Web Appendix for An Empirical Investigation of the Option Value of College Enrollment

By KEVIN M. STANGE*

This web appendix provides supplementary materials for "An Empirical Investigation of the Option Value of College Enrollment," including more detail about dataset construction, model solution, model alternatives, and model fit.

A. DATASET CONSTRUCTION

The dataset used in estimation and simulation was constructed from several sources. Table A1 provides an overview of the main variables used in the analysis. The sample of individuals comes from the National Educational Longitudinal Study (NELS). The NELS is a longitudinal survey of a representative sample of U.S. 8th graders in 1988. Interviews were conducted in 1988, 1990, 1992, 1994, and 2000 and complete college transcripts were obtained for most individuals in 2000. The core schooling outcome variables, including yearly grade point average and indicators for enrollment were constructed directly from the college transcripts. The transcripts consist of course-specific records, including student ID, college IPEDS ID number, subject, month and year, credits, letter grade, and standardized numeric grade on a four-point scale. Course-level records were aggregated up to the student x college x term level to identify the primary school enrolled in, and then to the student x year level. The final transcript data contains student x year records of credits attempted, credits earned, grade point average, and several other variables. Individuals were considered enrolled during academic year t if they attempted at least six course credits (the traditional definition of part-time enrollment) at a two- or four-year college during both the Fall and Spring semesters of year t.[1] The model describes college dropout, so I categorize people according to their number of years of continuous enrollment. Students who "stop-out," but eventually return and possibly graduate are grouped with students who dropout permanently in the same year. From the 1992 NELS surveys I utilize high school grade point average, standardized test scores, parents' highest education level, and family income during high school. I convert NELS senior year test scores into AFQT percentile scores using the cross-walk developed by RAND researchers in M. Rebecca Kilburn, Lawrence M. Hanser, and Jacob A. Klerman (1998).

* Stange: Ford School of Public Policy, University of Michigan, 735 S. State Street #5236, Ann Arbor, MI, 48109-3091, kstange@umich.edu.

[1]Enrollment at private (for-profit or non-profit) two-year colleges, for-profit four-year colleges, or less than two-year schools were counted as non-enrollment.

TABLE A1—VARIABLE DESCRIPTIONS AND SOURCES

Variable	Description	Source
high school gpa	Cumulative grade point average in high school on 4.0 scale	NELS.
afqt score	Armed Forces Qualifying Test percentile score	Constructed from NELS test score variables using method developed by RAND (see text).
parent education	Years of school attended by most educated parent	NELS.
parent has ba	Indicator for whether at least one parent earned a BA degree	NELS. Constructed from pareduc variable.
low income family	Indicator for whether family income during high school was below $35,000 (approximately the median)	NELS. Constructed from faminc variable.
urban	Attended urban high school	NELS. Constructed from phsurban variable.
region northeast	High school in Northeast	NELS. NLSY categorization.
region northcentral	High school in Northcentral	NELS. NLSY categorization.
region south	High school in South	NELS. NLSY categorization.
region west	High school in West	NELS. NLSY categorization.
white	Ethnicity white	NELS
black	Ethnicity black	NELS
latino	Ethnicity latino	NELS
distance to 2year	Distance from high school to nearest public two-year college.	Computed from lat/long coordinates of high school (NELS) and each public 2-year college in state (IPEDS)
distance to 4year	Distance from high school to nearest public four-year college.	Computed from lat/long coordinates of high school (NELS) and all public 4-year college in state (IPEDS)
tuition at public 2year	Average tuition ($1992) of public two-year colleges in high school state	IPEDS
tuition at public 4year	Average tuition ($1992) of public four-year colleges in high school state	IPEDS
income1	Expected present discounted value of lifetime income if do not enter college in first year after high school. (thousands of $1992)	Estimated using out-of-sample prediction from NLSY (see text).
income2	Expected present discounted value of lifetime income if exit college after first year (thousands of $1992)	Estimated using out-of-sample prediction from NLSY (see text).
income3	Expected present discounted value of lifetime income if exit college after second year (thousands of $1992)	Estimated using out-of-sample prediction from NLSY (see text).
income4	Expected present discounted value of lifetime income if exit college after third year (thousands of $1992)	Estimated using out-of-sample prediction from NLSY (see text).
income5	Expected present discounted value of lifetime income if complete four years of college (thousands of $1992)	Estimated using out-of-sample prediction from NLSY (see text).
gpa(t)	Grade point average during year (t) of college	Computed from NELS college transcripts for all courses taken for credit (including failures).
enroll(t)	Indicator for enrollment in college during year (t)	Computed from NELS college transcripts. Individual must have attempted at least six units of college credit (approx part-time) in each semester during year (t).
contenroll	Years of continuous enrollment in college after high school graduation.	Constructed from enroll(t).
fouryear(t)	Indicator for enrollment in four-year college during year (t)	Constructed from enroll(t) and college type from IPEDS. Equals one if enroll(t) = 1 and enrolled in a four-year school in either semester
twoyear(t)	Indicator for enrollment in two-year college during year (t)	Constructed from enroll(t) and fouryear(t)

I supplemented the NELS dataset with institutional characteristics obtained from the Department of Education's 1992 Integrated Postsecondary Education Data System (IPEDS) Institutional Characteristics survey. IPEDS surveys the universe of public and private two- and four-year colleges in the United States. From the IPEDS, I calculated average tuition levels at public two-year and four-year colleges in each state and merged this data onto the NELS. Latitude/longitude coordinates were then assigned to each college in IPEDS and high school in the NELS by zip code from the US Census 1990 Gazetteer Files (http://www.census.gov/geo/www/gazetteer/gazette.html). From this, I calculated distance from each NELS high school to the nearest public two-year and four-year college (in miles). Table A2I displays summary statistics.

One limitation of the NELS dataset is that respondents are relatively young (approximately 26 years old) at the time of the final survey year. Income at this age is a poor indicator of ultimate lifetime income due to job instability, graduate school attendance, and the steep return to initial labor market experience. I instead estimate individuals' expectation of lifetime income using data from an earlier cohort. This procedure is described in the next section.

I restrict the dataset to on-time high school graduates with complete information on key baseline variables and complete college transcripts (unless no claim of college attendance). I also exclude residents of Alaska, Hawaii, and the District of Columbia. From the initial 5,782 men in the NELS, these restrictions eliminate the following number of observations: not 1992 high school graduate (1,068), incomplete transcripts (314), high school missing or in AK/DC/HI (62), missing high school GPA (1,078), missing AFQT (408), missing parent education (193), missing family income (170), missing distance to nearest colleges (412, mostly private high schools for which address is not available), missing college GPA if enrolled (13). After these restrictions the final dataset contains 2,055 men. Though these restrictions reduce the sample considerably, the final unweighted analysis sample is very similar to a nationally representative sample of U.S. high school graduates. Panel A in Table A3 compares the analysis sample to the full NELS sample of 1992 high school graduates and 12th graders (weighted and unweighted). The unweighted analysis sample is generally very similar to the full representative sample, thus my results can be generalized to all U.S. high school graduates from 1992.

B. Estimating Conditional Income Expectations

Expectations of lifetime income under different schooling outcomes are a key factor in educational choices. One limitation of the NELS dataset is that respondents are relatively young (approximately 26 years old) at the time of the final survey year. Since income at this age may be a poor indicator of ultimate lifetime income, I do not estimate expectations using individual's actual labor market outcomes. Instead I estimate individuals' expectation of lifetime income using data from a cohort about 12 years earlier, the National Longitudinal Survey of Youth 1979 (NLSY79). This approach assumes students form "reference group expectations" referred to by Manski (1991).

The NLSY79 is a Department of Labor longitudinal survey of 12,686 men and women

TABLE A2—SUMMARY STATISTICS

Variable	Mean	Standard Deviation	Min	Max
Baseline variables				
high school gpa	2.70	0.68	0.14	4.00
afqt score	46.7	26.9	1	99
parent education (years)	14.2	2.2	10	19
parent has ba	0.28	0.45	0	1
low income family	0.55	0.50	0	1
urban	0.62	0.49	0	1
region northeast	0.16	0.37	0	1
region northcentral	0.31	0.46	0	1
region south	0.32	0.47	0	1
region west	0.20	0.40	0	1
white	0.73	0.45	0	1
black	0.08	0.28	0	1
latino	0.11	0.31	0	1
distance to 2year	15.5	20.5	0	162
distance to 4year	24.0	26.9	0	234
tuition at public 2year	1482	874	280	3476
tuition at public 4year	2298	770	1251	4265
Educational outcomes				
enroll year 1	0.53	0.50	0	1
year 2	0.50	0.50	0	1
year 3	0.43	0.50	0	1
year 4	0.40	0.49	0	1
start at 2year	0.15	0.36	0	1
start at 4year	0.38	0.49	0	1
gpa year 1	2.42	0.86	0.00	4.00
year 2	2.47	0.90	0.00	4.00
year 3	2.63	0.88	0.00	4.00
year 4	2.75	0.85	0.00	4.00
yrs of continuous enrollment	13.81	2.11	12	19
don't enroll	0.47	0.50	0	1
enroll year 1 only	0.10	0.30	0	1
enroll years 1-2 only	0.08	0.27	0	1
enroll years 1-3 only	0.06	0.24	0	1
enroll at least 4 years	0.29	0.45	0	1

Note: All variables have 2,055 observations, with the exception of GPA variables which are restricted to those enrolled in each year

TABLE A3—REPRESENTATIVENESS AND COMPARABILITY OF NELS AND NLSY SAMPLES

Panel A. NELS sample using full sample and sample weights

	Base		All (unweighted)		All (w=f4qwt92g)		All (w=f4f2pnwt)	
	obs	mean	obs	mean	obs	mean	obs	mean
high school gpa	2055	2.70	3520	2.69	3520	2.64	3474	2.65
afqt score	2055	46.66	3855	48.93	3855	46.44	3819	46.95
parent education (years)	2055	14.18	4315	14.47	4315	14.46	4276	14.45
parent has ba	2055	0.28	4315	0.35	4315	0.34	4276	0.35
low income family	2055	0.55	4007	0.60	4007	0.60	3972	0.62
urban	2055	0.62	4707	0.69	4707	0.69	4632	0.69
region northeast	2055	0.16	4672	0.20	4672	0.20	4624	0.19
region northcentral	2055	0.31	4672	0.28	4672	0.27	4624	0.26
region south	2055	0.32	4672	0.32	4672	0.34	4624	0.35
region west	2055	0.20	4672	0.20	4672	0.20	4624	0.20
white	2055	0.73	4711	0.72	4711	0.74	4636	0.74
black	2055	0.08	4711	0.08	4711	0.11	4636	0.10
latino	2055	0.11	4711	0.11	4711	0.09	4636	0.09
distance to 2year	2055	15.54	3672	14.90	3672	15.04	3614	15.02
distance to 4year	2055	24.02	3672	23.30	3672	22.90	3614	22.13
tuition at public 2year	2055	1482.12	4668	1473.77	4668	1477.21	4620	1458.47
tuition at public 4year	2055	2298.27	4672	2298.17	4672	2287.92	4624	2277.31
Total observations	2055		4714		4714		4638	

Panel B. NLSY sample vs. NELS sample

	Base		Cross-section only		Cross-section (weighted)		NELS sample	
	obs	mean	obs	mean	obs	mean	obs	mean
predicted pdv lifetime income	1982	529.70	1352	580.59	1352	601.14	2055	594.08
black	1982	0.26	1352	0.08	1352	0.03	2055	0.08
latino	1982	0.15	1352	0.05	1352	0.01	2055	0.11
regionnc	1982	0.29	1352	0.36	1352	0.38	2055	0.31
regionso	1982	0.35	1352	0.28	1352	0.25	2055	0.32
regionwe	1982	0.19	1352	0.17	1352	0.17	2055	0.20
urban14	1982	0.78	1352	0.75	1352	0.77	2055	0.62
gpahs	1982	2.39	1352	2.50	1352	2.54	2055	2.70
afqt89	1982	49.87	1352	57.25	1352	60.56	2055	46.66
parented	1982	12.34	1352	13.03	1352	13.33	2055	14.18
don't enroll	1982	0.59	1352	0.56	1352	0.54	2055	0.47
enroll year 1 only	1982	0.08	1352	0.07	1352	0.07	2055	0.10
enroll years 1-2 only	1982	0.10	1352	0.10	1352	0.10	2055	0.08
enroll years 1-3 only	1982	0.06	1352	0.06	1352	0.06	2055	0.06
enroll at least 4 years	1982	0.17	1352	0.21	1352	0.23	2055	0.29

Note: In Panel A, "All" refers to all male 1992 high school graduates in the NELS. Weight f4qwt92g corresponds to 1992 high school graduates and weight f4f2pnwt corresponds to 1992 12th graders. Number of observations varies by column due to missing values. In Panel B, samples include male high school graduates with non-missing covariates.

who were 14-22 years old in 1979. They have been surveyed annually or biennially since. Using variables that are common in both the NLSY79 and NELS (such as high school GPA, parental education, AFQT, ethnicity, urban and region), I first estimate the parameters of a lifetime income equation on the NLSY79 data. My NLSY79 analysis sample consists of all male high school graduates with non-missing covariates, including oversamples of minority and poor individuals. Panel B of Table A3 compares this analysis sample to the NLSY cross-section sample (which doesn't include these oversamples) and to my NELS analysis sample. The NLSY analysis sample is more disadvantaged than NLSY high school graduates generally and than members of my NELS analysis sample. A lack of comparability between the NLSY and the NELS could affect my option value estimates if the returns estimated using the NLSY are not reflective of all high school graduates in the NELS. I examine these comparability issues both by letting returns differ with student background and by restricting analysis to the NLSY cross-section sample (excluding the poor and minority oversamples).

Equation B1 is estimated on the NLSY high school graduate sample using OLS and is used to predict counterfactual lifetime income for individuals in the NELS sample.

$$\text{(B1)} \quad Income_i =$$
$$\omega_0 + \omega_{13} 1(S_i(t_i) = 13) + \omega_{14} 1(S_i(t_i) = 14) + \omega_{15} 1(S_i(t_i) = 15) + \omega_{16} 1(S_i(t_i) \geq 16)$$
$$+ \omega_b Black_i + \omega_l Latino_i + \omega_c Central_i + \omega_s South_i + \omega_w West_i + \omega_u Urban_i$$
$$+ \omega_g HSgpa_i + \omega_a AFQT_i + \omega_p ParentEd_i$$
$$+ \omega_{ga} HSgpa_i * AFQT_i + \omega_{gp} HSgpa_i * ParentEd_i + \omega_{ap} AFQT_i * ParentEd_i + \epsilon_i^{\omega}$$

The dependent variable $Income_i$ is the present discounted value of lifetime income from the period of first labor market entry (t_i) to age 62. The key dependent variable is years of continuous enrollment in school, $S_i(t_i)$, which is entered as a set of four dummy variables and is determined mechanically by period of first labor market entry (t_i) since re-enrollment is ignored. Since NLSY79 individuals are ages 39 to 47 in 2004, the most recent year for which data is available, so I assume that earnings are constant from age 39 to 62. The base specification permits the intercept of lifetime income to vary with observable background and ability variables, but restricts the lifetime income returns to each year of college to be constant across individuals. An alternative specification allows the return to some college (S = 13, 14, or 15) and a BA ($S \geq 16$) to vary with high school gpa, AFQT, and parent's education. If returns to education differ with student background, then permitting heterogeneous returns will partially mitigate concerns about the comparability of the NLSY and NELS analysis samples. In practice, these interactions are insignificant, so my main analysis uses the constant-returns estimates. Table B1 provides estimates of the parameters of the lifetime income equation for both the base and heterogeneous-returns model for different assumed values of the discount rate. The last two columns exclude the poor and minority oversamples from the analysis. Again, the estimated returns to each year of college are very similar using the full and smaller samples, so I use the former in my main analysis.

TABLE B1—PARAMETER ESTIMATES FROM LIFETIME INCOME EQUATION

	Dependent variable: PDV of lifetime income post-school					
	All Men in NLSY				NLSY Cross-section	
	d = 5% No weights (1)	d =10% No weights (2)	d = 5% No weights (3)	d =10% No weights (4)	d = 5% No weights (5)	d = 5% Weighted (6)
contenroll = 13	34.64	19.36	95.61	56.34	20.83	23.86
	(22.09)	(10.63)	(75.61)	(36.57)	-(29.86)	-(34.23)
contenroll = 14	55.54	32.10	126.74	76.04	62.53	53.26
	(24.77)	(11.35)	(82.67)	(39.35)	-(32.06)	-(35.60)
contenroll = 15	165.89	88.99	238.77	133.56	189.16	202.90
	(37.88)	(17.43)	(85.66)	(40.95)	-(48.70)	-(54.29)
contenroll > 15	328.13	183.50	-82.26	-6.75	327.79	333.55
	(30.08)	(14.17)	(154.00)	(72.66)	-(35.90)	-(38.25)
ParentEd	7.65	4.63	13.15	6.96	13.02	11.88
	(8.58)	(4.02)	(8.22)	(3.85)	-(13.52)	-(14.90)
Black	-81.17	-44.76	-80.82	-44.71	-56.53	-66.94
	(19.14)	(8.97)	(19.06)	(8.95)	-(31.02)	-(32.43)
Latino	5.93	2.64	1.23	0.71	3.29	-22.28
	(23.21)	(11.01)	(22.81)	(10.84)	-(39.90)	-(39.34)
NorthCentral	-45.96	-24.49	-42.48	-22.52	-40.72	-41.11
	(24.85)	(11.74)	(24.89)	(11.75)	-(29.02)	-(32.07)
South	-56.99	-29.31	-54.99	-28.10	-56.79	-50.44
	(24.54)	(11.61)	(24.52)	(11.60)	-(31.56)	-(35.96)
West	-56.01	-29.65	-52.13	-27.85	-63.45	-77.30
	(25.08)	(11.78)	(25.12)	(11.76)	-(31.05)	-(35.36)
Urban	32.60	13.06	31.70	12.65	39.88	42.69
	(15.71)	(7.51)	(15.57)	(7.43)	-(19.36)	-(21.76)
HSgpa	42.78	24.61	74.22	39.36	43.67	59.40
	(41.40)	(19.49)	(40.77)	(19.42)	-(64.64)	-(74.50)
AFQT	1.52	0.99	3.03	1.64	2.32	0.98
	(1.35)	(0.64)	(1.34)	(0.64)	-(1.95)	-(2.29)
HSgpa*AFQT	0.25	0.04	-0.19	-0.14	0.28	0.35
	(0.43)	(0.20)	(0.42)	(0.19)	-(0.56)	-(0.62)
HSgpa*ParentEd	-0.55	-0.36	-2.03	-1.14	-1.29	-2.51
	(3.95)	(1.84)	(3.81)	(1.80)	-(5.86)	-(6.50)
AFQT*ParentEd	-0.03	-0.03	-0.08	-0.05	-0.11	-0.05
	(0.08)	(0.04)	(0.09)	(0.04)	-(0.12)	-(0.15)
(s13-s15)*AFQT			-0.16	-0.27		
			(0.67)	(0.32)		
s16*AFQT			1.91	0.65		
			(1.33)	(0.64)		
(s13-s15)*HSgpa			0.47	-3.39		
			(28.99)	(13.57)		
s16*HSgpa			46.76	29.88		
			(47.09)	(22.43)		
(s13-s15)*ParentEd			-4.01	-1.15		
			(4.91)	(2.40)		
s16*ParentEd			9.97	3.94		
			(9.85)	(4.52)		
Constant	223.52	112.62	134.05	72.50	184.34	218.81
	(93.60)	(44.27)	(91.50)	(43.26)	-(153.82)	-(172.47)
Observations	1,982	1,982	1,982	1,982	1,352	1,352
R-squared	0.30	0.33	0.30	0.34	0.34	0.33

Note: Robust standard errors in parentheses. Specifications (1) to (4) use all male high school graduates in the NLSY with non-missing covariates, including the poor white, black, and hispanic supplemental samples. Specifications (5) and (6) use only male high school graduates in the cross-section sample.

TABLE B2—PREDICTED LIFETIME INCOME AND INCREMENTAL RETURNS BY YEARS OF CONTINUOUS ENROLLMENT

			Men in NELS Sample								
			Predicted Present Value of Lifetime Income (,000)					Predicted Incremental Income Increase (,000)			
Model	Discount rate		12	13	14	15	16	13	14	15	16
(1)	5%	mean	481	516	537	647	809	35	21	110	162
		stdev	89	89	89	89	89	0	0	0	0
(2)	10%	mean	244	263	276	333	428	19	13	57	95
		stdev	39	39	39	39	39	0	0	0	0
(3)	5%	mean	473	506	537	649	748	33	31	112	99
		stdev	72	66	66	66	151	11	0	0	94
(4)	10%	mean	241	259	279	336	401	18	20	58	65
		stdev	33	26	26	26	67	10	0	0	47

Note: Parameters of lifetime income model were estimated using the data from the NLSY and fitted to men in the NELS sample. See Table B1 for parameter estimates and model specifications.

For each individual in the NELS analysis sample, the model estimated in B1 is used to predict counterfactual lifetime income for the five possible schooling levels: $Income_{i1}$ (corresponding to $S_i = 12$) through $Income_{i5}$ (corresponding to $S_i \geq 16$). Table B2 presents the predicted lifetime income counterfactuals for the NELS sample.

C. FULL MODEL AND SOLUTION

C1. Structure of Choices and Preferences

I model the college enrollment and continuation decisions at four periods in time, corresponding to the four academic years after high school graduation. During the first period individuals decide whether to start at a four-year or two-year college, which I refer to as pathway choice, or to not enroll in college. The pathway chosen affects the level and timing of direct schooling costs (which may differ across individuals) and unmodeled college amenities. At each time period t an individual chooses whether to enter the labor market (receiving payoff $u^{w}_{i,t}$) or continue in school for another year, receiving payoff $u^{s}_{i,j,t}$ in period t and the option to make an analogous work-school decision in period $t+1$, where $j = 2, 4$ denotes the type of school currently attending. After period two, students that started at a two-year college must attend a four-year college if they want to continue in school.[2] After period four, there are no more decisions to make and all individuals enter the labor market.[3]

[2]In the estimation, I do not actually distinguish between people attending two- and four-year schools in their third year. I simplify by assuming that anyone who started at a two-year school that is enrolled in their third year faces the four-year school cost structure, even if they are actually enrolled in a two-year school.

[3]The model does not currently permit two-year and four-year colleges to affect earnings differently or allow for heterogeneity among four-year colleges. Thomas J.Kane and Cecilia E. Rouse (1995) find that the return to education received at two- and four-year institutions is comparable. They estimate that the average college student earned about 5% more than similar high school graduates for every year of credits completed, regardless of where those credits were earned.

Utility is in dollars. The indirect utility from discontinuing school and entering the labor market at period t equals the expected present discounted value of lifetime income from period t to age 62 ($Income_{i,t}$) plus a random component $\varepsilon^{w}_{i,t}$.

$$u^{w}_{i,t} = Income_{i,t} + \varepsilon^{w}_{i,t} \tag{C2}$$

The expected indirect utility derived from attending school during period t, $u^{s}_{i,j,t}$, depends linearly on a heterogeneous intercept ($\alpha_{i,j}$, specified later), expected unknown ability (A_i), direct tuition and commuting costs, and a random component $\varepsilon^{s}_{i,j,t}$. $Distance_{i,j,t}$ and $Tuition_{i,j,t}$ vary by the type of school currently attending (2-year or 4-year), so individuals that start at a two-year school will pay community college tuition for the first two years then four-year college tuition for their third and fourth years.

$$u^{s}_{i,j,t} = \alpha_{i,j} + \alpha_A E_t[A_i] - (\alpha_D Distance_{i,j,t} + Tuition_{i,j,t}) + \varepsilon^{s}_{i,j,t} \tag{C3}$$

The random shocks ($\varepsilon^{s}_{i,j,t}$,$\varepsilon^{w}_{i,t}$) are learned by the individual prior to making the period t decision. The term $\alpha_A E_t[A_i]$ captures the preference for school (in dollar terms) that covaries with its expected difficulty.[4] Individuals do not know A_i at any time, so they form expectations of it when making their period-t decisions. Utility is cumulative so individuals who attend a two-year school for two years then enter the labor market, for instance, will receive total lifetime utility of $u^{s}_{i,2,1}+\beta u^{s}_{i,2,2}+\beta^2 u^{w}_{i,3}$, where β is a discount factor.

$\overline{u}^{s}_{i,j,1}(\cdot)$ represents the non-stochastic component of the indirect utility of attending school. Individuals know baseline characteristics (X_i) as well as the first period shocks ($\varepsilon^{s}_{i,2,1}$,$\varepsilon^{s}_{i,4,1}$,$\varepsilon^{w}_{i,1}$) when making the initial enrollment decision, but learn future shocks and grade outcomes only after enrolling. All other parameters of the model are known to the individual throughout.

C2. Academic Performance

At the end of each year, students enrolled in college learn their performance during that year. Academic performance is measured by the college grade point average (on a four-point scale) during period t. I assume that grades provide a noisy signal of A_i:

$$g_{i,t} = A_i + \varepsilon^{g}_{i,t} \tag{C4}$$

The $\varepsilon^{g}_{i,t}$ is the component of grade outcomes that is not serially correlated. This represents idiosyncratic determinants of academic performance that do not persist across time. The conditional expectation of A_i on baseline characteristics (X_i) is given by the

[4]This specification can be motivated by a model where the difficulty of year t is distributed around a fixed and unobserved individual-specific mean, so $A_{i,t} = A_i + \varepsilon^{a}_{i,t}$. Individuals learn $A_{i,t}$ after each year, but cannot separate A_i from $\varepsilon^{a}_{i,t}$. If $\varepsilon^{a}_{i,t}$ is mean zero and serially uncorrelated, then $E_t[A_{i,t}] = E_t[A_i]$. Also, since I have assumed risk neutrality, the variance of $\varepsilon^{a}_{i,t}$ has no impact on expected utility or decisions, so can be ignored.

heterogeneous term γ_i, which is specified in the next subsection.

$$E[A_i|X_i] = \gamma_i \tag{C5}$$

C3. Heterogeneity

The variables $\alpha_{i,j}$ and γ_i represent persistent preferences for school and persistent determinants of academic aptitude, respectively, which may be correlated in the population. $\alpha_{i,j}$ varies with school type (j) so that individuals may have different tastes for attending a two- or four-year school. To permit a general structure of correlation between unobservable preferences and ability, I specify that $\alpha_{i,j}$ and γ_i come from a mass point distribution which describe the ability and schooling preferences of M different types of individuals.[5] Type is known to the individual throughout, but is unknown to the econometrician. I also make the parametric assumption that the conditional expectation of A_i on baseline characteristics is linear in high school grade point average $(HSgpa_i)$, percentile score on the AFQT, and whether a parent has a college degree $(ParBA_i)$.

$$\alpha_{i,j} = \alpha_{0,j} + \alpha_{m,j} \quad \text{for } m = 1, 2, ..., M \tag{C6}$$

$$\gamma_i = \gamma_0 + \gamma_m + \gamma_G HSgpa_i + \gamma_T AFQT_i + \gamma_P ParBA_i \tag{C7}$$

where γ_m measures the unobserved academic aptitude of people of "type" m and $\alpha_{m,j}$ is their preference for school of type j. I estimate models permitting up to three types $(M = 3)$. For Type I individuals, γ_m and $\alpha_{m,j}$ are normalized to zero. Essentially, the specification permits the intercepts of academic performance and of indirect utility to each take on three different values, corresponding to the three unobserved types. As a special case, I will also estimate models with no unobserved heterogeneity, which assumes that all correlation between preference for school and academic aptitude are captured linearly through $\alpha_A E_t[A_i]$.

C4. Solution

At each time t , the individual maximizes the expected discounted value of lifetime utility by choosing whether to discontinue schooling and receive $u^w_{i,t}$ or continue school for at least one more year. The decision problem can be solved for each individual by backwards recursion and by assuming a distribution for the preference and grade shocks $(\varepsilon^s_{i,j,t}, \varepsilon^w_{i,t}, \varepsilon^g_{i,t})$. Throughout I assume that $\varepsilon^s_{i,2,t}$,$\varepsilon^s_{i,4,t}$, and $\varepsilon^w_{i,t}$ are drawn from an Extreme Value Type I distribution with location and scale parameters zero and τ, respectively. Grade shocks are assumed to be normally distributed with $\varepsilon^g_{i,t} \sim N(0, \sigma_{Gt})$.

With learning, individuals update their belief about A_i in response to new information received through grades. I make the parametric assumption that the conditional

[5] The use of a mass-point distribution to approximate the distribution of preferences known to the agent but unknown to the econometrician is discussed by Heckman and Singer (1984) and is widely used in dynamic structural work such as Keane and Wolpin (1997) and Eckstein and Wolpin (1999).

expectation of A_i is a weighted average of the unconditional expectation and students' cumulative grade point average. The weights are parameters to be estimated.

$$\text{(C8)} \qquad \begin{aligned} E_t[A_i] &= E[A_i|X_i] \text{ if } t=1 \\ &= \gamma_{Xt} E[A_i|X_i] + (1-\gamma_{Xt}) \sum_{q=1}^{q=t-1} \frac{g_{i,q}}{t-1} \text{ if } t>1 \end{aligned}$$

This specification is an approximation of the normal learning model. The normal learning model imposes that $\gamma_{Xt} = \left(\frac{1/\sigma_a^2}{1/\sigma_a^2+(t-1)/\sigma_g^2}\right)$, where σ_a^2 is the variance of A_i and σ_g^2 is the variance of $\left(g_{i,t} - A_i\right)$. I have not imposed that the timing of learning follow the behavior implied by the normal learning model. Instead, I estimate γ_{Xt} and the variance of the residual $g_{i,t} - E_t[A_i]$ as parameters.

At period 4 the final enrollment decision is made by comparing the lifetime utility of entering the labor market without graduating to that of continuing for one more year. In periods 2 through 4, I omit the j subscripts.

$$\text{(C9)} \qquad \begin{aligned} V_{i,4}^w &= Income_{i,4} + \varepsilon_{i,4}^w \\ V_{i,4}^s &= \alpha_0 + \alpha_m + \alpha_A E_4[A_i] - Cost_{i,4} + \beta E_4[V_{i,5}] + \varepsilon_{i,4}^s \end{aligned}$$

where $Cost_{i,4} = \alpha_D Distance_{i,4} + Tuition_{i,4}$. At period 4, expectations are taken over the distribution of labor market shocks in period 5 ($\varepsilon_{i,5}^w$) and grade shocks in period 4 ($g_{i,4}$). Since all individuals enter the workforce upon reaching period 5, $V_{i,5} = V_{i,5}^w = Income_{i,5} + \varepsilon_{i,5}^w$ and $E_4[V_{i,5}] = Income_{i,5} + \tau\lambda$ from the extreme value assumption [$\lambda = 0.577$ is Euler's constant]. Future utility is discounted at the rate β. If individuals learn about unobserved ability through grades, then $E_4[A_i]$ is a weighted average of the unconditional expectation and previous grade realizations:
(C10)

$$V_{i,4}^s = \alpha_0+\alpha_m+\alpha_A \left[\gamma_{X4} E[A_i|X_i] + (1-\gamma_{X4}) \sum_{q=1}^{q=3} \frac{g_{i,q}}{3}\right] - Cost_{i,4} + \beta[Income_{i,5}+\tau\lambda] + \varepsilon_{i,4}^s$$

Individuals will continue to graduation if $V_{i,4}^s > V_{i,4}^w$.

At periods 2 and 3, the enrollment and continuation decisions are made by comparing the lifetime utility of entering the labor market immediately to that of continuing school for one more year.

$$\begin{aligned} V_{i,t}^w &= Income_{i,t} + \varepsilon_{i,t}^w \\ V_{i,t}^s &= \alpha_0 + \alpha_m + \alpha_A E_t[A_i] - Cost_{i,t} + \beta E_t[V_{i,t+1}] + \varepsilon_{i,t}^s \end{aligned}$$

where $V_{i,t+1} = \max(V_{i,t+1}^w, V_{i,t+1}^s)$. Expectations are again taken over the distribution of all future preference shocks ($\varepsilon_{i,q}^w, \varepsilon_{i,q}^s$ for $q > t$) and grade shocks ($g_{i,q}$ for $q \geq t$), but now both of these influence future educational decisions. Integrating out the grade shocks (due to conditional independence between grades and shocks, see Rust (1987)), the E max term can be written as:

$$E_t\left[\max(V^w_{i,t+1}, V^s_{i,t+1})\right] = \int E_t\left[\max(V^w_{i,t+1}, V^s_{i,t+1})|g_{i,t}\right] \cdot \Pi(dg_{i,t}|X_i, \{g_{i,1}...g_{i,t-1}\})$$

where $\Pi(dg_{i,t}|X_i, \{g_{i,1}...g_{i,t-1}\})$ is the pdf of the t-period grade outcome conditional on information available at time t. The conditional expectation is taken only over the future preference shocks ($\varepsilon^w_{i,q}, \varepsilon^s_{i,q}$ for $q > t$). Again with the assumption that the preference shocks are not serially correlated and are drawn from an extreme value distribution, this expectation has a closed-form representation[6]:

$$\begin{aligned} & E_t\left[\max(V^w_{i,t+1}, V^s_{i,t+1})\right] \\ = & \int \left[\tau\lambda + \tau \log\left\{\exp\left(\frac{1}{\tau}\overline{V}^s_{i,t+1}(g_{i,t})\right) + \exp\left(\frac{1}{\tau}\overline{V}^w_{i,t+1}\right)\right\}\right] \cdot \Pi(dg_{i,t}|X_i, \{g_{i,1}...g_{i,t-1}\}) \end{aligned}$$

In order to actually solve and estimate the model, I discretize $g_{i,t}$ into K values and approximate $\Pi(dg_{i,t}|X_i, \{g_{i,1}...g_{i,t-1}\})$ with a discretized version $p(g^k_{i,t}|X_i, \{g_{i,1}...g_{i,t-1}\})$.[7] The E max term can then be written as

$$\begin{aligned} & E_t\left[\max(V^w_{i,t+1}, V^s_{i,t+1})\right] \\ = & \sum_{k=1}^{K} \left[\tau\lambda + \tau \log\left\{\exp\left(\frac{1}{\tau}\overline{V}^s_{i,t+1}(g^k_{i,t})\right) + \exp\left(\frac{1}{\tau}\overline{V}^w_{i,t+1}\right)\right\}\right] \cdot p(g^k_{i,t}|X_i, \{g_{i,1}...g_{i,t-1}\}) \end{aligned}$$

And the indirect utility function becomes:

$$\begin{aligned} V^s_{i,t} = & \\ & \alpha_0 + \alpha_m + \alpha_A\left[\gamma_{Xt} E[A_i|X_i] + (1-\gamma_{Xt})\sum_{q=1}^{q=t-1}\frac{g_{i,q}}{t-1}\right] - Cost_{i,t} \\ +\beta & \left[\sum_{k=1}^{K}\left[\tau\lambda + \tau \log\left\{\exp\left(\frac{1}{\tau}\overline{V}^s_{i,t+1}(g^k_{i,t})\right) + \exp\left(\frac{1}{\tau}\overline{V}^w_{i,t+1}\right)\right\}\right] \cdot p(g^k_{i,t}|X_i, \{g_{i,1}...g_{i,t-1}\})\right] + \varepsilon^s_{i,t} \end{aligned}$$

Individuals will continue their education if $V^s_{i,t} > V^w_{i,t}$.

[6] Thomas A. Domencich and Daniel L. McFadden (1975, Chapter 4) show that the expected value of the maximum of an EV(1) random variable has this closed form representation.

[7] See John Rust (1987). Since grades are distributed normally, the transition probabilities can be computed directly using the standard normal cumulative distribution function. $p(g^k_{i,t}|X_i, \{g_{i,1}...g_{i,t-1}\}) = \Phi\left(\frac{g^k_{i,t}+(0.5)*kstep-E_t[g_{i,t}]}{\sigma_{t,g}}\right) - \Phi\left(\frac{g^k_{i,t}-(0.5)*kstep-E_t[g_{i,t}]}{\sigma_{t,g}}\right)$ where kstep is the distance between the points in the discretized grade space.

At period 1, the value of the two enrollment options takes a similar form:

$$V^s_{i,j,1} = \alpha_{0,j} + \alpha_{m,j} + \alpha_A E[A_i|X_i] - Cost_{i,j,t} + \beta \left[\sum_{k=1}^{K} \left[\tau\lambda + \tau \log \left\{ \exp\left(\frac{1}{\tau}\overline{V}^s_{i,2}(g^k_{i,1})\right) + \exp\left(\frac{1}{\tau}\overline{V}^w_{i,2}\right) \right\} \right] \cdot p(g^k_{i,1}|X_i,) \right] + \varepsilon^s_{i,j,1}$$

At period 1, individuals maximize expected lifetime utility by choosing between $V^s_{i,2,1}$, $V^s_{i,4,1}$, and $V^w_{i,1}$.

D. Model Alternatives and Extensions

The empirical model places two important restrictions on individuals' choices and information sets. I assume that (1) the labor market is an absorbing state; people no longer re-optimize once they enter the workforce. This assumption means that individuals "exercise their option" by leaving school. I also assume that (2) labor market draws persist following labor market entry. Individuals do not receive another labor market draw while in the workforce.

To see these assumptions more clearly, consider a more general model in which attending school and working both provide information - people learn about their enjoyment of each only through doing them (individual subscripts have been omitted):

$$\begin{aligned} V^w_t &= \alpha^w + Income^w_t(L_t, S_t) + \alpha^w_A E[A^w|\Im_o, \Im^s_t, \Im^w_t] - SwitchCost^w \cdot 1(Attend_{t-1} = 1) + \varepsilon^w_t \\ &\quad + \beta E\left[V_{t+1, Attend_t=0}\right] \\ V^s_t &= \alpha^s + Income^s_t(L_t, S_t) + \alpha^s_A E[A^s|\Im_o, \Im^s_t, \Im^w_t] - SwitchCost^s \cdot 1(Attend_{t-1} = 0) + \varepsilon^s_t \\ &\quad + \beta E\left[V_{t+1, Attend_t=1}\right] \end{aligned}$$

Individuals form expectations of the state-specific unknown component of indirect utility (A^w and A^s) based on information available at baseline ($\Im_o$), and that learned while working ($\Im^w_t$) and attending school ($\Im^s_t$) up to that point. Individuals make enrollment decisions each period to maximize expected lifetime utility, though moving between the labor market and school is costly. Income while working or attending school depends on labor market experience (L_t) and years of completed schooling (S_t) up to that point. The empirical model assumes $Income^s_t(L_t, S_t) = -(\alpha_D Distance_t + Tuition_t)$. Any income earned during school will be absorbed in the estimate of α^s.

Assumption (1) corresponds to the restriction that $V_{t+1,Attend_t=0} = \sum_{\tau=t+1}^{T} \beta^{\tau-t-1} Income^w_\tau(L_\tau, S_\tau)$ and $V_{t+1,Attend_t=1} = \max\{V^w_{t+1}, V^w_{t+1}\}$. The continuation value associated with enrollment contains the ability to re-optimize each period, while that for the labor market is fixed at the future expected lifetime income. Though $\sum_{\tau=t+1}^{T} \beta^{\tau-t-1} Income^w_\tau(L_\tau, S_\tau)$ is inclusive

TABLE D1—FRACTION OF SAMPLE THAT RETURN TO COLLEGE AFTER DROPPING OUT

Years of Continuous Educ.	Freq	Fraction Who Enroll in Year t 1	2	3	4	5	6	7	Fraction Who Earn BA
12	966	0.00	0.16	0.14	0.13	0.12	0.10	0.09	0.08
13	210	1.00	0.00	0.20	0.24	0.19	0.14	0.08	0.14
14	163	1.00	1.00	0.00	0.29	0.18	0.19	0.10	0.21
15	121	1.00	1.00	1.00	0.00	0.27	0.24	0.15	0.36
16+	595	1.00	1.00	1.00	1.00	0.50	0.22	0.15	0.87

of the expected financial gains of being able to return to school after entering the labor market at time t, I assume that individuals consider future re-enrollment a probabilistic (exogenous) event rather than an optimizing choice. Compared to a more general model where $V_{t+1,Attend_t=0} = \max\{V^w_{t+1}, V^w_{t+1}\}$, this restriction omits any option value arising from the ability to re-enroll. Assumption (1) would be innocuous if either (1a) $SwitchCost^s = \infty$ and $SwitchCost^w$ is small; or (1b) individuals do not learn about the relative desirability of schooling and work while in the labor market and thus have no incentive to re-enroll once they drop out. Assumption (1a) is unlikely to hold because it is clearly possible to re-enter college after leaving, though doing so is not the norm and those that do seldom earn a B.A. degree. Table D1 presents the fraction of students enrolled during each year, by the number of years of continuous schooling. In my sample, the fraction of students who return in the year after labor market entry is 16%, 20%, 29%, and 27% for those who enter the labor market in year one to four, respectively. Approximately three quarters of B.A. recipients never have a period of delay or nonenrollment. If re-enrollment were modeled, both $SwitchCost^s$ and $SwitchCost^w$ could be estimated directly from the data.[8]

Assumption (1b) corresponds to the restriction that $\Im^w_t = \Im_o$ for all t. High school graduates' expectation of the enjoyment of future work does not depend on their past experience. This assumption is innocuous if people are not able to return to school upon discovering that they don't like working. I also assume that $\Im_o = \{HSgpa, AFQT, ParBA, Type\}$ and $\Im^s_t = \{g_1, ..., g_{t-1}\}$. Allowing for learning about tastes for work is an important extension, but one that must be pursued with a different dataset. I use course grades to measure academic aptitude and to serve as a proxy for taste for school, but the NELS does not contain an obvious analog proxy for individuals' enjoyment of work. Not modelling re-enrollment has no impact on the estimated option value if any of assumptions (1), (1a), or (1b) hold.

Assumption (2) corresponds to replacing the labor market shock ε^w_t with $\varepsilon^w_t \cdot 1(Attend_{t-1} = 1)$. Individuals only receive a new labor market draw if they are currently attending school. I assume that each year of college provides access to a new set of labor market opportunities previously unavailable, which increases mean earnings and generates

[8]Keane and Wolpin (1997) estimate the cost of returning to school after dropping out to be $23,000 during high school and $10,000 during college.

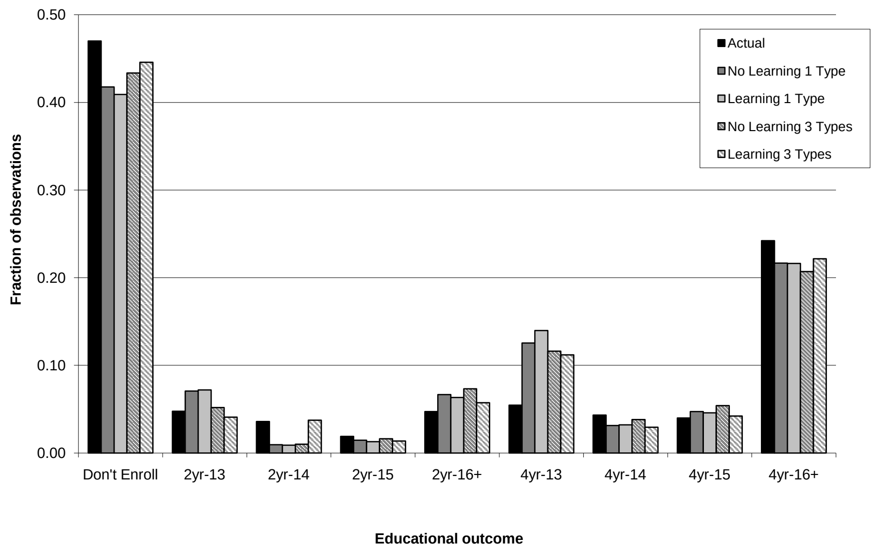

FIGURE E1. ACTUAL VS. SIMULATED EDUCATIONAL OUTCOMES

Note: To generate simulated outcomes, the unobserved type, grade and preference shocks, and choices of each observation is simulated 100 times, assuming individuals follow the choice models described in the text with parameter values equal to those in specifications (1)-(4) of Table 1.

a new draw. Consistent with this assumption, Philip Oreopoulos, Till von Wachter, and Andrew Heisz (2006) find that temporary labor market shocks (e.g. graduating college during a recession) have permanent effects on lifetime earnings. Significant initial earnings losses fade only after 8 to 10 years, generating large losses in the total present value of lifetime earnings.

These generalizations are beyond the scope of this current paper, but their implications for my empirical results are discussed in the body of the paper.

E. MODEL FIT AND ADDITIONAL ESTIMATES

Figures E1 to E5 extend Figures 5 to 8 to include the model fit for all four models estimated in Table 1. Generally, the preferred specification (Column (4) in Table 1) provides the best fit of the data.

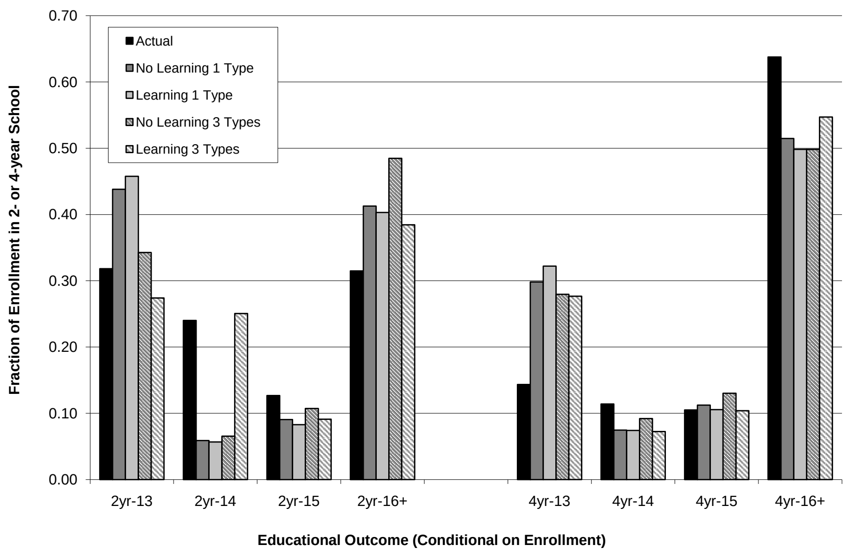

FIGURE E2. ACTUAL VS. SIMULATED OUTCOMES CONDITIONAL ON ENROLLMENT

Note: To generate simulated outcomes, the unobserved type, grade and preference shocks, and choices of each observation is simulated 100 times, assuming individuals follow the choice models described in the text with parameter values equal to those in specifications (1)-(4) of Table 1.

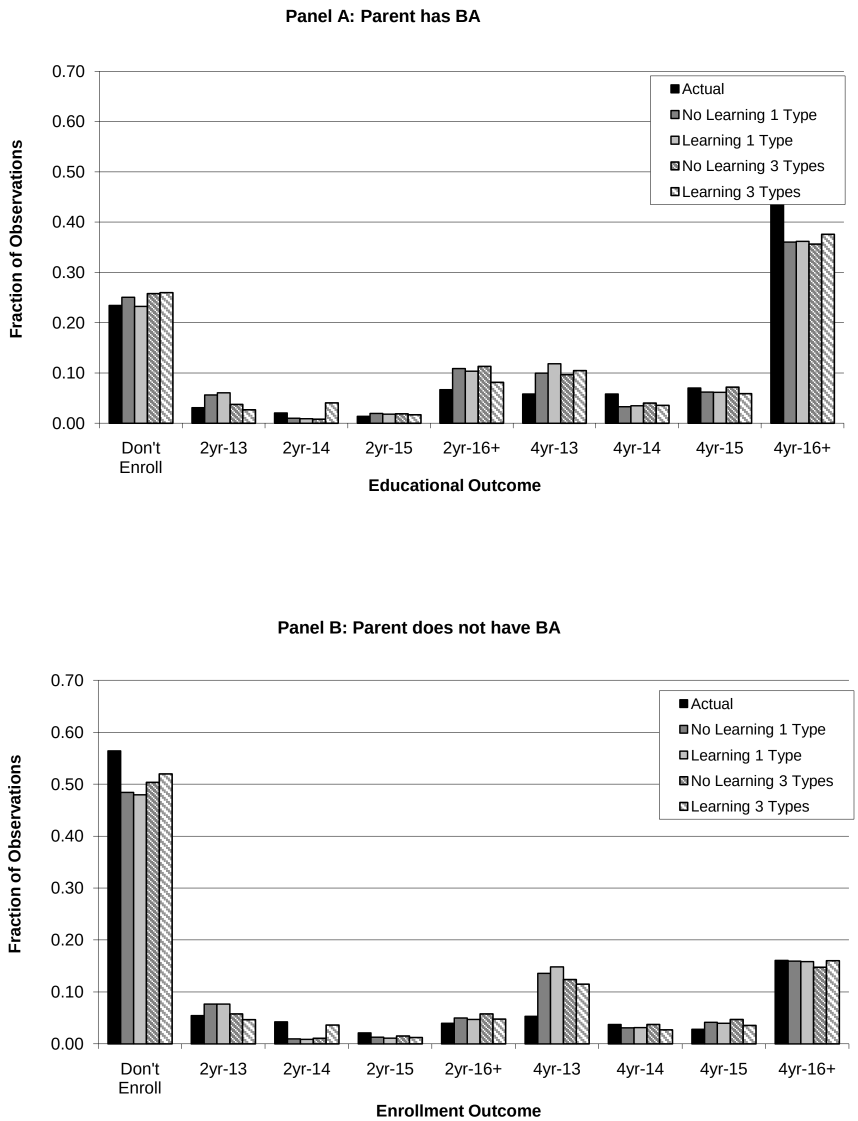

FIGURE E3. ACTUAL VS. SIMULATED EDUCATIONAL OUTCOMES, BY PARENT EDUCATION

Note: To generate simulated outcomes, the unobserved type, grade and preference shocks, and choices of each observation is simulated 100 times, assuming that individuals follow the choice models described in the text with parameter values equal to those in specifications (1)-(4) of Table 1.

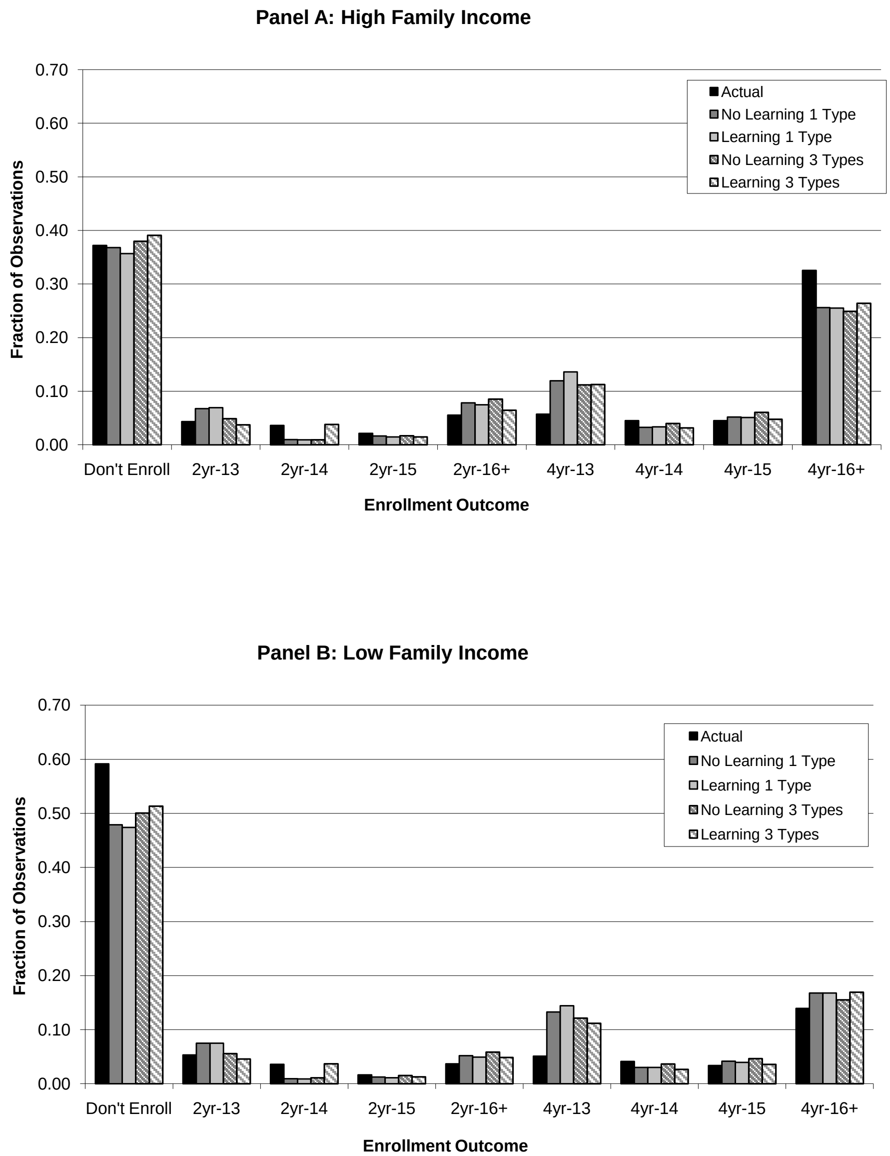

FIGURE E4. ACTUAL VS. SIMULATED EDUCATIONAL OUTCOMES, BY FAMILY INCOME

Note: To generate simulated outcomes, the unobserved type, grade and preference shocks, and choices of each observation is simulated 100 times, assuming that individuals follow the choice models described in the text with parameter values equal to those in specifications (1)-(4) of Table 1.

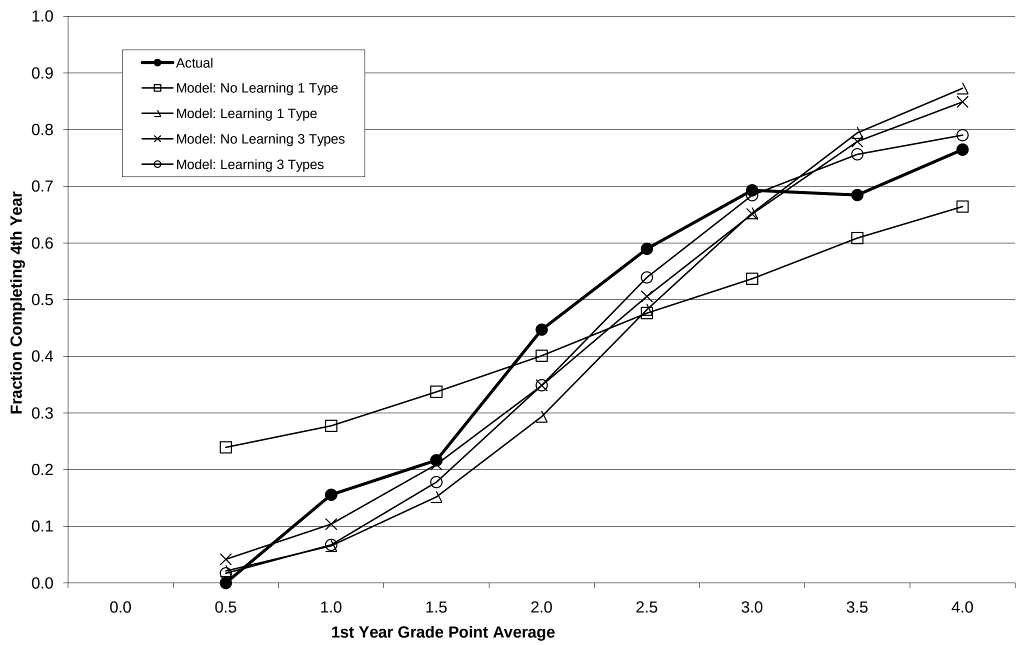

FIGURE E5. ACTUAL VS. SIMULATED GRADUATION RATE BY 1ST YEAR GPA

Note: To generate simulated outcomes, the unobserved type, grade and preference shocks, and choices of each observation is simulated 100 times, assuming that individuals follow the choice models described in the text with parameter values equal to those in specifications (1)-(4) of Table 1.

TABLE E1—ESTIMATES OF STRUCTURAL PARAMETERS - ALTERNATIVE SPECIFICATIONS

	Base Model (1)	Transfer Cost (2)	Different Learning Process (3) 4-year	Different Learning Process (3) 2-year	Enrollment Continuation Value (4)	Combined (5) 4-year	Combined (5) 2-year
Utility parameters							
E[Ai]	1.009	1.032	1.117		1.369	4.258	
	(0.154)	(0.140)	(0.160)		(0.224)	(1.024)	
Distance (x100 miles)	0.220	0.206	0.241		0.288	0.698	
	(0.065)	(0.058)	(0.072)		(0.093)	(0.223)	
Tau	0.642	0.628	0.698		0.914	1.401	
	(0.070)	(0.061)	(0.073)		(0.122)	(0.286)	
Transfer cost		-0.854				-4.251	
		(0.105)				(1.183)	
Continuation value at enrollment stage					0.831	0.728	
					(0.033)	(0.051)	
(1 = no difference)							
Grade parameters							
HS GPA	0.523	0.520	0.529		0.486	0.389	
	(0.029)	(0.028)	(0.030)		(0.029)	(0.027)	
AFQT	0.695	0.671	0.739		0.640	0.488	
	(0.072)	(0.070)	(0.075)		(0.065)	(0.052)	
Parent BA	0.336	0.327	0.332		0.313	0.232	
	(0.033)	(0.031)	(0.034)		(0.030)	(0.024)	
E[A|X] period 1 (fixed)							
E[A|X] period 2	0.528	0.525	0.605	0.403	0.485	0.525	0.426
	(0.034)	(0.033)	(0.041)	(0.064)	(0.033)	(0.034)	(0.061)
E[A|X] period 3	0.343	0.351	0.403	0.299	0.289	0.242	0.514
	(0.046)	(0.044)	(0.057)	(0.093)	(0.044)	(0.045)	(0.097)
E[A|X] period 4	0.206	0.233	0.284	0.138	0.147	0.139	0.314
	(0.057)	(0.054)	(0.079)	(0.180)	(0.055)	(0.056)	(0.117)
SD(gpa year 1)	0.617	0.614	0.588	0.658	0.628	0.628	0.623
	(0.016)	(0.016)	(0.020)	(0.031)	(0.015)	(0.017)	(0.028)
SD(gpa year 2)	0.521	0.519	0.488	0.578	0.524	0.506	0.568
	(0.013)	(0.013)	(0.015)	(0.029)	(0.013)	(0.014)	(0.028)
SD(gpa year 3)	0.520	0.519	0.494	0.595	0.523	0.507	0.593
	(0.014)	(0.014)	(0.016)	(0.037)	(0.014)	(0.015)	(0.037)
SD(gpa year 4)	0.545	0.544	0.532	0.593	0.547	0.537	0.594
	(0.016)	(0.016)	(0.017)	(0.043)	(0.016)	(0.017)	(0.043)
Log likelihood	5719	5692	5706		5690	5630	

Note: All specifications include three unobserved types, though the type-specific parameters are not reported. Utility is in units of $100,000. Income specification (1) from Table B1 was used to generate counterfactual income estimates. Standard errors (in parentheses) were calculated from the inverse of the numerical Hessian. All specifications use seventeen GPA categories for Emax approximation (0.0, 0.25, 0.50, … , 4.0).

*

REFERENCES

Domencich, Thomas A., and Daniel L. McFadden. 1975. *Urban Travel Demand: A Behavioral Analysis*. Amsterdam: North-Holland Publishing Company.

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.

Heckman, James J., and Burton Singer. 1984. "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data." *Econometrica*, 52 (2): 271-320.

Kane, Thomas J., and Cecilia E. Rouse. 1995. “Labor Market Returns to Two- and Four-Year College.” *The American Economic Review*, 85(3): 600-614.

Keane, Michael P., and Kenneth I. Wolpin. 1997. “The Career Decisions of Young Men.” *Journal of Political Economy*, 105(3): 473-522.

Kilburn, M. Rebecca, Lawrence M. Hanser, and Jacob A. Klerman. 1998. *Estimating AFQT Scores for NELS Respondents*. Santa Monica: RAND, MR-818-OSD/A, 1998.

Manski, Charles F., 1991. “Nonparametric Estimation of Expectations in the Analysis of Discrete Choice Under Uncertainty.” In *Nonparametric and Semiparametric Methods in Econometrics and Statistics.* ed. William A. Barnett, James Powell, and George E. Tauchen, 259-275. New York: Cambridge University Press.

Oreopoulos, Philip, Till von Wachter and Andrew Heisz. 2006. "The Short- and Long-Term Career Effects of Graduating in a Recession: Hysteresis and Heterogeneity in the Market for College Graduates." National Bureau of Economic Research Working Paper 12159.

Rust, John. 1987. "Optimal Replacement of GMC Bus Engine: An Empirical Model of Harold Zurcher." *Econometrica*, 55(5): 999-1033.