals in the skilled other (2.5), skilled manual labor (2.4), skilled non-manual labor (2.3), and unskilled occupations (2.1), respectively.[30]

4.2 Choice Construction

I construct each student's yearly high school field choice based on high school transcript data. First, each course a 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.[31] 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

---

[28] Employment percentages across industries are used because employment percentages across occupations are not available at the county level. Industry employment percentages closely match occupation employment percentages at the national level and at the MSA level (See Section C.2 of LaForest (2019) for a detailed discussion), and as such are likely a good approximation for occupation employment percentages at the county level.

[29] Wages are first adjusted for inflation into 2002 dollars. 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). 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 LaForest (2019), Section D.1.

[30] 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. While the ELS:2002 data set provides sample weights for each wave of the survey based on which sample members' information was missing in each wave I do not use these weights as I include the entire sample of 16,200 individuals in the structural analysis. Using ELS:2002 sample weights does not have an appreciable effect on 2SLS estimation results.

[31] 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).

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 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.[32]

Next, a single overall field concentration is constructed for each year of high school. Specifically, yearly field concentration is defined as the field in which the student took a plurality of courses each year.[33] The tiebreaking rule favors labeling a yearly concentration as vocational as opposed to non-vocational, though very few ties occur.[34]

Overall high school curriculum is determined based on the yearly field the individual selected for a plurality of years, as defined in Section 3.1.[35] 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.[36]

Next, ELS:2002 includes yearly information about post-secondary education enrollment

---

[32] The complete mapping of CSSC codes to curriculum types is provided in Section A.1 of LaForest (2019). 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. I separate "other" courses to restrict them from impacting the parameter estimates associated with general education, trade vocational, and business vocational high school curricula.

[33] 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).

[34] 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 2SLS estimation results.

[35] Curricula outcomes are very similar under my chosen construction rule relative to alternative specifications, as shown in Section A.3 of the online data appendix (LaForest, 2019).

[36] Note that this 7% number is around half the national average for high school dropouts by age 19 in 2005 (National Center for Education Statistics, 2015), implying that ELS:2002 under-sampled students who were at risk of dropping out of high school.

and completion. See Table 4.6 for the aggregate PSE attainment rates in the sample for each type of PSE institution at the time the study concluded in 2012. 40% of students in the sample had graduated from a four-year university, while 9% and 8% of students had graduated from (at most) trade school or community college, respectively. Table 4.7 displays PSE degree attainment by high school curriculum. Overall 73% of individuals who took academic courses completed four-year university degrees. Comparatively, 59% of individuals who took general education courses, 41% of individuals who took trade vocational courses, 51% of individuals who took business vocational courses, and 7% of individuals who had not graduated high school by age 19 had graduated from at least one 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). Professional occupations include professional and managerial occupations and 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. 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.[37] These occupation categories are similar to the categories used in the previous literature (e.g., Aram and Shavit, 1995), which in general follows the occupation schema created by Erikson, Goldthorpe, and Portocarero (1979). Table 4.8 displays 2012 employment outcomes by high school curriculum. Overall, academic concentrators were most likely to later work in professional occupations (49%), trade vocational concentrators were most likely to later work in skilled manual labor occupations (45%), and business vocational concentrators were most likely to later work in skilled non-manual labor occupations (35%).

Using the construction rules discussed above, I assign each individual an education or labor market choice during each year of the sample period.[38] Table 4.9 includes the aggregate

[37] Note that, while the other 15 occupation codes provided in ELS:2002 fit directly into one of the 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. Additional occupation mapping details can be found in LaForest (2019), Section B.
[38] When constructing individual-year choices, I treat an individual who worked part-time while attending high school 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

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.[39] Finally, the study asked very few labor market questions about the period between 2006-2010. While some of these values are imputed based on job start and end dates, many of them are coded as missing or "Work Unknown Type" during these years.[40]

5. Estimation Methodology

5.1 Unobserved Heterogeneity

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

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

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, while the elements of u_2 and the value of ζ are estimated in the model.[41]

5.2 Likelihood Function

I estimate the parameters in the model 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 $\omega_{it} = (\widehat{w}_{it}^1, d_{wit}^1, \widehat{w}_{it}^2, d_{wit}^2, \ldots, \widehat{w}_{it}^5, d_{wit}^5)$. 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

(1997). I only 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. 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. 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.

[39] 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. Also 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."

[40] Additional details about imputation rules are provided in Section D.2 of LaForest (2019). 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 Section 5.3.

[41] This follows the treatment of unobserved heterogeneity used in the previous literature (e.g., Keane and Wolpin, 1997, and Chan, 2013).

an individual each period.

Recall 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 ($F_{it}, H_{it}, N_{it}, P_{it}$), 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 current period 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 an observed residual log-wage error term for occupation *k*. As each $\tilde{\varepsilon}_{it}^{k}$ is assumed to be *iid*, the joint density of the other $\tilde{\varepsilon}_{it}^{k}$'s does not depend on the value of the 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 other occupations in period *t*.

Recall that $\bar{V}_{it}^{k}(S_{it})$ is a function of $w_{it}^{k}(S_{it})$ which is itself a function of $\tilde{\varepsilon}_{it}^{k}$. 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

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

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

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

Note that ω_{it} has two effects on the likelihood function when a wage is observed ($d_{wit}^{k} = 1$). First, the corresponding residual log-wage error term ($\hat{\tilde{\varepsilon}}_{it}^{k}$) is directly inserted into the likelihood function. Second, $\hat{\tilde{\varepsilon}}_{it}^{k}$ 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.

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

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

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

Define the path of choices over the individual's lifetime as $K_{pi} = \{k_{i1}, k_{i2}, \ldots, k_{iT}\}$, the associated pre-period state path over the individual's lifetime as $\bar{S}_{pi} = \{\bar{S}_{i1}, \bar{S}_{i2}, \ldots, \bar{S}_{iT}\}$, and the path of observed wages over the individual's lifetime as $\omega_{pi} = \{\omega_{i1}, \omega_{i2}, \ldots, \omega_{iT}\}$.[42] 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}):

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

5.3 Unobserved Events

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 $O_{pi} = \{O_{i1}, O_{i2}, \ldots, O_{iT}\}$, 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^o as the set of all time periods for which $d_{it}^{o} = 1$ for individual

[42] 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, 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. Conversely, the state space transition of $\bar{S}_{it} = \bar{S}_{it+1}$ can be caused by both 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*, $\psi_{it} = 0$).

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 ($L_{li}(K_{pi}, \bar{S}_{pi}, \omega_{pi})$). The conditional lifetime likelihood contribution of an individual with missing information can then 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:

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

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

Next, note that the probability the individual chose choice k in period t when k 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

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

where the second summation is over all K_{pi} such that $K_{pi}^o \in K_{pi}$. Note that $P(\bar{S}_{pi} | K_{pi})$ is comprised entirely of a product of θ_e's and $[1 - \theta_e]$'s based on whether O_{it}^k (occupation-specific human capital) increased each period the individual worked along choice path K_{pi}.[43] Also, note that $L_{li}(K_{pi}, \bar{S}_{pi}, \omega_{pi})$ is a product of the conditional period likelihood contributions ($L_{it}^k(\bar{S}_{it}, \omega_{it})$) for individual i for every period $t = 1,2, \dots, T$. 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 $L_{ui}(u_i, X_i, K_{pi}^o, \omega_{pi})$ is the lifetime likelihood contribution for an

[43]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 $P(\bar{S}_{pi} | K_{pi})$ = $[1 - \theta_{noHS}]^T$.

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:

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

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

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

I estimate the model by selecting parameters that maximize this sample likelihood function.[44]

5.4 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, is computationally burdensome. 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 also 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.[45] 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

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

Separately, 10 independent values of each ε_{it}^k and $\tilde{\varepsilon}_{it}^k$ are simulated for each available choice each period using antithetic acceleration, as are 10 independent values of ψ_{it} (related to

---

[44] Parameter values are chosen following the Berndt, Hall, Hall, and Hausman (1974) (BHHH) optimization algorithm. The covariance matrix of maximum simulated likelihood estimates is standard.

[45] 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 large enough to construct consistent estimates of V_{it}^* and L_{ui}.

human capital accumulation) each period. 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

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

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

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

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

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

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

Next, when $d_{it}^{o} = 0$ (the choice in period t) is unobserved the predicted value of k, 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

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

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

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 $\bar{S}_{\xi pi} = \{\bar{S}_{\xi i1}, \bar{S}_{\xi i2}, \dots, \bar{S}_{\xi iT}\}$ 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

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

Recall that T_i^o 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 can be approximated as the average of 10 simulated conditional lifetime likelihoods:

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

5.5 Identification

Variation across individuals over time allows me to identify each of the parameters in the model. First, each parameter in the wage equation ($\tilde{\beta}_X^k, \tilde{\beta}_P^k, \tilde{\beta}_H^k, \tilde{\beta}_{PH}^k, \tilde{\beta}_O^k$) is identified by variation in choices and wages over time across individuals. For example, the effect of gender on wages in occupation k ($\tilde{\beta}_{X_{MALE}}^k$) is identified by co-variation between gender and wages in occupation k among individuals with otherwise equivalent pre-period states. The effect of occupation-specific human capital in occupation j on wages in occupation k ($\tilde{\beta}_{O_j}^k$) is identified by co-variation in the number of years worked in occupation j and wages in occupation k among individuals with otherwise equivalent pre-period states.

Each parameter in the non-pecuniary utility equation ($\beta_X^k, \beta_H^k, \varphi$) 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 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 but with otherwise equivalent pre-period states. The total amount of additional utility (both pecuniary and non-pecuniary) males receive in occupation k ($\tilde{\beta}_{X_{MALE}}^k + \beta_{X_{MALE}}^k$) is identified by co-variation between gender and occupation choice among individuals with otherwise equivalent pre-period states. As the pecuniary portion of this utility ($\tilde{\beta}_{X_{MALE}}^k$) is identified from observed wages, the non-pecuniary portion of this utility ($\beta_{X_{MALE}}^k$) is identified by the difference between the estimate for total utility ($\tilde{\beta}_{X_{MALE}}^k + \beta_{X_{MALE}}^k$) and pecuniary utility ($\tilde{\beta}_{X_{MALE}}^k$).

Next, the distribution of unobserved heterogeneity values in the population ($\tilde{u}_2^k, u_2^k, \zeta$) 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, for individuals across the sample with persistently higher or lower observed wages than average in occupation k over time, 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, for individuals across the sample who persistently choose occupation k more than average, the extent of that persistence, among individuals with otherwise equivalent pre-period states and observed wages.

The variance of the normal wage error terms ($\sigma_{\tilde{\varepsilon}}^2$) is identified by the variation in residual log-wage error terms throughout the sample. 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 observed wages in each occupation discretely increase from period to period for individuals with each level of educational attainment.

5.6 Endogenous Course Selection

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 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 can influence 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 and community, and the number of CTE teachers per student in the individual's school (see Table 4.2A).[46] 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

[46] ELS:2002 includes a substantial number of variables about each high school's vocational offerings, academic offerings, and selection methods. I selected the variables in Table 4.2 to be indicative of the full set of high school-related variables available in ELS:2002. Changing this subset of variables does not affect the 2SLS parameter estimates in Section 6.1 or their statistical significance.

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 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 (see Table 4.2B).[47]

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 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, such as historic curriculum offerings at the school, a CTE teacher happening to live in the area, or school board superintendent preferences.

Another concern is if parents choose where to live based on the location of the school they want their child to attend. However, for lower income families whose children are more likely to take general education and vocational education classes, housing choice is substantially more likely to be driven by parental job opportunities and housing costs 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) in the model 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.[48]

---

[47] 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 work required to construct them for each of the 750 high schools in the sample.

[48] 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 are not subject to this potential school selection bias. 2SLS parameter estimates are robust to restricting the sample to rural students.

5.7 Structural vs. Non-Structural Estimates

The structural model has several advantages over non-structural models. First, by estimating a structural model, I can separately identify the intertemporal effects of education and labor market choices – how each choice impacts present and future utility – and the mechanisms underlying those effects. For example, by estimating a structural model, I can identify whether a student takes high school vocational education courses 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. By identifying these present and future effects of each choice, 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, with a structural model I can jointly estimate effects that pertain to multiple, interrelated research questions. For example, 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, as opposed to estimating each of these effects separately.

Third, I can use the structural model to conduct policy simulations. 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 in 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 (such as how decreasing the cost of community college would effect an individual's high school decisions). By estimating a structural model I can 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

The 2SLS regressions use data on each student's HS curriculum, PSE attainment, wages, and occupation at the time the final survey wave was conducted in 2012. Results are presented in Table 6.1. Column 1 presents estimates from an OLS regression of log hourly wages on high school curriculum without instruments that does not account for curricula self-selection or post-secondary education attainment. Column 2 presents 2SLS estimates from a second-stage OLS regression of log hourly wages on high school predicted probabilities and PSE predicted probabilities from two separate first stage regressions.[49]

Column 1 shows that, without accounting for selection, individuals who concentrate in vocational education courses receive higher later-life wages than individual who concentrate in general education courses. Specifically, as the probability of graduating with a trade or business vocational curriculum goes from zero to one (relative to graduating with a general education curriculum), average wages increase by 0.06 log dollars an hour. However, Column 2 shows that selection is driving this result. After instrumenting for high school curriculum selection, the results in Column 2 suggest that trade vocational education increases later-life wages (by .34 log dollars an hour) while business vocational education decreases later-life wages (by -.45 log dollars an hour) relative to general education. It also shows that the returns to an academic high school curriculum disappear after accounting for curricula self-selection and post-secondary education attainment, but that the returns from graduating from a four-year university are quite high (.32 log

[49] See Table 4.2 for a list of high school vocational and PSE instruments. The first-stage regressions, used to construct high school curriculum predicted probabilities, are multinomial logit regressions of high school curriculum and PSE attainment on personal characteristics, local labor market characteristics, and high school vocational and PSE instruments. The estimates from the first-stage regressions are presented in Sections E.1 and E.2 of LaForest (2019).

dollars an hour).[50]

Columns 3 and 4 present results from two different second-stage logit regressions – whether or not an individual is employed at age 26 (Column 3) and whether or not an individual is employed in a skilled occupation at age 26 conditional on employment (Column 4), on high school curricula and PSE predicted probabilities. The estimates in Column 3 suggest that concentrating in a business or trade vocational curriculum causes a positive but statistically insignificant increase in the chance of being employed at age 26, relative to concentrating in a general education curriculum.

The estimates in Column 4 suggest that taking trade vocational courses increase the chances of being employed in a skilled occupation conditional on being employed, relative to taking general education courses, while the effects for business vocational courses are positive but insignificant. The results also suggest that an academic high school curriculum has little effect on employment or skilled employment relative to a general education high school curriculum, but that graduating from a four-year university greatly increases the chances of being employed at age 26. Finally, the results suggest that individuals who graduate from community college are less likely to be employed in skilled occupations, conditional on employment, than other individuals.[51]

6.2 Structural Estimates

Selected structural estimates are presented in Tables 6.2-6.5.[52] Selected wage and utility parameters related to occupation choices are presented in Table 6.2. Looking vertically at each column in Section 1 of Table 6.2 provides a comparison of how each type of high school curriculum and PSE degree affects log wages in a specific occupation. First, graduation from high school in any field improves wages in the skilled manual labor, skilled non-manual labor, and unskilled labor occupations relative to dropping out. Next, a business vocational curriculum has the greatest effect of any high school curriculum on log hourly wages in the skilled non-manual

[50] Note that each result 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).

[51] Note that each result in Columns 3 and 4 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).

[52] The full set of structural parameter estimates are presented in LaForest (2019), Section F.

labor occupation (.29), while a trade vocational curriculum has the greatest effect of any high school curriculum on log hourly wages in the skilled manual labor occupation (.11).[53]

Recall that the 2SLS results suggest that a business vocational curriculum has a negative effect on wages relative to a general education curriculum. The structural results suggest a more nuanced relationship for two reasons. First, the structural estimates separate the effects on wages across occupations. These occupation-specific results suggest that a business vocational curriculum improves log hourly wages in the professional, skilled non-manual labor, and skilled manual labor occupations. However, as a large number of individuals who graduate in the business vocational field choose to work in the skilled non-manual labor occupation, which has low wages relative to other occupations, business vocational completers appear to receive lower average wages.

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. The choice is driven by the higher total utility (wage plus non-pecuniary utility) business vocational completers receive from the skilled non-manual labor occupation compared 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 that occupation (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 high amount of non-pecuniary utility the occupation provides in addition to the wage premium she receives in the occupation, despite the fact that the job provides lower total wages than other occupations available

[53] 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 that occupation (-.59), imply that high school dropouts receive very low wages in the "skilled other" occupation relative to individuals who graduate from high school. 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 professional occupations without having earned a bachelor's degree and that, of those individuals, high school dropouts had higher wages than individuals with only a high school degree.

to her. Similar incentives cause individuals who take trade vocational high school curricula to work in skilled manual labor occupations, and individuals who take "other" types of high school curricula to work in "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. As the model estimates suggest that a trade vocational curriculum provides higher wage returns across all skilled occupations relative to a general education curriculum, they imply that a trade vocational curriculum increases an individual's likelihood to be employed in a skilled occupation, confirming the 2SLS result in Column 4 of Table 6.1. As the estimates suggest that a business vocational curriculum provides higher wage returns in the professional, skilled manual labor, and skilled non-manual labor occupations, but lower wage returns in the "skilled other" occupation, relative to a general education curriculum, the model results are ambiguous about the effects of a business vocational curriculum on the likelihood of employment in a skilled occupation. Finally, as a general education curriculum increases the wage returns in the unskilled occupation, relative to a trade or business vocational curriculum, the structural results are ambiguous about the effects of high school CTE on the overall likelihood of being employed, confirming the 2SLS results in column 3 of Table 6.1.

Graduating from a four-year university provides high log hourly wage returns to all occupations, but particularly high returns to the professional occupation (.46). Community colleges and one-year trade schools provide much smaller returns overall, with community college graduation providing slight 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 scores 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 scores increase. Finally, occupation-specific human capital in each occupation accrues infrequently over an individual's lifetime (9%-14% chance each year based on educational attainment) but adds a large premium to log hourly wages (ranging from .71 to .83).

Selected PSE choice estimates are presented in Table 6.3. The estimates show that concentrating in an academic curriculum in high school, relative to a general education curriculum, 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 explains the reason for the lack of relationship between academic high school curriculum and labor market outcomes we observed in the 2SLS results: individuals choose an academic high school curriculum to directly increase their chances of attending a four-year university, which in turn greatly improves wages in all occupations. Concentrating in either trade or business vocational courses has a slight negative effect on four-year university enrollment, but each has a slight positive effect on two-year community college enrollment, relative to concentrating in general education courses. Obtaining a GED has a negative effect on attending a two-year community college or a four-year university relative to receiving a high school diploma.

Selected HS choice estimates are presented in Table 6.4. Increased vocational offerings and opportunities (such as offering marketing courses on site, precisions courses on site, and the percent of students in the previous year's class who took vocational courses) increase the utility of taking a vocational curriculum in high school. These estimates imply that as the vocational opportunities in high school increase the high school drop-out rate decreases, as each opportunity increases the utility of concentrating in a vocational curriculum relative to dropping out of high school to pursue occupations or the "not employed" option. Additionally, women receive higher non-pecuniary utility than men in all high school fields except the trade vocational field, and individuals with high socio-economic status and test scores receive a large amount of non-pecuniary utility from attending high school in any field relative to dropping out of high school.

Lastly, Table 6.5 presents unobserved heterogeneity parameter estimates for the second type of individual in the population (recall that parameters for the first type of individual are standardized to zero). First, note that the constants for high school curricula in the bottom row of Table 6.4 are quite large (23.2 to 27.1 utils) relative to other parameters. These large high school curriculum constants indicate that type-one individuals never drop out of high school. For type-two individuals, estimated to be 34.3% of the population, high school unobserved heterogeneity parameter estimates are negative and of similar magnitude (-33.71 to -32.0 utils) to these constants. These results suggest that type-two individuals will often drop out of high school as their total non-pecuniary utility from attending high school (calculated by combining the constant and unobserved heterogeneity parameter) is slightly negative before accounting for observed personal and school characteristics. Individuals with the second type of unobserved heterogeneity also receive lower non-pecuniary utility from working and from attending PSE institutions and are substantially more likely to choose to be "neither working nor attending school" than individuals with the first type of unobserved heterogeneity. These result suggests that interventions to decrease the high school dropout rate should be tailored to this subgroup of students.

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 estimates discussed in Section 6.2. The aggregate simulated student outcomes closely match the aggregate student outcomes observed in the data. However, the model over-predicts the percent of individuals who graduate from a four-year university by age 26 (48% instead of 41%) and the number of individuals attending PSE institutions at age 26 (11% instead of 5%). This over-prediction is driven by the assumption in the model that the non-pecuniary utility from attending a PSE institution does not change with age. In reality, the non-pecuniary utility from attending a PSE institution likely decreases with age as an individual become older than their potential peers at each PSE institution. Since this relationship is not included in the model the simulation over-predicts the number of individuals that choose to attend college in their early and mid-20s.

7 Policy Analysis

I use the model and structural estimates to conduct four policy simulations. The simulated percentage point change in population outcomes for each policy are presented in Table 7.1 Columns 2-5, relative to simulated outcomes under current policy settings in Column 1.[54] Table 7.2 presents simulated differences in average log hourly wages and total utility for each policy simulation, relative to current policy settings, as well as the percent of the population the model

[54] 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 and should be taken into account when drawing conclusions from these simulations.

predicts would be directly affected by each policy.[55]

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 certain non-college bound students. The first policy simulation investigates whether expanding vocational curricula offerings would incentivize more students to concentrate in these curricula and improve their later life outcomes. Specifically, it simulates the effects of a federal mandate requiring business and trade CTE 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 from 8.4% to 13.2%. This change in high school curricula choice, in turn, causes a few additional individuals to complete two-year community college degrees (an increase of 0.3 percentage points) and a few less individuals to work in unskilled labor occupations at age 26 (a decrease of .01 percentage points). Table 7.2 shows that this policy slightly increases the average log wages of individuals who switch their high school curricula to vocational high school curricula (by 1.7%) and slightly increases average lifetime utility for these individuals (by 0.7%). Overall, this policy has relatively minor long-term effects on individuals' PSE attainment and labor market outcomes.

7.2 Vocational Certificates in High School

The second policy simulation investigates the effects of incorporating vocational certifications into high school 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 exams independently, to become certified (Castellano et al., 2005). Over the last few years, however, there has been a notable increase in the number of high school vocational programs that confer vocational certifications due to the re-authorization of the Carl D.

[55] 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 differ. 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 differ between the baseline simulation and the policy simulation.

Perkins Career and Technical Education Act of 2006 (U.S. Department of Education, 2013). This policy simulation investigates the effects of this change on students' high school education, PSE attainment, and labor market outcomes.

To run this simulation, I change 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, the individual 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 from her high school field choice that year.[56] The results of this policy simulation are presented in Column 3 of Tables 7.1 and 7.2. This policy incentivizes additional students to concentrate in a trade vocational curriculum (from 4.3% to 7.2% of U.S. high school students) as it allows them to receive both a high school diploma and an industry certification concurrently. Fewer individuals graduate from a community college (-2.6 percentage points) or a four-year university (-1.1 percentage points), however, because fewer individuals take academic and general education courses in high school. Finally, the policy leads to more individuals working in the skilled non-manual labor occupation (0.4 percentage points) and skilled manual labor occupation (0.5 percentage points) and a decrease in the number of individuals working in the unskilled occupation (-0.3 percentage points) or choosing not to work (-0.3 percentage points). Among individuals who change their behavior, average log wages increase (by 9.1%) as does expected lifetime utility (by 2.2%). Overall, the simulation predicts that incorporating vocational certifications into high school vocational curricula will have large positive effects on students' labor market outcomes.

7.3 German-Style High School Tracking

Next, I simulate the effects of the United States instituting a high school tracking system similar to the system used in Germany. In Germany, students are split into three 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

[56] Note that this specification assumes that the returns to high school CTE degrees and vocational certifications are driven by the knowledge a student learns and the degrees that are conferred as opposed to the signaling value of pursuing each degree separately. If the latter is true the results of this policy simulation would be upward biased.

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 based on student and parent preferences. By comparison, relatively little tracking occurs in the United States – most students retain substantial control over the high school courses they take. This policy simulation investigates the effects of requiring students to take specific high school courses based on their test scores and prior grades, and how it would impact students' educational attainment and labor market outcomes.

To run this simulation, I separate students in the sample into three tracks at the beginning of 9th grade – an academic track, a general education track, and a vocational track – based on the test score they received when the ELS:2002 survey was first administered in 2002. I assign students with the lowest third of test scores to the vocational track, students with middle third of test scores to the general education track, and students with the highest third of test scores to the academic track, to match the percentages in each type of German 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 or trade vocational courses. 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.[57]

The results of this simulation are presented in Column 4 of Tables 7.1 and 7.2. The policy pushes many students to take academic or vocational courses in high school who otherwise would have chosen general education courses, leading to a substantial increase in the percentage of students who graduate with academic (from 22.8% to 31.0% of U.S. high school students) and vocational concentrations (from 8.4% to 20.3% of U.S. high school students). However, due to restricted high school options, many more students decide not to finish high school and instead complete GEDs (from 3.5% to 13.0% of U.S. high school students). 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

[57] 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 difficult for students who graduate from Realschule and Hauptschule to attend four-year universities (though not impossible) relative to students who graduate from Gymnasium. A question of future work involves incorporating 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.

an overall slight decrease in the percent of individuals who attain bachelor's degrees (by -0.4 percentage points). 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 (0.4 percentage points) and skilled non-manual labor occupations (1.1 percentage points).

Overall, individuals who are forced onto academic and vocational tracks, who otherwise would have concentrated in the general education field, realize better labor market outcomes conditional on completing 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 general education courses had they been available. Students who do not complete high school degrees and instead complete GEDs realize lower non-pecuniary utility in high school, worse PSE outcomes, and worse labor market outcomes then they would have received if they had been able to choose their own high school curriculum. Overall, the simulation predicts that this policy would lead to slightly higher average labor market log wages (2.4%) and later life utility (2.2%) among individuals who change their behavior, with benefits concentrated among non-GED high school graduates, which would be more than offset by a sharp decrease in average early life utility (-2.8%) among individuals who change their behavior.

7.4 Free Community College

The final policy simulation investigates the effects of providing free community college for all United States high school graduates. A version of this policy was proposed by President Barack Obama in 2015 and, more recently, several presidential candidates including Senator Bernie Sanders, Senator Hillary Clinton, and Vice-President Joe Biden (Obama, 2015; Sanders, 2016; Clinton, 2016; Biden, 2020).[58] To conduct this simulation I decrease the cost of attending community college in the model by the average cost of a year of community college in 2004 ($2,700). Practically, I convert this yearly cost into a log hourly cost for someone who works a normal 40-hour workweek. Then, I multiply this value by my estimate for φ (1.37), the parameter

[58] Bernie Sanders and Hillary Clinton 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. 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.

that relates pecuniary wage utility to non-pecuniary utility in the model. Finally, I add this value to the total utility an individual receives from attending community college each year.

While the monetary cost of community college is the same for all individuals, the non-pecuniary utility associated with this cost is likely higher for poorer students than for richer students due to the diminishing marginal utility of wealth. To incorporate this difference, I vary the reduction in the non-pecuniary cost of community college across individuals based on their reported socio-economic status. For the simulation presented here, the individual with the highest socio-economic status in the sample receives no additional non-pecuniary utility from attending community college while the individual with the lowest socio-economic status in the sample receives twice the average non-pecuniary cost-savings when attending community college.[59]

The results of this simulation are presented in Column 5 of Tables 7.1 and 7.2. Decreasing the cost of community college causes many more individuals to graduate from community college (from 11.7% to 27.0% of U.S. students) as well as more individuals to concentrate in general education courses in high school (from 44.9% to 46.0% of U.S. students) – as completing a high school general education curriculum improves the utility of attending community college – at the expense of taking academic courses in high school. In addition, fewer individuals drop out of high school and have no high school degree by age 26 (from 4.9% to 4.2% of U.S. students) as high school graduation is required to attend community college.

Next, the simulation predicts that fewer individuals will graduate from four-year universities by the age of 26 (-3.4% percentage points), as some individuals now choose to attend community college instead of a four-year university. However, note that this estimate is affected by the assumption in the model that community college credits are not transferable to four-year universities. In reality, many community college credits are transferable 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 a weak assumption that the 20% transfer rate would remain constant under this policy, the simulation predicts a small net increase in the percent of individuals who graduate from four-year universities (0.7 percentage points).

Overall, the simulation predicts an increase in average welfare (by 0.8%) in the population.

---

[59] 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 involves incorporating 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.

However, this estimate does not take into account the costs of the policy. Under an assumption that these costs are bourn equally by every individual in the population this policy would decrease average welfare. Under an assumption that the costs are disproportionately bourn by individuals with the highest socio-economic statuses in the population, who have the lowest marginal utilities of wealth, this policy could increase average welfare in the population even after accounting for cost. The extent of this increase (or decrease) in welfare, however, depends on one's assumptions about relative social marginal welfare across individuals of different socio-economic status.

8. Conclusion

This work suggests that a high school trade vocational curriculum is very beneficial for a student's later labor market wages and chances of being employed in a skilled occupation relative to a general education curriculum. The benefits of a high school business vocational curriculum, relative to a general education curriculum, are instead concentrated in skilled non-manual labor occupations which provide higher non-pecuniary utility and lower wages relative to other occupations. In addition, the work suggests that concentrating in a vocational high school curricula modestly decreases a student's propensity to attend four-year PSE institutions, but that additional high school vocational and academic opportunities decrease a student's high school dropout propensity, particularly for the one-third of students at high risk of dropping out.

Policy simulations predict that improving the quality of high school vocational education (by incorporating vocational certifications into vocational curricula) will provide greater labor market benefits for students than increasing the availability of high school vocational education options. They also predict that a high school tracking system that pushes more individuals to take academic and vocational courses will improve the labor market outcomes of high school graduates at the expense of their non-pecuniary utility, while increasing the percent of students who drop-out of high school. Finally, simulations predict that providing free community college for all U.S. high school graduates will increase the number of students graduating from community college, increase the number of students who take general education courses in high school, and slightly increase the number of students who graduate from four-year universities (due to community college transfer students). Considering the cost, the overall effect of this policy on social welfare depends on one's assumptions about who bears the cost and relative social marginal welfare.

Building upon this work, a pertinent areas of 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 Longitudinal Study of the High School Class of 1972, High School and Beyond, and the National Education Longitudinal Study of 1988) and the one panel data set conducted subsequently (the High School Longitudinal Study of 2009). Estimating the model across these alternative decade data sets would provide context on whether, and how, the returns to high school vocational education have changed over time in the United States. Estimating the model across these alternative data sets would also provide context about how well the model can fit out-of-sample data across time periods, and the extent to which it can be used, today, to predict the returns of high school vocational education in future decades.

References

Agodini, Roberto and John Deke, 2004. *The Relationship Between High School Vocational Education and Dropping Out.* Princeton, NJ: Mathematica Policy Research.

Arum, Richard and Yossi Shavit, 1995. "Secondary Vocational Education and the Transition from School to Work." *Sociology of Education* 68: 187-204.

Berkovec, James and Steven Stern, 1991. "Job Exit Behavior of Older Men." *Econometrica* 59(1): 189-210.

Berndt, Ernst, Bronwyn Hall, Robert Hall, and Jerry Hausman, 1974. "Estimation and Inference in Nonlinear Structural Models." *Annals of Economic and Social Measurement* 3: 653–665.

Biden, Joe, 2019. "The Biden Plan for Education Beyond High School." *https://joebiden.com/beyondhs/*, retrieved Jan 26, 2020.

Bishop, John H. and Ferran Mane, 2004. "The Impacts of Career-Technical Education on High School Labor Market Success." *Economics of Education Review* 23: 381-402.

Borsch-Supan, Axel and Vassilis Hajivassiliou, 1993. "Smooth Unbiased Multivariate Probability Simulators for Maximum Likelihood Estimation of Limited Depended Variable Models." *Journal of Econometrics* 58: 347-368.

Bozick, Robert and Benjamin Dalton, 2013. "Career and Technical Education and Academic Progress at the End of High School: Evidence from the Education Longitudinal Study of 2002." Research Triangle Park, NC: RTI International.

Bureau of Labor Statistics, 2019. "College Enrollment and Work Activity of Recent High School and College Graduates – 2018." Bureau of Labor Statistics Economic News Release, April 25, 2019.

Card, David, 1995. "Using Geographic Variation in College Proximity to Estimate the Return to Schooling." *Aspects of Labor Market Behaviour: Essays in Honour of John Vanderkamp*. Toronto: University of Toronto Press.

Castellano, Marisa, James R. Stone III, and Sam Stringfield, 2005. "Earning Industry Recognized Credentials in High School: Exploring Research and Policy Issues." *Journal of Career and Technical Education* 21(2): 7-34.

Chan, Marc K., 2013. "A Dynamic Model of Welfare Reform." *Econometrica* 81: 941-1001.

Clinton, Hillary, 2016. "Making college debt-free and taking on student debt." *https://www.hillaryclint on.com/issues/college/*, retrieved October 13, 2016.

Council of Economic Advisors, 2010. "2010 Economic Report of the President." Washington, D.C.

Current Population Survey, U.S. Census Bureau, 2012. "2012 Annual Social and Economic Supplement." Washington, D.C.

Curtin, Thomas R., Steven J. Ingels, Shiying Wu, Ruth Heuer, and Jeffrey Owings, 2002. *Base-year to fourth follow-up data file user's manual*. Washington, DC: National Center for Education Statistics.

Dougherty, Shaun M., 2018. "The Effect of Career and Technical Education on Human Capital Accumulation: Causal Evidence from Massachusetts." *Education Finance and Policy* 13(2):

119-148.
Davis, Tracy and Kaitlin Obenauf, 2011. "Participation in Vocational Education and Its Effects on Labor Market Earnings." Presented at the 2011 Conference for the Association for Education Finance and Policy.
Diermeier, Daniel, Michael Keane, and Antonio Merlo, 2005. "A Political Economy Model of Congressional Careers." *American Economic Review* 95, 347–373.
Duflo, Esther, Rema Hanna, and Stephen Ryan, 2011. "Incentives Work: Getting Teachers to Come to School," *American Economic Review* 102(4): 1241-1278.
Eckstein, Zvi and Kenneth I. Wolpin, 1999. "Why Youths Drop Out of High School: The Impact of Preferences, Opportunities, and Abilities." *Econometrica* 67(6): 1295-1339.
Education Commission of the States, 2013. "School Attendance Age Limits." *http://www.ecs.org/clearinghouse/01/07/04/10704.pdf*, retrieved October 13, 2016.
Education Commission of the States, 2015. "Free and Compulsory School Age Requirements in the United States" *http://www.ecs.org/clearinghouse/01/18/68/11868.pdf*, retrieved October 14, 2016.
Erikson, Robert, John Goldthorpe, and Lucianne Portocarero, 1979. "Intergenerational Class Mobility in Three Western European Societies: England, France, and Sweden." *British Journal of Sociology* 30: 415-430.
Flood, Sarah, Miriam King, Steven Ruggles, and J. Robert Warren, 2015. Integrated Public Use Microdata Series, Current Population Survey: Version 4.0. [Machine-readable database]. Minneapolis: University of Minnesota.
Francesconi, Marco, 2002. "A joint dynamic model of fertility and work of married women." *Journal of Labor Economics* 20, 336–380.
Geweke, John, 1988. "Antithetic Acceleration of Monte Carlo Integration in Bayesian Inference." *Journal of Econometrics* 38, 73-89.
Heckman, James J., 1979. "Sample Selection Bias as a Specification Error." *Econometrica* 47(1): 153–162.
Hossler, Don, Doug Shapiro, Afet Dundar, Mary Ziskin, Jin Chen, Desiree Zerquera, and Vasti Torres, 2012. "Transfer & Mobility: A National View of Predegree Student Movement in Postsecondary Institutions." National Student Clearinghouse Research Center and Project on Academic Success, Indiana University.
Hotchkiss, Lawrence and Linda Dorsten, 1987. "Curriculum Effects on Early Post-High School Outcomes." *Research in the Sociology of Education and Socialization* 7: 191-219.
Independent Advisory Panel of the National Assessment of Career and Technical Education, 2014. "Putting "Career" in "College and Career Ready": The Report of the Independent Advisory Panel of the National Assessment of Career and Technical Education." Washington, DC.
Kaboski, Joseph and Robert M. Townsend, 2011. "A Structural Evaluation of a Large-Scale Quasi-Experimental Microfinance Initiative." *Econometrica* 79(5): 1357-1406.
Keane, Michael P. and Kenneth I. Wolpin, 1997. "The Career Decisions of Young Men." *The Journal of Political Economy* 105(3): 473-522.

Kreisman, Daniel and Kevin Stange. 2020. "Vocational and Career Tech Education in American High Schools: The Value of Depth Over Breadth." *Education Finance and Policy* 15(1): 11-44.

LaForest, Michael, 2019. "Data Appendix for The Effects of High School Career and Technical Education for Non-College Bound Students." *https://michaellaforest.github.io/CTE_Data_Appendix.pdf,* retrieved March 14th, 2019.

Lareau, Annette, 2011. "*Unequal Childhoods: Class, Race, and Family Life*." Berkeley, CA: University of California Press.

Levesque, Karen, Jennifer Laird, Elisabeth Hensley, Susan P. Choy, Emily F. Cataldi, and Lisa Hudson, 2008. "Career and Technical Education in the United States: 1990–2005." (NCES 2008-035). Washington, DC: National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education.

Mane, Ferran, 1999. "Trends in the Payoff to Academic and Occupation-Specific Skills: the Short and Medium-Run Returns to Academic and Vocational High School Courses for Non-College Bound Students." *Economics of Education Review* 18: 417–437.

Meer, Jonathan, 2007. "Evidence on the Returns to Secondary Vocational Education." *Economics of Education Review* 26: 559-573.

Meyer, Robert and David Wise, 1982. "High School Preparation and Early Labor Force Experience." Pg. 277-339 in *The Youth Labor Market Problem: Its Nature, Causes, and Consequences*, edited by Richard Freeman and David Wise. Chicago: University of Chicago Press.

Monaghan, David B. and Paul Attewell, 2014. "The Community College Route to the Bachelor's Degree." *Educational Evaluation and Policy Analysis*, published online March 18, 2014; doi: 10.3102/ 0162373714521865

National Center for Education Statistics, U.S. Department of Education, 2002. "Private School Universe Survey." *https://nces.ed.gov/surveys/pss/tables.asp*, retrieved November 4, 2016.

National Center for Education Statistics, U.S. Department of Education, 2015. "The Condition of Education 2015." NCES 2011-144, released May 2015.

National Center for Education Statistics, U.S. Department of Education, 2016. "High School Transcript Studies - CSSC Courses/Course Codes." *https://nces.ed.gov/surveys/hst/course s.asp*, retrieved March 4, 2016.

Neal, Derek, 1999. "The Complexity of Job Mobility among Young Men." *Journal of Labor Economics* 17(2): 237-261.

Obama, Barack, 2015. "Remarks by the President in State of the Union Address, January 20, 2015." Office of the Press Secretary, The White House. *https://www.whitehouse.gov/the-press-office/2015/01/20/remarks-president-state-union-address-january-20-2015*, retrieved September 4th, 2015.

Pavan, Ronni, 2010. "The Role of Career Choice in Understanding Job Mobility" *Review of Labour Economics and Industrial Relations* 24(2): 107-127.

Sanders, Bernie, 2016. "It's Time to Make College Tuition Free and Debt Free." *https://berniesanders.com/issues/its-time-to-make-college-tuition-free-and-debt-free/*, retrieved Oct 13, 2016.

Silverberg, Marsha, Elizabeth Warner, Michael Fong, and David Goodwin, 2004. “National Assessment of Vocational Education (NAVE).” Washington, DC: Policy and Program Studies Service, Office of Under Secretary, U.S. Department of Education.

Stromback, Thorsten, 2010. “Earnings, Schooling and Vocational Education and Training.” *Australian Journal of Labour Economics* 13(3): 241-263.

Sullivan, Paul, 2010. “A Dynamic Analysis of Educational Attainment, Occupational Choices, and Job Search.” *International Economic Review* 51: 289–317.

Todd, Petra and Kenneth I. Wolpin, 2006. “Assessing the Impact of a School Subsidy Program in Mexico: Using a Social Experiment to Validate a Behavioral Model of Child Schooling and Fertility.” *American Economic Review* 96(5): 1384-1417.

Todd, Petra and Kenneth I. Wolpin, 2010. “Structural Estimation and Policy Evaluation in Developing Countries,” *Annual Review of Economics* 2: 21-50.

Topel, Robert, and Michael Ward, 1992. ‘‘Job Mobility and the Careers of Young Men.’’ *Quarterly Journal of Economics* 107(2): 439–479.

Train, Kenneth E., 2003. “*Discrete Choice Methods with Simulation*,” New York, NY: Cambridge University Press.

U.S. Census Bureau, 2000. “Census of Population and Housing, 2000.” Washington, D.C.

U.S. Department of Education, Office of Planning, Evaluation and Policy Development, Policy and Program Studies Service, 2013. “National Assessment of Career and Technical Education: Interim Report.” Washington, D.C.

Figure 1: Individual Choices

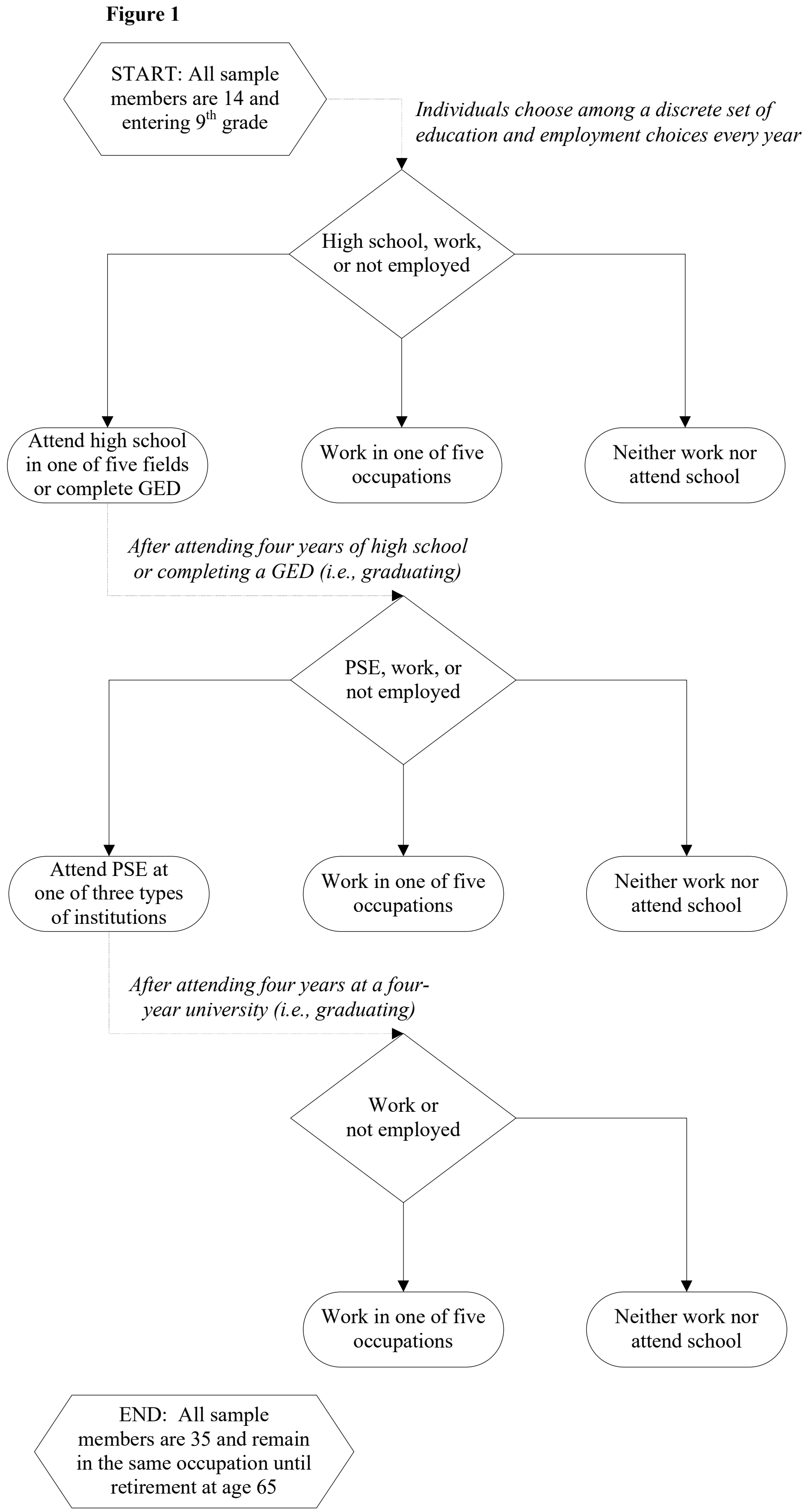

Table 4.1: Student Characteristics

Variable	Mean	Std Dev	2000 U.S. HS Pop Avg
Male	0.50	0.50	0.52
Black	0.13	0.34	0.15
Hispanic	0.15	0.36	0.15
Other Race	0.16	0.36	0.15
Midwest	0.25	0.43	0.23
South	0.36	0.48	0.35
West	0.20	0.40	0.23
Suburban	0.48	0.50	0.51
Rural	0.18	0.39	0.21
Catholic School	0.12	0.33	0.05
Private School	0.09	0.29	0.04
Socio-Economic Status	0	1	--
Test Score	0	1	--

Notes:

1) Baseline options are as follows: Race - White; Region - Northeast; Urbanicity - Urban; School - Public.

2) Population averages for gender, race, region, and urbanicity are from the U.S. Census Bureau (2000) over all individuals in the U.S. in the year 2000 aged 15-17, 14-17, 5-17, and all ages respectively. Population averages for public versus private secondary school enrollment in the year 2000 are from the National Center 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).

3) Total # observations is 16,200 for all variables except Test Score, for which total # observations is 15,890. Sample sizes are rounded to the nearest ten to comply with secure data disclosure requirements.

4) 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 first administered in 2002. The range of both variables were readjusted to have a mean of zero and a standard deviation of one.

5) Other Race is a composite variable comprised of Asian individuals, Native American individuals, and individuals of more than one race.

Table 4.2: School Characteristics

Variable	Mean	Std Dev	# Obs
A. High School Curricula Instruments			
Voc Taught in High School	0.35	0.48	15,450
Voc Taught in Area School	0.07	0.25	15,450
Voc Taught in Both HS & Area Sch	0.31	0.46	15,450
Marketing Courses Taught On-Site	0.58	0.49	10,310
Marketing Courses Taught at Area Sch	0.12	0.32	10,310
Precisions Courses Taught On-Site	0.61	0.49	10,150
Precisions Courses Taught at Area Sch	0.22	0.41	10,150
# Vocational Teachers per 100 Students	0.52	0.59	12,370
Career Pathways Prog Available	0.74	0.44	11,010
Admission Based on Geography	0.74	0.44	11,790
Student Infl on Course Selection (0-3 Scale)	2.52	0.71	11,090
% Students Take Academic Courses	0.65	0.31	10,260
% Students Take Vocational Courses	0.17	0.19	7,460
% Students Free or Reduced Price Lunch	0.24	0.25	15,690
% Prev Students Enter Labor Market (0-5 Scale)	1.54	0.92	11,360
GED Confered by High School	0.12	0.32	11,650
2. High School PSE Enrollment Instruments			
Academic Counseling Available	0.96	0.20	13,680
% Students Attend College Fairs	0.15	0.14	10,940
% Students in College App Prog (0-5 Scale)	3.57	1.58	11,030
% Prev Students Attend 4yr College (0-5 Scale)	3.59	1.16	11,490
% Prev Students Attend 2yr College (0-5 Scale)	2.33	0.98	11,400

Notes:

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

2) "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). "% Prev Students Enter Labor Market", "% Prev Students Attend 4yr College", and "% Prev Students Attend 2yr College", 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).

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

Table 4.3: Local Labor Market Characteristics

Variable	Mean	Std Dev
Unemployment Rate	0.04	0.02
(ln) Average Hr Wage	2.93	0.25
% Professional Industry	0.07	0.03
% Manual Labor Industry	0.23	0.07
% Non-Manual Labor Industry	0.24	0.04

Notes:

1) Baseline options are as follows: Industry - Other.

2) Total # observations is 16,200 for all variables. Sample sizes are rounded to the nearest ten to comply with secure data disclosure requirements.

3) 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 average hourly wage and logged.

4) 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. Additional details about local labor market variable construction rules are available in Section C.1 of LaForest (2017).

Table 4.4: Log Hourly Wages

Variable	Mean	Std Dev	# Obs
(ln) Professional Hr Wage	2.67	0.49	6,310
(ln) Skilled Manual Labor Hr Wage	2.43	0.44	5,870
(ln) Skilled Non-Manual Labor Hr Wage	2.30	0.41	7,120
(ln) Skilled Other Hr Wage	2.50	0.46	1,140
(ln) Unskilled Hr Wage	2.07	0.36	2,290

Notes:

1) Each observation is an individual-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 logged.

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

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.

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.

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. HS Curriculum and/or PSE attainment is unknown for 3,620 sample members.

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

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) Total # observations is 10,330. HS Curriculum and/or 2012 employment is unknown for 5,870 sample members.

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

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 aggregate top to bottom.

2) Total # observations is 16,200.

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

Table 6.1: HS Curricula on Labor Market Outcomes (Age 26)

	Wages (w/o instruments)		Wages		Employed		Skilled Occupation	
Variable	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Prob Academic	**0.13** ***	*(.01)*	-0.02	*(.07)*	-0.81	*(.55)*	0.12	*(.56)*
Prob Business Vocational	**0.06** ***	*(.02)*	**-0.45** **	*(.21)*	0.74	*(1.38)*	1.29	*(1.78)*
Prob Trade Vocational	**0.06** **	*(.02)*	**0.34** ***	*(.12)*	0.77	*(.83)*	**3.03** ***	*(1.04)*
Prob Other Curriculum	-0.01	*(.02)*	0.01	*(.11)*	**-2.55** ***	*(.69)*	-0.45	*(.86)*
Prob GED	**-0.08** ***	*(.02)*	0.12	*(.20)*	-0.40	*(1.28)*	-0.19	*(1.35)*
Prob HS Dropout	**-0.17** ***	*(.02)*	**-0.23** ***	*(.08)*	**-1.92** ***	*(.55)*	-0.52	*(.68)*
Prob 1-yr Trade School	-	-	**-0.45** *	*(.23)*	2.51	*(1.64)*	-0.88	*(1.94)*
Prob 2-yr Community College	-	-	0.00	*(.21)*	2.28	*(1.42)*	**-3.57** **	*(1.74)*
Prob 4-yr University	-	-	**0.32** ***	*(.09)*	**2.33** ***	*(.69)*	1.26	*(.81)*
Male	**0.08** ***	*(.01)*	**0.06** ***	*(.01)*	**0.91** ***	*(.12)*	0.18	*(.14)*
Black	**-0.08** ***	*(.01)*	**-0.07** ***	*(.02)*	0.15	*(.12)*	0.15	*(.14)*
Hispanic	-0.01	*(.01)*	-0.01	*(.02)*	**0.24** **	*(.12)*	0.18	*(.13)*
Other Race	0.02	*(.01)*	0.01	*(.02)*	**-0.18** *	*(.11)*	-0.18	*(.13)*
Socio-Economic Status	**0.04** ***	*(.01)*	0.01	*(.01)*	-0.01	*(.06)*	-0.08	*(.07)*
Testscore	**0.07** ***	*(.01)*	**0.03** **	*(.01)*	0.09	*(.09)*	0.10	*(.11)*
Midwest	**-0.07** ***	*(.02)*	**-0.06** ***	*(.02)*	**0.33** **	*(.13)*	-0.05	*(.15)*
South	**-0.08** ***	*(.02)*	**-0.06** ***	*(.02)*	0.08	*(.11)*	-0.17	*(.14)*
West	-0.03	*(.02)*	-0.02	*(.02)*	-0.03	*(.14)*	-0.01	*(.16)*
Suburban	**0.03** **	*(.01)*	**0.03** **	*(.01)*	0.07	*(.08)*	0.03	*(.10)*
Rural	**0.03** *	*(.02)*	**0.03** *	*(.02)*	0.09	*(.11)*	0.23	*(.15)*
Catholic School	**0.08** ***	*(.02)*	**0.05** **	*(.02)*	-0.14	*(.19)*	0.09	*(.20)*
Non-Catholic Private School	**0.07** ***	*(.02)*	0.02	*(.02)*	**-0.81** ***	*(.17)*	**0.52** **	*(.23)*
Unemployment Rate	0.22	*(.34)*	0.16	*(.36)*	-1.60	*(2.63)*	0.86	*(2.46)*
(ln) Average Hourly Wage	**0.07** *	*(.04)*	**0.08** **	*(.04)*	**-0.49** **	*(.24)*	0.24	*(.28)*
% Professional Employment	**0.61** **	*(.28)*	0.37	*(.29)*	**3.78** *	*(2.11)*	-0.10	*(2.04)*
% Manual Labor Employment	0.09	*(.09)*	0.12	*(.10)*	**-1.72** ***	*(.62)*	**1.26** *	*(.73)*
% Non-Manual Labor Employment	0.02	*(.14)*	0.06	*(.14)*	0.17	*(1.02)*	**2.07** *	*(1.21)*
Constant	**2.17** ***	*(.11)*	**2.12** ***	*(.12)*	**2.77** ***	*(.83)*	0.65	*(1.01)*

Notes:

1) Column 1 presents Ordinary Least Squares (OLS) regression estimates of log hourly wage on high school curriculum, without instruments. Columns 2-4 present regression estimates of log hourly wages (OLS), employment (logit - employed (1) vs not employed (0)), and skilled employment (logit - employed in skilled occupation (1) vs employed in unskilled occupation (0), conditional on working) on high school predicted probabilities and PSE predicted probabilities from two separate first stage regressions. See Table 4.3 for the list of instruments and Tables E.1 and E.2 of the online appendix (LaForest, 2019) for first stage regression results.

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 and 2, 12,100 for regression 3, and 10,590 for regression 4.

Table 6.2: 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 Capital	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).

Table 6.3: Selected PSE Structural Parameters

Variable	2-yr CC Estimate		2-yr CC *SE*	4-yr University Estimate		4-yr University *SE*
1. Previous Education						
Academic	-0.66	***	*(.042)*	0.43	***	*(.034)*
Business Vocational	0.14	**	*(.058)*	-0.09	*	*(.042)*
Trade Vocational	0.14	*	*(.068)*	-0.09	*	*(.048)*
Other Curriculum	0.03		*(.043)*	0.06	*	*(.030)*
GED	-0.20	**	*(.089)*	-0.58	***	*(.064)*
2. Personal Characteristics						
Male	0.08	**	*(.037)*	-1.09	***	*(.041)*
Black	0.09	*	*(.054)*	2.12	***	*(.051)*
Hispanic	-0.04		*(.049)*	0.61	***	*(.050)*
Other Race	-0.09	*	*(.046)*	1.94	***	*(.052)*
Socio-Economic Status	0.45	***	*(.019)*	2.15	***	*(.022)*
Testscore	0.64	***	*(.021)*	3.31	***	*(.024)*
Constant	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).

Table 6.4: 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).

Table 6.5: 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) Parameter estimates are for type-two individuals. Parameters for type-one individuals are normalized to zero in the model.

2) The estimate for the percentage of the population with type-two unobserved heterogeneity is 34.3%.

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

4) Total # Observations is 16,200.

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

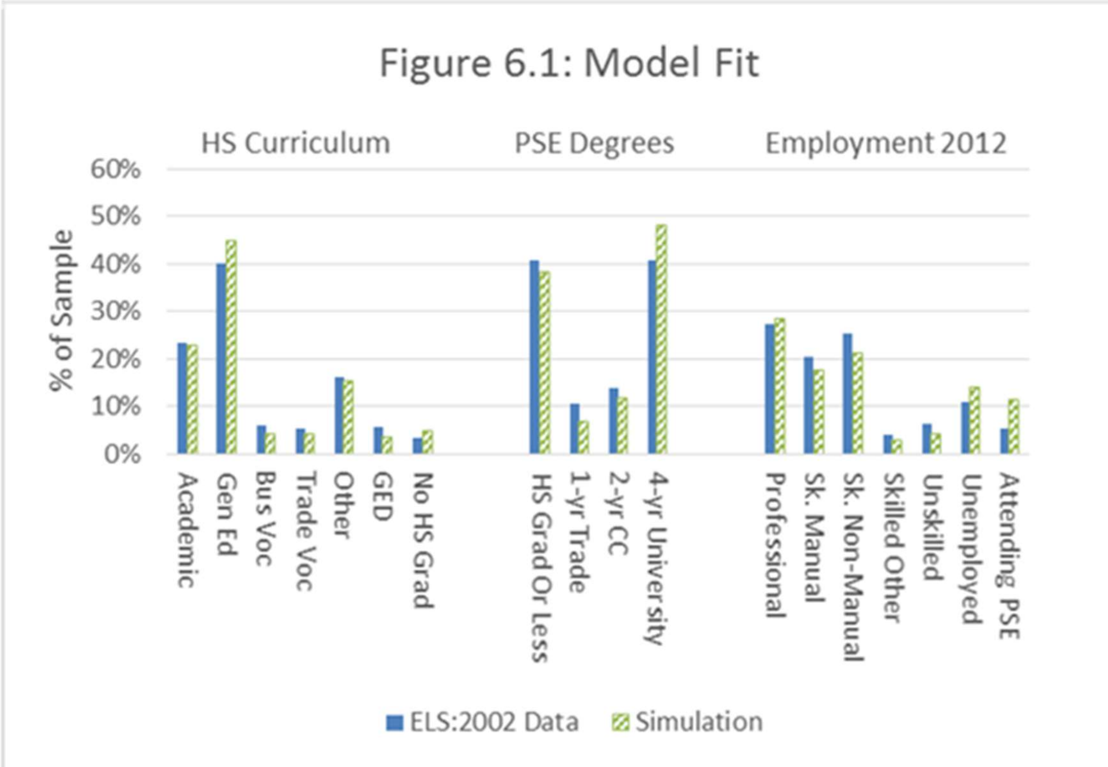
Figure 6.1: Model Fit
HS Curriculum
PSE Degrees
Employment 2012
60%
50%
40%
30%
20%
10%
0%
% of Sample
Academic
Gen Ed
Bus Voc
Trade Voc
Other
GED
No HS Grad
HS Grad Or Less
1-yr Trade
2-yr CC
4-yr University
Professional
Sk. Manual
Sk. Non-Manual
Skilled Other
Unskilled
Unemployed
Attending PSE
ELS:2002 Data
Simulation

Table 7.1: Policy Simulation Choice Outcomes

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

Notes:

1) Column (1) displays simulated outcomes, as population percentages, given the model, structural parameters, and initial conditions in the ELS:2002 data set. Columns (2-5) display the percentage point 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, and 7.4 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.

Table 7.2: Policy Simulation Wage and Utility Outcomes

Variable	Simulation No Policies	Voc In Every School	HS Voc Certification	HS Tracking	Free CC
Wages 2012					
Average (ln) Hourly Wage	2.42	1.8%	9.1%	2.4%	-3.7%
Lifetime Utility					
Realized Utility Ages 16-26	104.7	0.1%	-0.4%	-2.8%	0.9%
Expected Utility Ages 27+	45.3	2.0%	8.4%	2.2%	0.4%
# Changed Observations					
# Observations Average (ln) Hourly Wage		630	2,560	6,530	2,150
# Observations Realized Utility Ages 16-26		4,350	4,480	11,770	10,480
# Observations Expected Utility Ages 27+		890	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 (2-5) display the percent difference between the baseline simulation in column (1) and the average simulated outcomes for the four policy simulations discussed in sections 7.1, 7.2, 7.3, and 7.4, respectively, among individuals whose outcome value changed between the baseline outcome and simulated outcome, and in the case of wages conditional 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.