The Return to College: Selection and Dropout Risk
Online Appendix

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A High School & Beyond Data

We obtain data on the academic performance of college students and on their incomes and expenditures from data collected by the National Education Longitudinal Studies (NELS) program of the National Center for Education Statistics (NCES). The High School & Beyond (HS&B) survey covers the 1980 senior and sophomore classes (see United States Department of Education. National Center for Education Statistics 1988). Both cohorts were surveyed every two years through 1986. The 1980 sophomore class was also surveyed in 1992, at which point postsecondary transcripts from all institutions attended since high school graduation were collected under the initiative of the Postsecondary Education Transcript Study (PETS).[1] We restrict attention to male sophomores that are surveyed at least through 1986.

A.1 Enrollment and Dropout Statistics

The sample contains 5,837 students who graduated from high school in 1982. We split these students into quartiles according to their HS GPA, which is available for 90% of our sample. For the remaining 10%, we impute HS GPA by estimating a linear regression with self-reported HS GPA , cognitive test score, and race as independent variables. The cognitive test was conducted in the students' senior year and was designed to measure quantitative and verbal abilities.

Using PETS transcript data, we count the number of credits each student attempts and completes in each year in college. Credits are defined as follows. We count withdrawals that appear on transcripts as attempted but unearned credits. We drop transfer credits to avoid double counting. We drop credits earned at vocational schools, such as police academies or health occupation schools.

We count a student as entering college if he attempts at least 9 credits in a given academic year. Using this definition, 48% of the cohort enters college immediately upon high school graduation. Another 2.7% of the cohort enter in the following year. Students obtaining a bachelor's degree within 6 years of initial enrollment are counted as college graduates, even in the presence of breaks in their enrollment. The 52.5% of immediate entrants are college graduates. Students that earn bachelor's degrees later than 6 years after their initial enrollment are dropped from the sample.[2]

For each HS GPA quartile, Table 1 shows the fraction of college entrants who graduate from college and who drop out at the end of each year. These statistics are computed from 2,052 college entrants with complete transcript histories. We refer to a college

[1] PETS data files were obtained through a restricted license granted by the National Center for Education Statistics.

[2] These students typically drop out within two years of initial enrollment, experiencing a long enrollment break before returning to school. Counting these students as college graduate would raise the graduation rate to 55%.

Table 1: School Attainment of College Entrants

	All Entrants	Q. 1	Q. 2	Q. 3	Q. 4
Fraction graduating	0.52	0.11	0.25	0.51	0.74
Fraction dropping out, year 1	0.17	0.37	0.30	0.15	0.08
Fraction dropping out, year 2	0.15	0.28	0.19	0.19	0.07
Fraction dropping out, year 3	0.08	0.15	0.14	0.07	0.05
Fraction dropping out, year 4	0.05	0.04	0.09	0.05	0.03
Fraction dropping out, year 5	0.02	0.04	0.03	0.02	0.02
N	2,052	195	355	593	909

Notes: The table shows the fraction of college entrants in each HS GPA quartile that drops out of college at the end of each year. N is the number of observations.

entrant as a year x dropout if he/she enrolled continuously in years 1 through x, attempted fewer than 7 credits in year $x+1$, and failed to obtain a bachelor degree within 6 years. 98.4% of the college graduates in our sample are enrolled continuously until graduation.

A.2 Financial and Work Variables

In the second and third follow-up interviews (1984 and 1986), all students reported their education expenses, various sources of financial support, and their work experience. Table 2 shows the means of all financial variables for students who are enrolled in college in a given year.

We construct total parental transfers as the sum of school-related and direct transfers to the student. The school-related transfer refers to "payments on [the student's] behalf for tuition, fees, transportation, room and board, living expenses and other school-related expenses." It is available only for the first two academic years after high school graduation.

Direct transfers are observed for all high school graduates regardless of college attendance. They include in-kind support, such as room and board, use of car, medical expenses and insurance, clothing, and any other cash or gifts. We set the transfer values to the midpoints of the intervals they are reported in. For the highest interval, more than \$3,000 in current prices, we assign a value of \$3,500. Direct transfers are reported at calendar year frequencies. To impute values for academic years, we assume that half of the transfer is paid out in each semester of the calendar year for which the transfer is reported.

Tuition and fees, the value of grants and student loans are available for each academic year. Grants refer to the total dollar value of the amount received from scholarships, fellowships, grants, or other benefits (not loans) during the academic year.

Table 2: Financial Resources

	Year 1	Year 2	Year 3	Year 4
Net cost, q	3,750	7,831	14,773	21,985
	(1,864)	(1,572)	(1,161)	(1,028)
Tuition	4,270	8,929	16,481	24,291
	(1,875)	(1,582)	(1,226)	(1,081)
Grants, scholarships	1,430	2,892	4,433	6,097
	(1,989)	(1,687)	(1,303)	(1,157)
Earnings	5,625	10,806	15,856	20,458
	(2,042)	(1,728)	(1,444)	(1,269)
Hours worked	803	1,535	2,174	2,736
	(2,006)	(1,690)	(1,396)	(1,223)
Loans	917	2,058	3,226	4,500
	(1,997)	(1,687)	(1,320)	(1,165)
Fraction in debt	0.26	0.35	0.41	0.47
	(1,997)	(1,687)	(1,320)	(1,165)
Parental transfers	5,620	11,576	.	.
	(1,459)	(1,240)	(0)	(0)

Notes: Dollar amounts are cumulative and in year 2000 prices. Average amounts include zeros. Number of observations in parentheses.

In the model, we interpret annual college costs q as collecting all college related payments that are *conditional* on attending college. In the data, we measure q as the average of tuition and fees net of scholarships and grants over the first two years in college plus \$987 for other college expenditures, such as books, supplies, and transportation.[3] q does not include room and board, which are included in consumption.

Job history information contains start and end date of each job held since high school graduation, typical weekly hours on the job, and wages. We define academic years as running from July 1st to June 30. For each year, we measure total hours and total earnings on each job, and in total. Hours on unpaid jobs such as internships are not counted towards total hours. Wages are used to infer total earnings, and (the few) missing wages in the presence of available hours are imputed as sample averages. Observations with missing hours in the presence of available wages and observations with outlier hours (top 1%) are flagged. Annual hours for flagged observations are imputed as self-reported calendar year earnings divided by the sample average wage. 1983 calendar year earnings are used to infer information for the 82/83 academic year, and so on.

[3] Since HS&B lacks information on these expenditures, we compute them as the average cost for 1992-93 undergraduate full-time students in the National Postsecondary Student Aid Study, conducted by the U.S. Department of Education. These costs are defined as the amount student reported spending on expenses directly related to attending classes, measured in year 2000 prices.

Table 3: Summary Statistics for the NLSY79 Sample

	HSG	CD	CG	All
Fraction	46.6	25.3	28.1	100.0
Avg. schooling	12.1	14.1	17.0	14.0
Range	9 - 13	13 - 20	12 - 20	9 - 20
AFQT percentile	34.3	51.3	75.0	50.0
N	1,447	800	675	2,922

Notes: For each school group, the table shows the fraction of persons achieving each school level, average years of schooling and the range of years of schooling, the mean AFQT percentile, and the number of observations.

B NLSY79 Data

The NSLY79 sample covers men born between 1957 and 1964 who earned at least a high school diploma. We use the $1979 - 2006$ waves. We drop persons who were not interviewed in 1988 or 1989 when retrospective schooling information was collected. We also drop persons who did not participate in the AFQT (about 6% of the sample). Table 3 shows summary statistics for this sample.

B.1 Schooling Variables

For each person, we record all degrees and the dates they were earned. At each interview, persons report their school enrollments since the last interview. We use this information to determine whether a person attended school in each year and which grade was attended. For persons who were not interviewed in consecutive years, it may not be possible to determine their enrollment status in certain years.

Visual inspection of individual enrollment histories suggests that the enrollment reports contain a significant number of errors. It is not uncommon for persons to report that the highest degree ever attended declined over time. A significant number of persons reports high school diplomas with only 9 or 10 years of schooling. We address these issues in a number of ways. We ignore the monthly enrollment histories, which appear very noisy. We drop single year enrollments observed after a person's last degree. We also correct a number of implausible reports where a person's enrollment history contains obvious outliers, such as single year jumps in the highest grade attained. We treat all reported degrees as valid, even if years of schooling appear low.

Many persons report schooling late in life after long spells without enrollment. Since our model does not permit individuals to return to school after starting to work, we ignore late school enrollments in the data. We define the start of work as the first 5-year spell without school enrollment. For persons who report their last of schooling before 1978, we treat 1978 as the first year of work. We assign each person the highest degree earned and the highest grade attended at the time he starts working. Persons who attended at least grade 13 but report no bachelor's degree are counted as college dropouts. Persons who report 13 years of schooling but fewer than 10 credit hours are counted as high school graduates. The resulting school fractions are close to those obtained from the High School & Beyond sample.

B.2 Lifetime Earnings

Lifetime earnings are defined as the present value of earnings up to age 70, discounted to age 19. Our measure of labor earnings consists of wage and salary income and 2/3 of business income. We assume that earnings are zero before age 19 for high school graduates, before age 21 for college dropouts, and before age 23 for college graduates.

Since we observe persons at most until age 48, we need to impute earnings later in life. For this purpose, we use the age earnings profiles we estimate from the CPS (see Appendix C). The present value of lifetime earnings for the average CPS person is given by $Y_{CPS}(s) = \sum_{t=19}^{70} g_{CPS}(t|s)R^{19-t}$. The fraction of lifetime earnings typically earned at age t is given by $g_{CPS}(t|s)R^{19-t}/Y_{CPS}(s)$.

For each person in the NLSY79 we compute the present value of earnings received at all ages with valid earnings observations. We impute lifetime earnings by dividing this present value by the fraction of lifetime earnings earned at the observed ages according to the CPS age profile, $g_{CPS}(t|s)R^{19-t}/Y_{CPS}(s)$.

An example may help the reader understand this approach. Suppose we observe a high school graduate with complete earnings observations between the ages of 19 and 40. We compute the present value of these earnings reports, including years with zero earnings, X. According to our CPS estimates, 60% of lifetime earnings are received by age 40. Hence we impute lifetime earnings of $X/0.6$.

In order to limit measurement error, we drop individuals who report zero earnings for more than 30% of the observed years. We also drop persons with fewer than 5 earnings observations after age 35 or whose reported earnings account for less than 30% of lifetime earnings according to the CPS profile. Table 4 shows summary statistics for the persons for which we can estimate lifetime earnings. One concern is that the NLSY79 earnings histories are truncated around age 45, which leaves 20 to 30 years of earnings to be imputed. Fortunately, the fitted CPS age profiles imply that around 70% of lifetime earnings are earned before age 45.

Table 4: Lifetime Earnings

	HSG	CD	CG
exp(mean log)	600,061	643,153	944,269
Standard deviation (log)	0.51	0.55	0.50
N	578	343	319

Notes: The table show exp(mean log lifetime earnings), the standard deviation of log lifetime earnings, and the number of observations in each school group.

C CPS Data

C.1 Sample

In our main source of wage data, the NLSY79, persons are observed only up to around age 45. We use data from the March Current Population Survey (King et al., 2010) to extend the NLSY79 wage profiles to older ages. Our sample contains men between the ages of 18 and 75 observed in the $1964 - 2010$ waves of the CPS. We drop persons who live in group quarters or who fail to report wage income.

C.2 Schooling Variables

Schooling is inconsistently coded across surveys. Prior to 1992, we have information about completed years of schooling (variable higrade). During this period, we define high school graduates as those completing 12 years of schooling (higrade=150), college dropouts as those with less than four years of college (151,...,181), and college graduates as those with 16+ years of schooling (190 and above). Beginning in 1992, the CPS reports education according to the highest degree attained (educ99). For this period, we define high school graduates as those with a high school diploma or GED (educ99=10), college dropouts as those with "some college no degree," "associate degree/occupational program," "associate degree/academic program" (11,12,13). College graduates are those with a bachelors, masters, professional, or doctorate degree (14,...,17).

C.3 Age Earnings Profiles

Our goal is to estimate the age profile of mean log earnings for each school group. This profile is used to fill in missing earnings observations in the NLSY79 sample and to estimate individual lifetime earnings.

First, we compute the fraction of persons earning more than $\$2,000$ in year 2000 prices for each age t within school group s, $f(t|s)$. This is calculated by simple averaging across all years. For the cohorts covered by the NLSY79, the fractions are similar to their NLSY79 counterparts.

Next, we estimate the age profile of mean log earnings for those earnings more than $\$2,000$ per year, which we assume to be the same for all cohorts, except for its intercept. To do so, we compute mean log earnings above $\$2,000$ for every [age, school group, year] cell. We then regress, separately for each school group, mean log earnings in each cell on age dummies, birth year dummies, and on the unemployment rate, which absorbs year effects. We retain the birth cohorts $1935 - 1980$. We use weighted least squares to account for the different number of observations in each cell.

Finally, we estimate the mean earnings at age t for the 1960 birth cohort as:

$$g_{CPS}(t|s) = \exp\left(1960 \text{ cohort dummy} + \text{age dummy}(t) + \text{year effect}(1960 + t)\right) f(t|s) \tag{1}$$

For years after 2010, we impose the average year effect. Figure 1 shows the fitted age profiles together with the actual age profiles for the 1960 birth cohorts calculated from the CPS and the NLSY79. We find substantially faster earnings growth in the NLSY79 data compared with the CPS data. The discrepancies are modest until around age 30 (year 1990), which is consistent with the validation study by MaCurdy et al. (1998). The reason for the discrepancies is not known to us.

D Model Fit

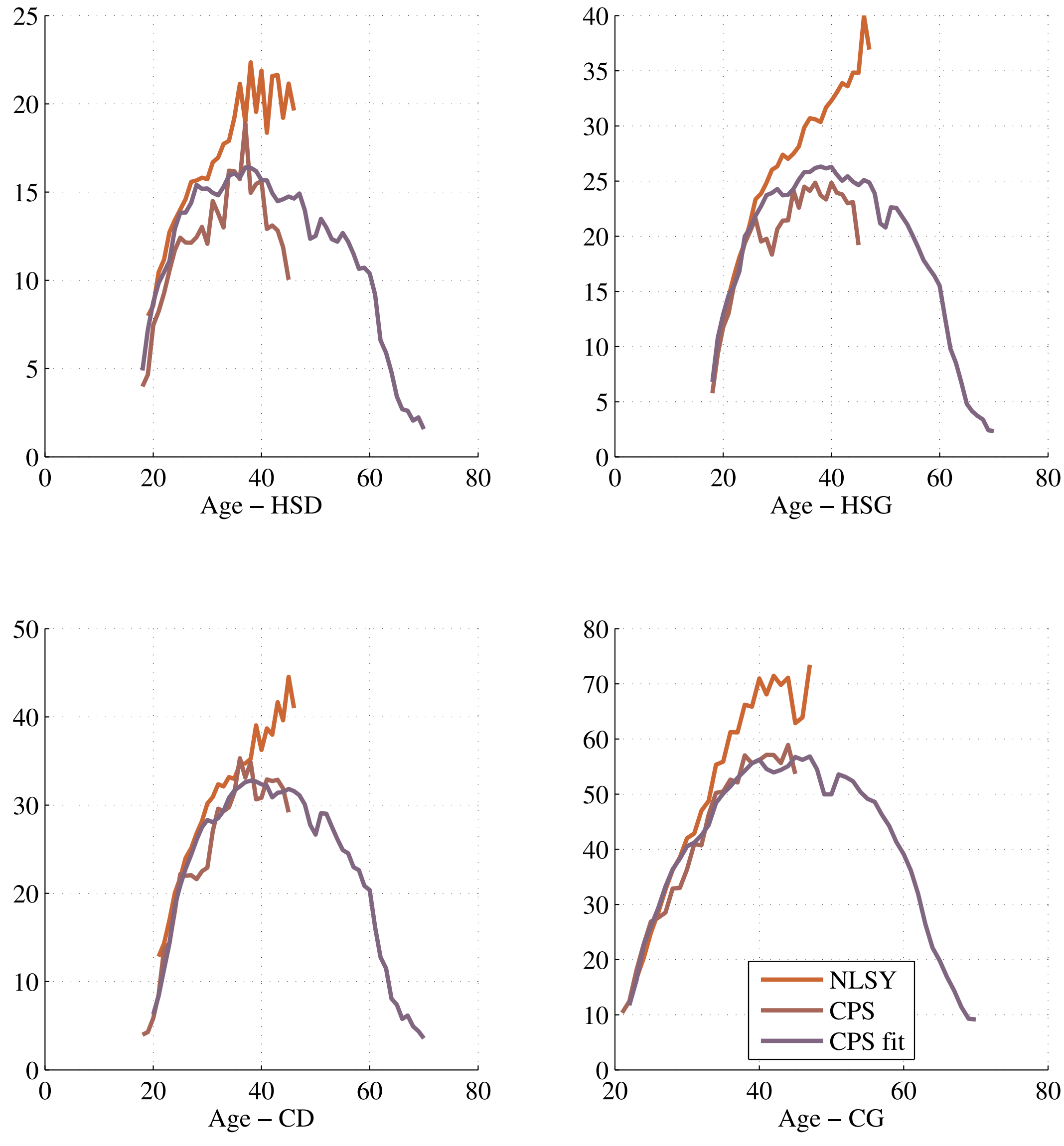
This Appendix assesses how closely the model attains each set of calibration targets. It also highlights features of the data that are important for our main results.

College credits. Figure 2 shows the distribution of credits earned at the end of the first 4 years in college. Each bar represents a decile. The model is overall successful, but fails to replicate two data features. First, in year 1, the model admits too few distinct values for earned credits (0 through 6) to match the finer empirical distribution. This is a mechanical, rather than a substantive, problem. Second, the model misses the very low number of credits earned by students in the bottom decile. The gap between the first and the second decile suggests that the lowest credit realizations result from shocks that we do not model.

Figure 3 and Figure 4 show the distribution of credits earned at the end of the first 4 years in college broken for students who eventually drop out and who eventually graduate, respectively. The model is again overall successful, but misses the lowest credit decile among dropouts.

Figure 5 shows the distribution of credits broken down by year and HS GPA quartile. The model replicates the fact that controlling for HS GPAs does not substantially reduce the dispersion of credits. The main discrepancies between model and data occur

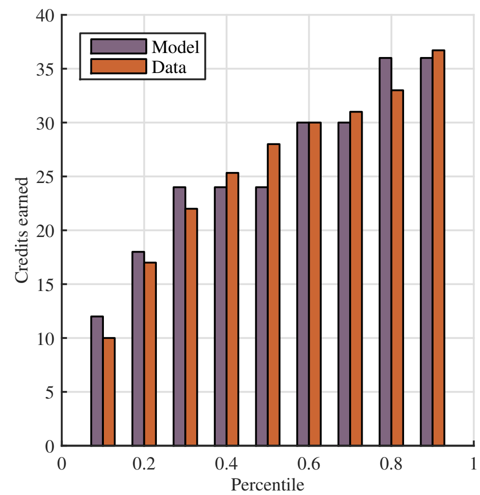
Figure 1: Age-earnings Profiles



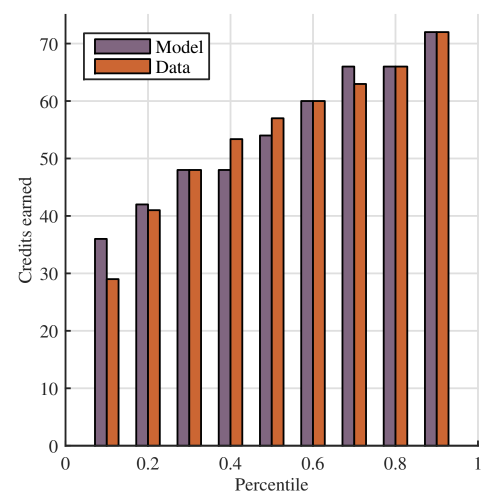
Notes: The figures show the exponential of mean log earnings by schooling and age in thousands of year 2000 dollars. Earnings are adjusted for the fraction of persons working at each age as described in the text.

Figure 2: Distribution of Credits by Year

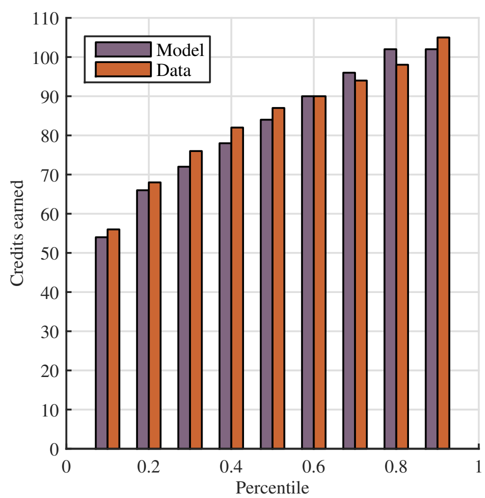
(a) Year 1



(b) Year 2



(c) Year 3



(d) Year 4

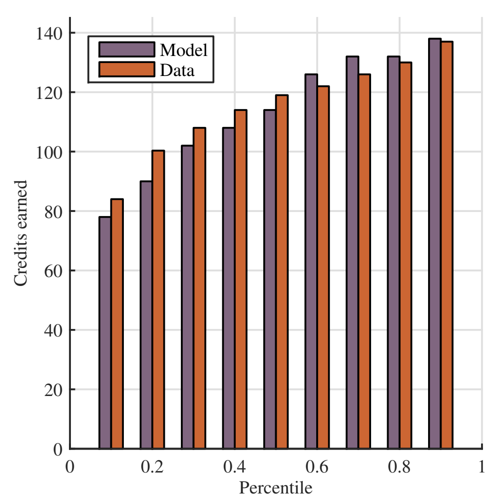
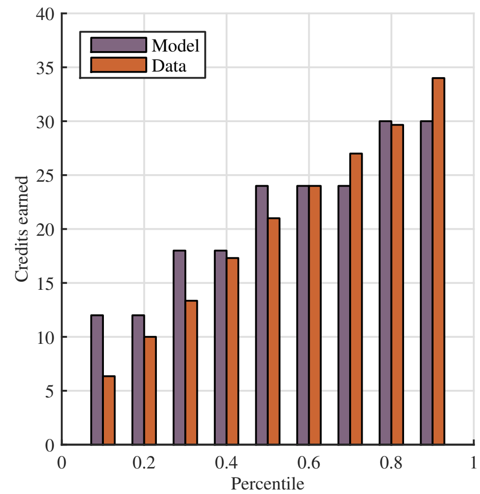
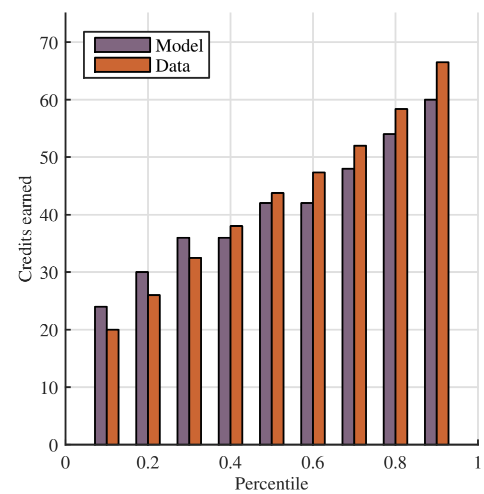


Figure 3: Distribution of Credits among Dropouts

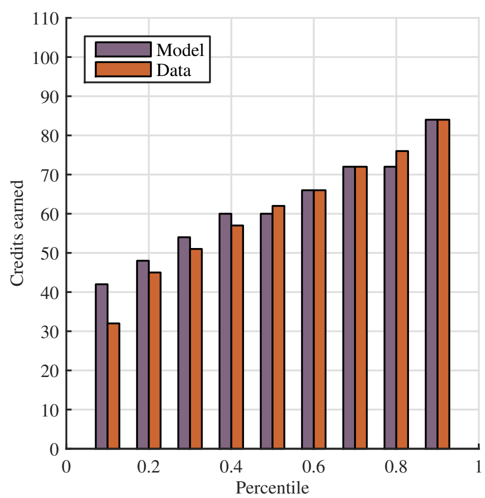
(a) Year 1



(b) Year 2



(c) Year 3



(d) Year 4

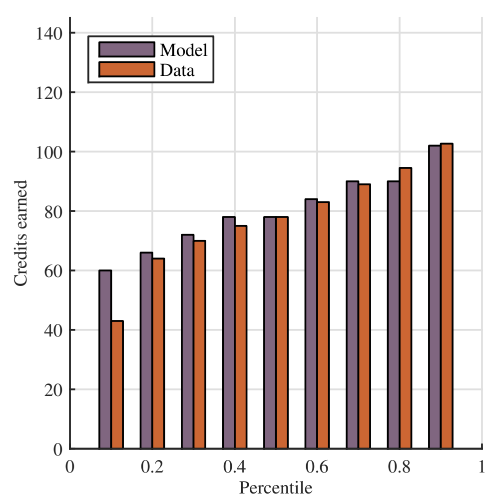
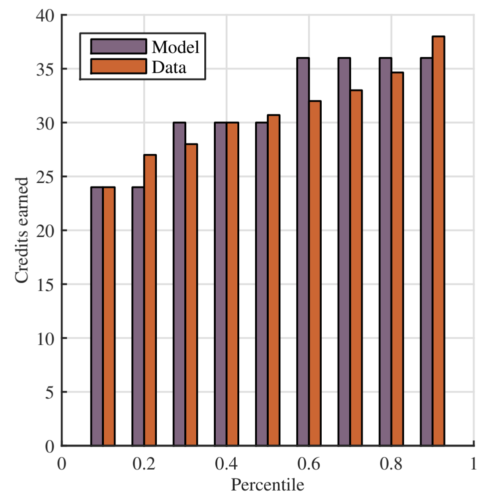
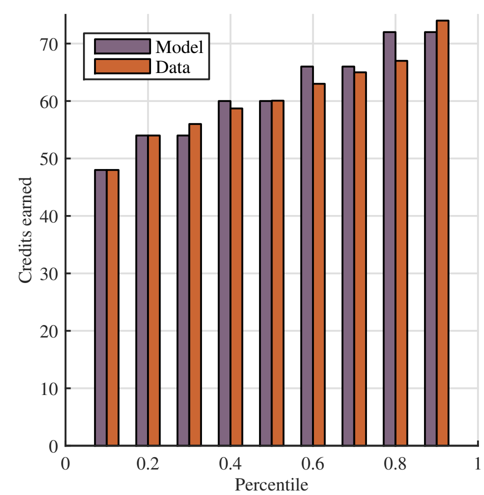


Figure 4: Distribution of Credits among Graduates

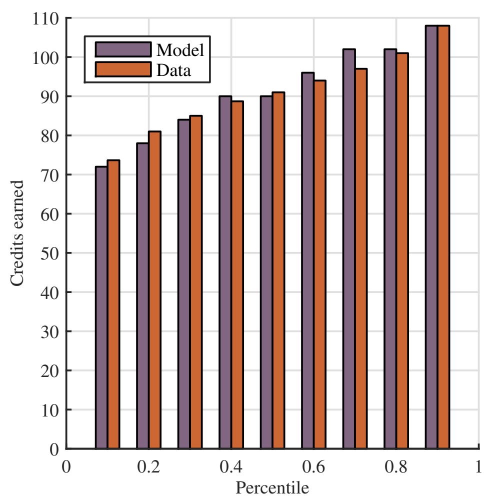
(a) Year 1



(b) Year 2



(c) Year 3



(d) Year 4

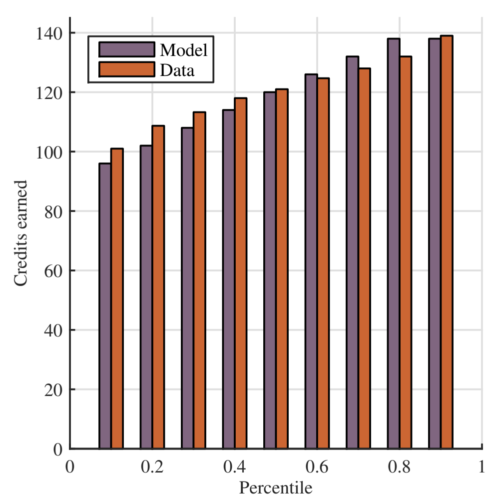


Table 5: Schooling and Lifetime Earnings

	School group		
	HS	CD	CG
Fraction			
Data	51.9	22.9	25.2
Model	51.9	23.2	24.9
Gap (pct)	-0.0	1.6	-1.4
Lifetime earnings			
Data	600	643	944
Model	601	637	946
Gap (pct)	0.2	-1.0	0.2

Note: The table shows the fraction of persons that chooses each school level and the exponential of their mean log lifetime earnings, discounted to age 1, in thousands of year 2000 dollars. "Gap" denotes the percentage gap between model and data values. Source: NLSY79.

among students in the lowest HS GPA quartile, who make up a small fraction of college students.

Schooling and lifetime earnings. Table 5 shows that the model closely fits the observed fraction of persons attaining each school level and their mean log lifetime earnings. Key features of the data are: (i) 47.5% of those attempting college fail to attain a bachelor's degree. (ii) College graduates earn 45 log points more than high school graduates over their lifetimes. For college dropouts, the premium is only 7 log points.

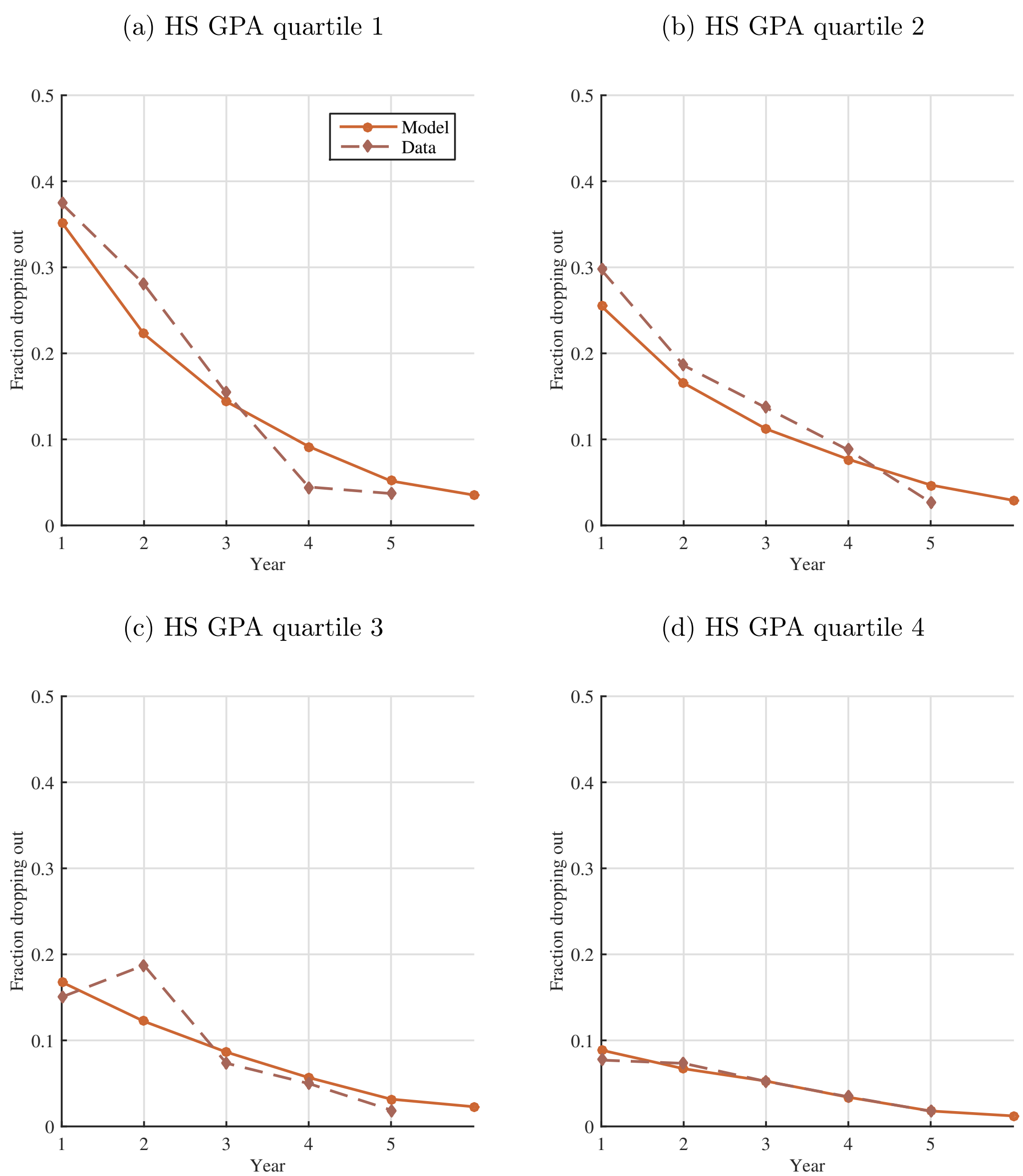
Table 6 shows mean log lifetime earnings by school group and HS GPA quartile. The model broadly matches the data cells with large numbers of observations. The largest discrepancy occurs for college graduates in the lowest HS GPA quartile, which are quite rare (32 observations).

Dropout rates. Figure 6 shows college dropout rates, defined as the number of persons dropping out at the end of each year divided by the number of college entrants in year 1. Dropout rates decline strongly with HS GPAs and with time spent in college. They help identify the rate at which students learn about their graduation prospect as they move through college.

Financial resources. Table 7 shows the means of college costs, parental transfers, and college earnings for students in each HS GPA quartile. In the data, higher ability students face slightly higher college costs, but they also receive larger parental transfers.

Figure 5: Distribution of Credits by HS GPA Quartile

Figure 6: Dropout Rates



Notes: The figure shows the fraction of persons initially enrolled in college who drop out at the end of each year in college.
Source: High School & Beyond.

Table 6: Lifetime Earnings

	HS GPA quartile			
	1	2	3	4
HS, model	4.03	4.10	4.15	4.19
data	3.93 (0.04)	4.12 (0.03)	4.22 (0.04)	4.22 (0.08)
CD, model	4.03	4.13	4.19	4.25
data	3.83 (0.08)	4.16 (0.05)	4.24 (0.05)	4.26 (0.06)
CG, model	4.41	4.47	4.52	4.58
data	4.11 (0.08)	4.57 (0.06)	4.46 (0.05)	4.60 (0.04)

Notes: The table shows mean log lifetime earnings, discounted to model age 1, for each school group and HS GPA quartile. Standard errors in parentheses.
Source: NLSY79.

This allows them to work less. The average net cost of attending college, $q - y_{coll}$, is negative, especially for low HS GPA students.[4] As a measure of dispersion, the table also shows the 25th, 50th and 75th percentile values of each variable.[5]

Table 8 shows student debt levels at the end of the first 4 years in college. Even after 4 years in college, only half of the students report owing any debts. Conditional on being in debt, the average debt amounts to roughly half of the borrowing limit. These results suggest that financial constraints do not bind for most of the students in our sample.

E Varying Selected Model Parameters

This section investigates which data moments are primarily responsible for the values of selected model parameters. Since our model is computationally efficient, we are able to compute how the model fit changes as each parameter's value varies over a grid. For each grid point, we recalibrate all other model parameters.

We focus on parameters that we expect to be important for ability selection: the effect of college credits on earnings μ, and the scale of preference shocks π. To conserve space, we summarize the results without presenting the details for each case.

Effect of credits on earnings. The value of μ is mainly identified by the relationship between lifetime earnings and HS GPA and by the timing of dropouts.

Holding other parameters constant, higher values of μ increase the relative earnings of college dropouts and college graduates. The calibration offsets this by reducing ability

[4] This is consistent with Bowen et al. (2009) who report that average tuition payments for public 4-year colleges roughly equal average scholarships and grants.

[5] Because of potential measurement error, we do not target standard deviations of the financial moments. Doing so does not change our findings significantly.

Table 7: Financial Moments

	HS GPA quartile				Percentile		
	1	2	3	4	25	50	75
q, model	3,964	3,500	3,462	4,115	1,158	3,468	6,340
data	3,122	3,097	3,828	4,280	1,354	2,705	5,378
(s.e.)	(385)	(246)	(186)	(160)	–	–	–
N	99	215	456	802	–	–	–
z, model	2,294	3,636	4,607	5,274	0	2,391	6,710
data	2,942	3,506	3,870	6,286	432	2,409	6,491
(s.e.)	(195)	(199)	(170)	(209)	–	–	–
N	334	499	740	990	–	–	–
y_{coll}, model	7,624	5,809	5,023	5,395	–	–	–
data	6,571	5,879	5,440	5,069	–	–	–
(s.e.)	(524)	(325)	(203)	(156)	–	–	–
N	122	255	512	839	–	–	–

Notes: The table shows how the model fits data on college costs q, parental transfers z, and earnings in college y_{coll}. Means are shown by HS GPA quartile. Parental transfers are observed for all high school graduates, regardless of college attendance. All figures are in year 2000 dollars. "s.e." denotes the standard deviation of the sample mean. N is the number of observations.
Source: High School & Beyond.

Table 8: Student Debt

	Mean debt		Fraction with debt	
Year	Model	Data	Model	Data
1	3,153	3,511 (42)	18.2	26.1
2	5,641	5,945 (87)	26.7	34.6
3	7,805	7,871 (137)	51.4	41.0
4	10,722	9,486 (187)	57.5	47.4

Notes: The table shows the fraction of students with college debt ($k < 0$) at the end of each year in college. Mean debt is conditional on being in debt. Standard errors are in parentheses.
Source: High School & Beyond.

dispersion (ϕ_s). The alternative would be to reduce y_{CG}, but this does not lower the college dropout premium. It would also violate the constraint $y_{CG} \geq y_{HS} = y_{CD}$ and imply that graduating from college reduces earnings for low ability students. The lower ability dispersion flattens the relationship between HS GPA and lifetime earnings (Table 6).

Higher values of μ increase the incentives to stay in college longer, even for students who expect not to graduate. This leads college dropouts to stay in college longer than in the data (Figure 6).

Preference shocks. When preference shocks are smaller than in the baseline case, the model fails to account for the timing of dropout decisions. Too many low ability students stay in college until T_c. The intuition is that students with low q and high k_1 have no reason to drop out. They know from the outset that they will not graduate. For these students, college is mainly a consumption good. However, their dropout decisions are sensitive to shocks because the financial stakes are so small. Preference shocks prevent these students from staying in college too long. Small preference shocks also lead the model to understate the lifetime earnings gaps between school groups.

Larger preference shocks weaken the association between college costs and college attendance. As a result, the model greatly overstates the rise in debt as students go through college. The baseline model avoids this because college students select more strongly on college costs. Larger preference shocks are associated with more ability dispersion and thus increase the role of ability selection for the college premium.

F Robustness

This section investigates the robustness of our main finding. Table 9 shows how the importance of ability selection varies with the value of selected parameters.

To illustrate how to read the Table, consider the first row. It varies ϕ_{HS} over a grid of values that range from 0.1 to 0.25, compared with a baseline value of 0.15. The model is recalibrated, fixing ϕ_{HS} at each grid point. The "selection" column reports the smallest and the largest fraction of the mean log lifetime earnings gap between college graduates and high school graduates that is due to ability selection. This is defined as in **??**. The remaining rows of Table 9 vary the values of μ, $\alpha_{a,m}$, π, and σ (the curvature parameter in $u(c) = c^{1-\sigma}/(1-\sigma)$) in similar ways.[6]

Across all parameter values covered in Table 9, we find that ability selection accounts for more than one-third of the college lifetime earnings premium. We have also experimented with alternative ways of constructing the calibration targets and with restricted

[6] We tried wider ranges for some of the parameters, but found that the model fit deteriorates dramatically.

Table 9: Robustness

Variable	Base value	Range	Selection
ϕ_{HS}	0.150	0.10–0.25	38.9–80.0
μ	0.010	0.005–0.020	56.6–38.8
$\alpha_{a,m}$	2.854	1.00–3.00	51.7–58.1
$\alpha_{IQ,m}$	1.158	0.50–2.00	51.0–51.8
π	1.206	0.40–2.00	54.9–50.4
σ	1.000	1.00–3.00	54.1–44.5

Notes: Each row varies one parameter over a grid of values. "Variable" indicates which parameter is varied. "Base value" shows the parameter's value in the baseline model. "Range" shows the range over which the parameter is varied. "Selection" shows the fraction of the mean log lifetime earnings gap between college graduates and high school graduates that is due to ability selection.

or extended models. For example, we explored alternative functional forms for the probability of passing a course, we shut down the non-pecuniary schooling costs $U(s)$, and we allowed for a direct consumption utility of being in college. In all cases, we found our main result to be highly robust.

F.1 Two Abilities

In the baseline model, agents are endowed with a single ability that affects credit accumulation and earnings. Here, we consider an extension where the agent is endowed with a second ability b that affects credit accumulation but that either does not affect earnings or that is not correlated with GPA.[7]

To motivate this extension, consider two students who choose different college majors. The student choosing the hard major accumulates credits more slowly, even if his ability is the same as that of the student choosing the easy major. This raises two concerns about our identification strategy:

- Case 1: b does not affect earnings.

  If college outcomes and entry or dropout choices depend mostly on b rather than a, then selection on ability (mostly b) contributes little to the college earnings premium.

- Case 2: b is not correlated with HS GPA.

  Suppose that HS GPA is a precise measure of a. Since we infer its precision from the relationship between HS GPA and course outcomes (governed by $a + b$), we

[7] We thank an anonymous referee for this suggestion.

would infer incorrectly that HS GPA is a *noisy* measure of a. This would lead us to overstate the effect of a on lifetime earnings.

In addition to college majors, b could represent colleges of different qualities or learning abilities that either do not affect earnings or that are not measured by HS GPAs (e.g., "grit").

F.1.1 Model Details

Incorporating a second ability modifies the baseline model as follows. In addition to the endowments described in the main text, high school graduates draw a second ability $b \sim N(0,1)$. b affects the probability of passing a course, which is now given by

$$\Pr{}_c(a,b) = \gamma_{min} + \frac{1-\gamma_{min}}{1+\gamma_1 e^{-\gamma_2 a - \gamma_b b}}. \tag{2}$$

We also consider the possibility that b affects lifetime earnings, which are now given by

$$\exp\left(\phi_s a + \hat{\phi} b + \mu n_\tau + y_s\right). \tag{3}$$

Finally, we allow for the possibility that ability measures (GPA) may be correlated with both abilities:

$$GPA = \frac{\alpha_m m + \alpha_b b + \varepsilon}{\left(\alpha_m^2 + \alpha_b^2 + 1\right)^{0.5}}. \tag{4}$$

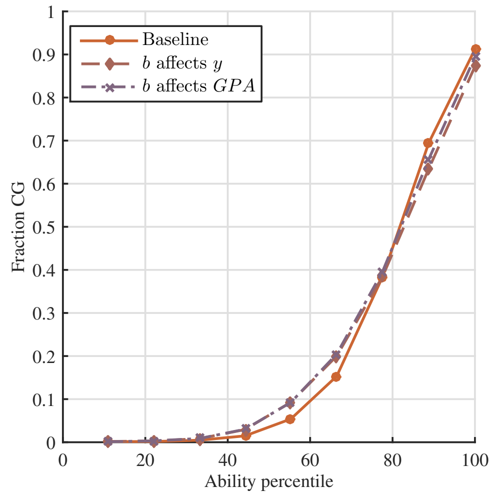
Motivated by tractability concerns, we also assume that b is orthogonal to the student's other endowments and that b is known at the time of high school graduation. Aside from the formulas that govern students' beliefs about their abilities for any given state (n,j,t), the solution to the household problem is unchanged.

We let the model decide whether b affects lifetime earnings and GPA. Note, however, that the case where b affects both is not interesting. It effectively makes b and a the same object. Therefore, we consider two versions of the model that align with the two concerns about identification highlighted above:

- Case 1 sets $\hat{\phi} = 0$ (b does not affect earnings) and calibrates α_b.
- Case 2 sets $\alpha_b = 0$ (b is not correlated with GPA) and calibrates $\hat{\phi}$.

We recalibrate the model for each case and compare it with the baseline model (with a single ability).

Figure 7: Probability of Graduating from College by Ability



F.1.2 Results

In both model cases, we find that the differences compared with the baseline model are minor. When we calibrate the effect of b on lifetime earnings (case 2), we find that the calibrated value of $\hat{\phi}$ is very close to zero. Thus, in both cases, selection on b contributes nothing to the college premium and it suffices to consider selection on a.

Figure 7 gives a sense of how the presence of the second ability affects school sorting. It shows how the probability of graduating from college varies with ability a. The baseline model is compared with the two versions of the two ability model described earlier. Ability sorting gets slightly weaker in the two ability models, but the quantitative changes are minor. As a result, the fraction of the college earnings premium that is due to selection is above 0.5 in all cases.

The main reason why the second ability matters so little is that the calibrated values of the parameters that govern the role of b are small relative to the corresponding parameters that govern the role of a. For example, in both model versions, the calibrated values of γ_b are near 0.8, compared with values near 1.9 for γ_1. As a result, college entry and dropout decisions are mainly based on a rather than b.

Finally, we investigate whether the data moments used in the calibration are sufficient to identify the role of the second ability. To do so, we recalibrate the model, fixing γ_b at 2.1 (the value of γ_1 in the baseline model). In both cases, we find that the model fit deteriorates along many dimensions. The second ability increases credit persistence over time, which is now stronger than in the data. The correlation between college outcomes and abilities a becomes weaker. In Case 2, where b does not affect GPA, this results in a weaker relationship between college outcomes and GPA. Ability selection still accounts for 43% of the college lifetime earnings premium in Case 1 and for 49%

in Case 2.

We conclude that our results are robust when agents are endowed with persistent traits other than "abilities" (a) that affect credit accumulation.

G Income, Hours Worked, and Course Outcomes Among College Students

This Appendix summarizes empirical evidence on the following questions:

1. Do students from low income families work more hours?
2. Do students who work more study less?
3. Does working more lead to worse course outcomes?

While summarizing published evidence on these questions, we also present summary statistics based on our own data. Our reading of the literature suggests that the poor academic performance of (some) low income students is likely not due to long work hours that cut into their study times.

G.1 Do Low Income Students Work More Hours?

Published evidence, as well as our own data, show that there is little variation in hours worked across family income groups.

1. Scott-Clayton et al. (2012) (figure 3) displays a time series of hours worked by full-time college students (based on October CPS data). Mean hours worked do not vary systematically across family income quartiles.
2. Bozick (2007) finds that the fraction of college students who work more than 20 hours per week differs by 2.5% between the highest and the lowest parental income quintiles (based on Beginning Postsecondary Study 1996 data).
3. Hendricks et al. (2015) document a 10% gap in hours worked between students from the top and bottom SES quartiles (based on NLSY79 data).
4. Kalenkoski and Pabilonia (2010) finds that variation in parental transfers has a "quite small" effect on hours worked.

Table 10: Hours Worked and Socio-economic Status

SES q	annual earnings	fraction FT	annual hours
1	4.246	0.061	670
2	4.834	0.082	758
3	4.688	0.065	698
4	4.232	0.047	606

Note: HS&B students that persist for at least 2 years of college. Earnings are measured in thousands of 2000 dollars.

These results from our HS&B dataset are consistent with these studies. Table 10 reports average annual earnings and hours by socio-economic status (SES) of the parents' household.[8] Students in the highest SES quartile work 64 hours less per year compared to students in the lowest SES quartile (about 1.2 hours per week). The fraction of students working full time (i.e., over 35 hours per week and 50 weeks per year) is small (6%) and varies little across SES quartiles.

Quantitatively, a gap in hours worked of 1.2 hours per week is not likely large enough to have substantial effects on course outcomes, even if working more in college has an adverse impact on credit accumulation. Below, we summarize the literature and our own findings on the effect of working on course outcomes. The general finding is that these effects are not large either.

The finding that high SES students work nearly as much as low SES students may be surprising to the reader. One possible reason is that low income students face lower net costs of college, even after conditioning on the type of college they attend. This is because they receive more financial aid (see Bozick 2007; we also find this in our data).

The notion that low income students do not work long hours in order to pay for college may be surprising to readers who have followed recent debates on college affordability. It is important to keep in mind, however, that we are studying a time period of generous financial aid and loan limits relative to tuition. More recently, financial constraints have tightened (Belley and Lochner, 2007) and the gap in hours worked between high and low income students has increased. Notably, Scott-Clayton et al. (2012) (table 2) find that low income students work 25% more than high income students (based on 2003-2004 NPSAS data). In NLSY97 data, the gap is 35% (Hendricks et al., 2015).

[8] The universe is students that persist in college for 2 or more years. The SES composite score is based on five components: fathers occupation and education, mothers education, family income, and material possessions. It is a simple average of standardized components. Similar results are obtained if using parental income in place of the SES composite.

G.1.1 Do Low Income Students Study Less?

Ideally, we would like to know how being poor (or working long hours) affects students' study time. Unfortunately, the evidence on this question is quite limited.

1. Walpole (2003) finds a gap in study time of 10% between students in the top and bottom SES quintiles. This is based on the 1985-94 CIRP freshmen surveys (where one may question the quality of the responses).

2. Stinebrickner and Stinebrickner (2004) no difference in study times between high and low income students for Berea College.

3. Babcock and Marks (2011) report a gap in study time of about 1.5 hours per week between the children of college graduates and the children of parents without college education (with some variability across studies that cover the period 1961-2004). Of course, there may be reasons other than income why the children of highly educated parents study more.

G.2 Does Working in College Lead to Worse Course Outcomes?

This question has been studied extensively. Most recent research finds that working in college is associated with worse course outcomes, but the estimated effects are small.

Most of the evidence measures course outcomes by grades.

1. DeSimone (2008) and Kalenkoski and Pabilonia (2010) both find that increasing work by 1 hour per week reduces GPA by about 0.01 points.

2. Stern and Nakata (1991) summarize earlier research as: "available research does not give any consistent indication that working students perform either better or worse than nonworking students" (p. 32).

3. Ehrenberg and Sherman (1987) is a well-known study that finds no significant effects of hours worked on grades.

4. Using HSB data, Gleason (1993) finds "that employment does not harm students' grades, except perhaps for a small group of students who work a large number of hours" (p. 8).

This is consistent with our own findings from the HS&B dataset. We regress college GPA on hours worked and controls (proxies for academic ability, type of college, year in college, and gender). The point estimates imply that working an extra hour per week is associated with a 0.001 point reduction in GPA (not statistically significant) (see column 1 of Table 11). The association between hours worked and course passing rates is similarly small (see column 2).

Interestingly, even **study time** seems to have little effect on college GPAs. For example, Plant et al. (2005) summarize the evidence as follows: "Researchers have consistently found a weak or unreliable relationship between the weekly amount of reported study time and grade point average (GPA) for college students" (p. 97; see also Nonis and Hudson (2006) for a similar summary of the literature).

Published evidence on the effect of working in college on **credit accumulation** is scarce. The only study we are aware of is Scott-Clayton (2011) who finds no significant effect of working in college on earned credits (or any other academic outcomes).[9]

In our data, we find weak association between hours worked and credits attempted (column 3 of Table 11) or credits earned (column 4). Our point estimates imply that an extra hour of work per week is associated with a 0.058 credit hour reduction in the annual course load (or 0.2% of mean attempted credits) and with a 0.065 credit hour reduction in annual credits earned. The course passing rate drops by 0.0004. Thus, a student who works full time (35 hours per week) is expected to attempt and earn about 2 fewer credit hours compared with a student who does not work at all. While this is not a negligible reduction, recall that only 6% of students in our sample work full time.

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[9] In contrast to much of the literature, this paper aims to identify the causal effect of working on outcomes (not just a correlation) using the Federal Work Study program as a source of exogenous variation in hours worked.

Table 11: Course Outcomes and Hours Worked

	college GPA	passing rate	cred. earned	cred. attempted
weekly hrs	-0.001	-0.000	-0.065***	-0.058***
HS GPA	0.012***	0.002***	0.091***	0.048***
senior test	0.003***	0.000	0.010	0.007
Private HS	0.075*	0.008	0.176	-0.251
SES percentile	0.090***	0.018*	0.216	-0.182
parents CD	-0.044	-0.012	-0.467	-0.205
parents CG+	-0.085*	-0.016	-0.341	0.032
y = 1	0.000	0.000	0.000	0.000
y = 2	-0.018	-0.034***	-1.630***	-1.011***
female	0.000	0.000	0.000	0.000
type = 2	-0.266***	0.034***	1.971***	1.432***
type = 3	-0.284***	0.027**	1.297**	0.919*
type = 4	-0.318***	0.023*	1.965***	1.749***
private	0.127***	0.032***	1.620***	0.816*
Constant	1.750***	0.771***	20.642***	26.355***
Observations	2910	2924	2924	2924
R^2	0.240	0.122	0.157	0.086

*p below 0.05, **p below 0.01, ***p below 0.001

Notes: The table shows the results of regressing course outcomes on hours worked, proxies for student abilities and college characteristics.

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