The Return to College: Selection and Dropout Risk

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Abstract

This paper studies the effect of graduating from college on lifetime earnings. We develop a quantitative model of college choice with uncertain graduation. Departing from much of the literature, we model in detail how students progress through college. This allows us to parameterize the model using *transcript data*. College transcripts reveal substantial and persistent heterogeneity in students' credit accumulation rates that are strongly related to graduation outcomes. From this data, the model infers a large ability gap between college graduates and high school graduates that accounts for 54% of the college lifetime earnings premium.

JEL: E24, J24 (human capital), I21 (analysis of education).

Key words: Education. College premium. College dropout risk.

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1 Introduction

A large literature has investigated the causal effect of college attendance on earnings.[1] In U.S. data, college graduates earn substantially more than high school graduates. However, part of this differential may be due to selection as students with superior abilities or preparation are more likely to graduate from college. While various approaches have been proposed to control for selection, no consensus has been reached about its importance.

The challenge. To understand why controlling for selection is hard, consider a simple model of lifetime earnings. Each person starts life as a high school graduate, endowed with a random ability a. He chooses to work as a high school graduate ($s = HS$) or as a college graduate ($s = CG$). Log lifetime earnings are given by $\phi a + y_s$, where $\phi > 0$ and y_s determine the effects of ability and schooling on lifetime earnings, respectively. The observed lifetime earnings gap between college graduates and high school graduates can be decomposed into a term reflecting the return to college, $y_{CG} - y_{HS}$, and a term reflecting ability selection, $\phi \left[\mathbb{E} \left\{ a | CG \right\} - \mathbb{E} \left\{ a | HS \right\} \right]$. The challenge is then to estimate the ability gap between college graduates and high school graduates and the effect of ability on lifetime earnings ϕ.

If abilities were observable, e.g. as test scores, estimating ability selection would be easy. The ability gap could be computed from the joint distribution of test scores and schooling, while ϕ could be estimated by regressing log lifetime earnings on test scores and schooling dummies. However, since test scores are noisy measures of abilities, these simple calculations would be biased. Since the precision of test scores as measures of abilities is not known, correcting for this bias is difficult.

Transcript data. The central idea of this paper is that transcript data provide information about both of the terms needed to estimate ability selection (the ability gap and ϕ). Transcripts reveal how rapidly students progress towards earning a bachelor's degree. We think of the number of credits a student earns in each year as determined by ability and luck. Thus, credit accumulation rates provide additional noisy measures of the relationship between abilities and college outcomes. In contrast to commonly used test scores, transcripts provide *repeated* observations for the same individual. This helps to estimate how

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[1] For a recent survey, see Oreopoulos and Petronijevic (2013).

precisely test scores measure abilities. It is then possible to correct for the biases introduced when test scores are used in lieu of abilities.

Implementation. To implement this idea, we develop a quantitative model of college choice (section 3). The model follows a single cohort from high school graduation through college and work until retirement. At high school graduation, agents are endowed with heterogeneous financial resources and abilities. Following Manski and Wise (1983), we assume that students observe only noisy signals of their abilities. High school graduates choose between working and attempting college. While in college, students make consumption-savings and work-leisure decisions.

Our main departure from the literature is to model students' progress through college in detail.[2] This allows us to map transcript data directly into model objects. We model credit accumulation as follows. In each period, a college student attempts a fixed number of courses. He passes each course with a probability that increases with his ability. At the end of each year, students who have earned a given number of courses graduate. The remaining students update their beliefs about their abilities based on the information contained in their course outcomes. Then they decide whether to drop out or continue their studies in the next period. Students must drop out if they lack the means to pay for college, or if they fail to earn a degree after 6 years in college.

We calibrate the model using a rich set of data moments for men born around 1960 (section 4). Our main data sources are High School & Beyond and the Postsecondary Education Transcript Study (PETS, section 2), from which we obtain college transcripts and financial variables, and NLSY79, from which we estimate lifetime earnings.

Findings. Our model implies that ability selection is important (section 5). We measure its contribution as the fraction of the lifetime earnings gap between college graduates and high school graduates that would remain if both groups worked as high school graduates. In the main specification, this fraction is 54% (24 log points). We show that this result is robust (Appendix F).

To understand why the model has this implication, we highlight the following features of transcript data:

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[2] In much of the literature, college is a black box. Exceptions include Arcidiacono et al. (2012), Garriga and Keightley (2007), and Stange (2012).

1. There is large dispersion in credit accumulation rates across students. By the end of the second year in college, students in the 80th percentile of the credit distribution have earned 52% more credits than students in the 20th percentile.

2. Individual credit accumulation rates exhibit substantial persistence. The correlation between credits earned in adjacent years is 0.43.

3. Credit accumulation rates are strongly related to college graduation. By the end of their second year in college, students who eventually graduate have earned 40% more credits per year than those who eventually drop out.

4. Controlling for test scores does not greatly reduce the dispersion in credits.

Our model of credit accumulation decomposes the dispersion in earned credits into persistent heterogeneity (abilities) and shocks (luck). To account for the persistence of credits, the model must limit the role of luck and instead rely on credit accumulation rates that rise sharply with ability. Given the limited role of luck, the gap in credits between college graduates and college dropouts identifies the ability gap between the two groups. The fact that controlling for test scores does not greatly reduce credit dispersion implies that test scores must be noisy measures of ability. Given these estimates of test score noise and the ability gap, we can use the observed joint distribution of lifetime earnings and test scores to estimate ϕ. The structural model then interprets the strong association between test scores and college outcomes to mean that high school graduates have precise information about their abilities.

The economic mechanism by which the structural model generates a large ability gap between college graduates and dropouts is the following. The fact that credit passing rates increase sharply with ability implies a large heterogeneity in *graduation prospects*. By this we mean the probability that a student earns enough credits to graduate within the permitted 6 years in college. This, in turn, implies that the ex ante return to attending college depends strongly on individual ability.

Low ability students rarely graduate from college, even if they persist for 6 years. For these students, the main benefit of college (human capital accumulation) is roughly offset by the main cost (foregone earnings). The net effect of college attendance on lifetime earnings is small. As a result, low ability students are easily persuaded to drop out in response to adverse shocks, such as poor course outcomes. By contrast, high ability students expect to graduate if they persist in college. Since graduating entails substantial earnings gains,

these students are not easily persuaded to drop out before graduation. The result is a large ability gap between college graduates and dropouts.

Heterogeneity in graduation prospects also generates ability selection at college entry. Low ability students are deterred from entering college by their poor graduation prospects. By contrast, high ability students expect to graduate with high probability and therefore enter college in large numbers. The result is a large ability gap between college entrants and high school graduates.

The same logic implies that high and low ability students respond differently to changes in the costs and benefits associated with attending college. The entry decisions of low ability students are quite sensitive to the direct costs of college. This feature allows our model to account for college dropout behavior and for the large effects of tuition changes on college enrollment estimated in the literature (see subsection 5.4). By contrast, the entry decisions of high ability students respond strongly to changes in the wages earned by college graduates, but not to tuition changes.

Even though our model implies substantial heterogeneity in college costs and financial resources, the role of financial frictions is limited. Relaxing borrowing limits or providing additional college funding has only minor effects on college entry and graduation rates.

1.1 Related Literature

This paper relates to a vast literature that estimates returns to schooling. One strand of this literature uses econometric approaches, such as instrumental variables, to control for selection bias in wage regressions.[3] These studies abstract from degrees and treat schooling as a continuous variable and are therefore silent about the college premium and completion risk.

A more recent literature has developed structural discrete choice models of schooling decisions. A large share of this is based on Roy models which abstract from college completion risk.[4] Models with college completion risk have, for the most part, abstracted from heterogeneity in abilities that directly affect earnings.[5] These models cannot address the question

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[3] Card (1999) surveys this literature and discusses how its findings may be interpreted.

[4] A seminal contribution is Willis and Rosen (1979). More recent work includes Heckman et al. (1998), Cunha et al. (2005), and Navarro (2008).

[5] See Altonji (1993), Caucutt and Kumar (2003), Akyol and Athreya (2005), Garriga and Keightley (2007), Chatterjee and Ionescu (2012), and Athreya and Eberly (2013). In Stange (2012), the contribution of ability selection to the college premium is not identified (see pp. 63-64 in his paper).

of how ability selection affects measured college wage premiums.

A number of recent papers feature both ability heterogeneity and college completion risk. Much of this work builds on the seminal contribution of Keane and Wolpin (1997).[6] In these models, all students can attain college degrees simply by staying in college for a fixed number of periods. Some students are exposed to shocks, such as wage offers or preference shocks, while in college and therefore *choose* to forego the college wage premium. We depart from this literature by modeling in detail how students progress towards fulfilling the requirements for a college degree. This allows us to introduce additional evidence, based on college transcripts, that contains information about students' graduation prospects at various stages in college. In this respect, our work resembles Eckstein and Wolpin (1999) who study high school dropouts.

Trachter (2014) also develops a model where graduating from college requires a fixed number of earned credits. Since his model features only two types of students (high and low ability) and perfect school sorting by students' beliefs about their abilities, it is not well suited to measure ability selection. Where we differ fundamentally from Trachter is in the empirical approach. At the center of our analysis is the idea that credit accumulation rates provide direct information about students' abilities and their chances of earning a college degree. The observed heterogeneity in credit accumulation rates implies that the payoffs from attending college differ greatly between high and low ability students. This results in large ability selection. Since the data Trachter uses to calibrate his model do not contain transcripts, he is unable to exploit this information. Our model also features richer heterogeneity in unobserved student characteristics and their financial constraints.

Other studies of risky college completion that use transcript data include Arcidiacono (2004; 2012) and Stange (2012). In these models, college grades contain information about student abilities that affect the utility derived from attending college or earnings. Our empirical approach is very different. Our model recognizes that only academically successful students can graduate from college. We use data on earned credits to measure how students' progress towards graduation varies with their abilities. In work in progress, Heckman and Urzua (2008) study a model of risky college completion where students learn about their abilities and schooling preferences.

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[6] See Keane and Wolpin (2001), Belzil and Hansen (2002), Johnson (2013), and Stange (2012).

2 Measuring Ability Selection

This section discusses how we use transcript data to measure ability selection. To focus ideas, consider a simple model of lifetime earnings. Individuals are endowed with random abilities $a \sim N(0, 1)$. They choose a schooling level $s \in \{HS, CD, CG\}$ where CD denotes college dropouts. Their log lifetime earnings are then given by $\phi a + y_s$. $\phi > 0$ and y_s determine how much abilities and schooling affect lifetime earnings, respectively.

In this simple model, the lifetime earnings gap between college graduates and high school graduates is the sum of a term representing selection, $\phi [\mathbb{E}\{a|CG\} - \mathbb{E}\{a|HS\}]$, and a term representing the return to college, $y_{CG} - y_{HS}$. To estimate the contribution of selection, we need to determine the scale parameter ϕ and the ability gap between college graduates and high school graduates.

This is challenging because abilities are not observable, although we may observe noisy proxies, such as high school GPAs or cognitive test scores. The central idea of this paper is that transcript data can help to overcome this problem. Observing how rapidly students accumulate college credits provides us with information about their abilities and their chances of graduation. We can exploit the fact that this signal is observed repeatedly for the same individual to bound the signal noise. This allows us to estimate ability selection.

2.1 Data Description

We obtain college transcripts from the Postsecondary Education Transcript Study (PETS), which is part of the High School & Beyond dataset (HS&B; see United States Department of Education. National Center for Education Statistics 1988). The data cover a representative sample of high school sophomores in 1980. Participants were interviewed bi-annually until 1986. In 1992, postsecondary transcripts from all institutions attended since high school graduation were collected. We retain all students who report sufficient information to determine the number of college credits attempted and earned, the dates of college attendance, and whether a bachelor's degree was earned. HS&B also contains information on college tuition, financial resources, parental transfers, earnings in college, and student debt, which we use to calibrate the structural model presented in section 3. Appendix A provides additional details.

Table 1: College Credits

| | Credit distribution | | | Median credits | | Fraction |
GPA quartile	20th	50th	80th	CD	CG	graduating
1	21	38	57	32	57	10.7
2	36	50	62	46	57	24.9
3	37	55	64	44	58	50.8
4	50	61	68	45	62	73.6
All	41	57	66	44	60	52.5

Notes: The table shows the distribution of credits earned at the end of the second year in college. Students are divided into quartiles according to their high school GPAs. CD and CG denotes college dropouts and graduates, respectively. "Fraction graduating" is the fraction of college entrants earning a bachelor's degree.
Source: High School & Beyond.

2.2   Facts

Table 1 shows the distribution of credits earned at the end of the second year in college. We highlight features of the data that play a central role in measuring ability selection.[7]

1. Students who eventually graduate earn 40% more credits than do students who eventually drop out. This is consistent with the notion that academic failure is an important reason for dropping out.[8]

2. The dispersion in credits is large. Students in the 80th percentile earn 52% more credits than do students in the 20th percentile.

3. Controlling for high school GPA does not reduce the dispersion in credits dramatically. Even within GPA quartiles, college dropouts perform far worse than graduates.

The data admit two interpretations.

1. Luck dominates. If students are endowed with similar abilities and thus credit accumulation rates, the dispersion in credits represents mostly luck. This would explain

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[7] Focusing on the second year is a compromise. On the one hand, later years are preferable because students have attempted more courses, which reduces the effects of "luck" on earned credits. On the other hand, students in later years are more selected. The structural model of section 3 uses data for the first 4 years of college.

[8] Stinebrickner and Stinebrickner (2012) provide survey evidence supporting this notion.

Table 2: Persistence of Credit Accumulation Rates

	Year $1-2$	Year $2-3$	Year $3-4$
Correlations	0.48	0.42	0.39
Eigenvalues	0.51	0.47	0.41
N	1665	1378	1196

Notes: "Correlations" shows the correlation coefficients of credits earned in adjacent years. "Eigenvalues" shows the second largest eigenvalues of quartile transition matrices. Source: High School & Beyond.

why conditioning on GPA does not reduce credit dispersion much, even if GPA is a precise measure of ability. The fact that college dropouts earn fewer credits than graduates then represents mostly luck, not ability differences. In this case, ability selection is weak.

2. Heterogeneity dominates. If students differ greatly in their abilities and thus credit accumulation rates, luck accounts for a small fraction of credit dispersion. The low credit accumulation rates of dropouts reveal their low abilities, so that ability selection is strong. The fact that conditioning on GPA does not reduce credit dispersion much implies that GPA must be a noisy measure of ability.

A single cross-section of data cannot distinguish between the two interpretations. Fortunately, our data allow us to follow individuals over time and observe their credit accumulation rates repeatedly. Table 2 shows that individual credit accumulation rates exhibit substantial persistence over time. We construct two measures of persistence. First, the correlation between accumulation rates in consecutive years (computed for all students who are enrolled in both years, averaged over the first 3 years in college) is 0.43. Second, we construct transition matrices for quartiles of credits earned in t and $t+1$. The average of the second largest eigenvalues of these transition matrices is 0.47. These findings suggest that heterogeneity in persistent student characteristics (which we label abilities) accounts for a substantial fraction of the dispersion in credits.

In order to quantify what this implies for ability selection, we develop a reduced form model of credit accumulation. It makes a simple assumption that effectively decomposes dispersion in credits earned into the contributions of ability and luck. This allows us to back out the contribution of ability selection to the college lifetime earnings gap.

In , we embed a similar model of credit accumulation in a structural model of college choice. This allows us to deal with selection issues and to relax some arbitrary assumptions. The main purpose of the reduced form model is to present the logic of how the structural model backs out ability selection from transcript (and other) data in a transparent setting. Using the calibrated structural model, we can defend our model of credit accumulation by showing that it accounts for a range of data statistics, including the dispersion and persistence of credit accumulation rates.

2.3   A Reduced Form Model

The model elements are as follows:

1. There is a population of college freshmen. At the start of year $t = 1$, each student is endowed with $n_1 = 0$ completed courses, with a random ability $a \sim N(0, 1)$, and with a noisy signal of ability given by $IQ = a + \varepsilon$ where $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. In the data, we observe high school GPAs, which we assume are arbitrarily scaled increasing functions of IQ.

2. In each year, a college student tries $n_c = 12$ courses. Passing a course yields 3 credits. The value of n_c is chosen such that passing all courses yields the number of credits earned per year by students in the 90th percentile of the credit distribution (the number is the same in years 1 through 3).

3. A student of ability a passes each course with probability $p(a) = \gamma_{min} + \frac{1 - \gamma_{min}}{1 + \gamma_1 e^{-\gamma_2 a}}$. $p(a)$ is a generalized logistic function.

4. A student graduates when he passes $n_{grad} = 42$ courses (earns 125 credits).

5. If a student fails to pass n_{grad} courses by the end of year $T_c = 6$, he drops out of college. In HS&B data, only 5% of students remain in college for more than 6 years.

Estimating credit accumulation rates by ability.   By calibrating the model to transcript data, we aim to decompose the observed dispersion in earned credits into the contributions of heterogeneity in credit accumulation rates p and luck. To do so, we search for a distribution of accumulation rates p that allows the model to match the empirical distribution and persistence of earned credits.

To motivate this approach, consider what the model implies for the case where all students share the same p, given by the median fraction of credits earned by the end of a given year t. The distribution of n_{t+1} is then Binomial. Focusing on year 2, the 20th and 80th percentiles of the Binomial distribution with $2n_c$ trials and an average passing probability of $p = 54/(2n_c)$ are 48 and 60 credits, respectively. In the data, the corresponding values are 41 and 66 credits. Clearly, heterogeneity in p is needed to account for the observed dispersion of credits.

To estimate the dispersion of p, we calibrate the parameters of the $p(a)$ function to minimize the sum of squared deviation between the following model-implied and observed moments: (i) the number of earned credits for the 1st through 9th decile of the credit distribution; and (ii) the correlation of earned credits between the first and the second year in college.

Figure 1 shows the implications of the calibrated model. Panel 1a compares the distribution of credits implied by the model with the data. The correlation of credits implied by the model of 0.56 is higher than in the data. One reason is that, in the data, the students with the worst course performance tend to drop out. Panel 1b shows that the calibrated distribution of $p(a)$ is not far from uniform over the range [0.4, 1].

The large heterogeneity in p has an implication that is central for the structural model. The binomial distribution of credits implies that the probability of earning enough credits for graduation, which we call the *graduation prospect*, increases sharply in p (see Panel 1d). Together with the calibrated distribution of p, this implies that a large fraction of students face graduation prospects near 0 or 1 (Panel 1c). Since, in the structural model, the incentives for persisting in college depend strongly on students' graduation prospects, the large dispersion in graduation prospects implies a large ability gap between college graduates and dropouts.

Estimating the ability gap between college graduates and dropouts. Next, we ask what the distribution of credit accumulation rates shown in Figure 1 implies for the ability gap between college graduates and dropouts. The idea is to ask the model to replicate the large gap in earned credits between the two groups (see Table 1).

In the structural model, we expect graduation rates to increase with student abilities. In order to illustrate how transcript data help to identify this relationship, we assume that the probability of graduating from college, conditional on entering, is a logistic function of ability. It has the same functional form as $p(a)$. For simplicity, we set $\gamma_{min} = 0$. We calibrate the parameters of this function to match the distribution of credits earned at

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Figure 1: Reduced Form Model: Credit Accumulation Rates and Graduation Prospects

(a) Distribution of credits

(b) Credit accumulation rates

(c) Distribution of graduation prospects

(d) Graduation prospects and abilities
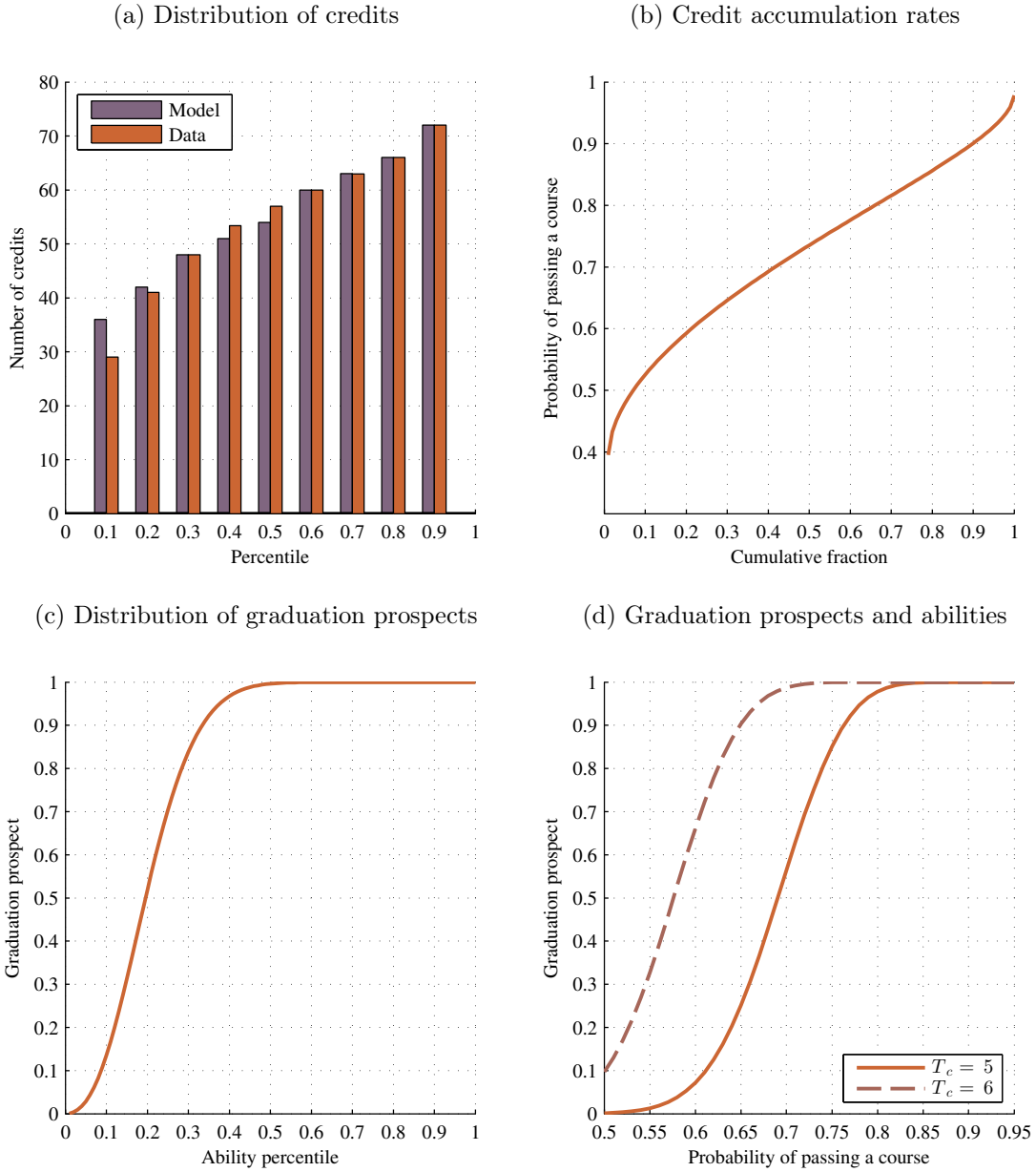
Notes: Panel(a) compares the CDFs of credits implied by the reduced form model with HS&B data. Panel(b) shows the distribution of course passing rates, while Panel(c) shows the distribution of graduation prospects implied by the model. Panel(d) shows how graduation prospects vary with the probability of passing a course.

the end of year 2 for college dropouts and college graduates. Specifically, the calibration searches for parameter values that minimize the sum of squared deviations between the model-implied and the observed numbers of credits earned for each decile of the credit distribution between the 1st and the 9th. A penalty is added to the objective function when the overall graduation rate implied by the model differs from the data.

Figure 2 shows the implications of the calibrated model. The overall dropout rate among college entrants is 48.8% vs 47.5% in the data. Panels 2a and 2b show how well the model fits the CDFs of earned credits for college dropouts and college graduates, respectively. The model implies that the graduation rate increases sharply with ability (Panel 2c). This allows the model to account for the large gap in credits between college graduates and college dropouts. As a result, the distribution of graduation probabilities differs greatly between the two groups. The gap in mean abilities between college graduates and dropouts is $\mathbb{E}\{a|CG\} - \mathbb{E}\{a|CD\} = 1.29$ (Panel 2d). This is the first ingredient needed to estimate ability selection.

Estimating ϕ. The second ingredient is the effect of ability on lifetime earnings, ϕ. We estimate its value from the relationship between log lifetime earnings, given by $\phi a + y_s$, and test scores. If abilities were observable, we could regress log lifetime earnings on a and school dummies (standing in for y_s). If we use test scores instead of a, we expect the resulting coefficient, β_{IQ}, to be smaller than the true ϕ (attenuation bias). However, we can correct for this bias using simulated data from the reduced form model. Specifically, given values of ϕ and test score noise σ_ε^2, we can regress simulated log lifetime earnings on simulated standard normal test scores and school dummies (each model agents graduates with a known probability). We can then search for the value of ϕ that replicates the estimated value of β_{IQ}.

Implementing this idea requires an estimate of how precisely GPA measures ability.[9] We obtain this by calibrating the model to match the distribution of credits within GPA quartiles. The idea is that conditioning on GPA will reduce the dispersion in earned credits only if GPAs measure abilities with high precision. Recall that we think of GPA as an increasing transformation of $IQ = a + \varepsilon$. We search for the value of σ_ε^2 that minimizes the sum of squared deviations between model-implied and observed credits for the 1st through 9th deciles of each GPA quartile's credit distribution.[10] The calibrated value of $\sigma_\varepsilon^2 = 2.1$

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[9] Hendricks and Schoellman (2014) bound the noise in test scores using the correlation of multiple tests taken by the same individuals. Their approach only yields a lower bound for test score noise.

[10] The calibrated model replicates the observed distribution of credits reasonably well. Details are available

Figure 2: Reduced Form Model: Ability Selection

(a) Distribution of credits: Dropouts

(b) Distribution of credits: Graduates

(c) Graduation probabilities

(d) Ability densities
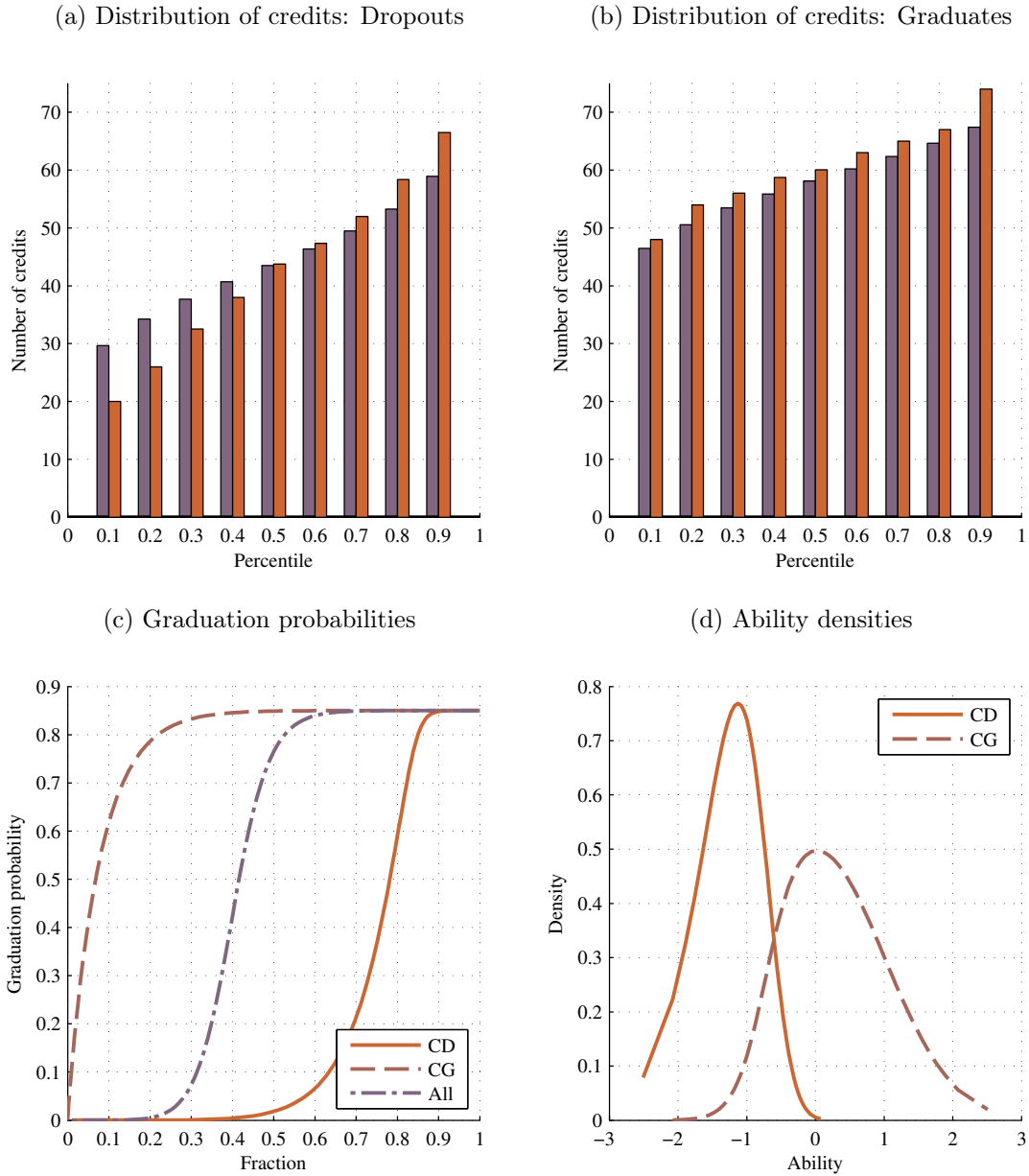
Notes: Panels (a) and (b) compare the CDFs of earned credits at the end of the second year of college implied by the reduced form model with HS&B data for college dropouts and college graduates, respectively. Panel (c) shows the CDF of graduation probabilities for college dropouts (CD), college graduates (CG), and all college entrants (All). Panel (d) shows the densities of abilities for college dropouts and graduates.

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implies that GPAs are noisy measures of abilities. The implied correlation between a and IQ is 0.57.

To illustrate what this implies for ϕ, we take $\beta_{IQ} = 0.07$ from a literature that regresses log wages (rather than lifetime earnings) on test scores and schooling.[11] The implied value of ϕ is 0.22. Selection, together with substantial noise in test scores, implies a large downward bias in β_{IQ}.

Implications for ability selection. We can now quantify what the reduced form model implies for ability selection. Recall that the contribution of ability selection to the college lifetime earnings premium is given by $\phi\left[\mathbb{E}\left\{a|CG\right\} - \mathbb{E}\left\{a|HS\right\}\right]$. The reduced form model produced an estimate of the ability gap between college graduates and college dropouts. We assume that the gap between college graduates and high school graduates is the same (1.29). The structural model will, of course, relax this assumption. It follows that selection accounts for 0.22×1.29 or 28 log points of the college lifetime earnings gap. Since we calculate from NLSY79 data that the lifetime earnings gap is 45 log points (section 4), selection accounts for 63% of the college lifetime earnings premium. This result is not too far from the implication of the structural model (54%).

To summarize, our approach for identifying ability selection in college works as follows. We use credit accumulation rates as noisy, repeated signals of individual abilities. We posit a model of credit accumulation that decomposes the observed dispersion in credit accumulation rates into ability heterogeneity and luck. Since the contribution of luck is not large, accounting for the large gap in credits earned by college graduates and dropouts requires a large ability gap between the two groups. Accounting for the fact that dropouts earn far fewer credits than graduates with the same GPA requires that GPA is a noisy measure of ability. Hence, the effect of abilities on earnings must be large. We validate our model of credit accumulation by showing that it is consistent with a range of empirical observations, including the persistence of credit accumulation rates.

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on request.

[11]See Bowles et al. (2001). For the structural model, we use estimates of individual lifetime earnings instead.

3 The Model

3.1 Model Outline

This section describes the structural model that we use to measure ability selection. We follow a single cohort, starting at the date of high school graduation ($t = 1$), through college (if chosen), and work until retirement. When entering the model, each high school graduate goes through the following steps:

1. The student draws an ability a that is not observed until he starts working. More able students are more likely to graduate from college and earn higher wages in the labor market.

2. The student draws a type $j \in \{1, ..., J\}$ which determines his initial assets $\hat{k}_j \geq 0$, his ability signal $\hat{m}_j$, a net price of attending college $\hat{q}_j$, and a parental transfer $\hat{z}_j$.

3. The student chooses between attempting college or working as a high school graduate.

A person who studies in period t faces the following choices:

1. He pays the college cost $\hat{q}_j$, receives transfers $\hat{z}_j$, and decides how much to work v_t, consume c_t, and save k_{t+1}.

2. He attempts n_c college courses and succeeds in a random subset, which yields n_{t+1}. More able students accumulate courses faster, as in Garriga and Keightley (2007).

3. Based on the information contained in n_{t+1}, the student updates his beliefs about a.

4. If the student has earned enough courses for graduation ($n_{t+1} \geq n_{grad}$), he must work in $t + 1$ as a college graduate. If the student has exhausted the maximum number of years of study ($t = T_c$), he must work in $t + 1$ as a college dropout. Otherwise, he chooses between staying in college and working in $t + 1$ as a college dropout.

An agent who enters the labor market in period t learns his ability a. He then chooses a consumption path to maximize lifetime utility, subject to a lifetime budget constraint that equates the present value of income to the present value of consumption spending. Agents are not allowed to return to school after they start working.

The details are described next. Our modeling choices are discussed in subsection 3.5.

3.2 Endowments

Agents enter the model at high school graduation (age $t = 1$) and live until age T. At age 1, a person is endowed with $n_1 = 0$ completed college courses, ability $a \in \{\hat{a}_1, ..., \hat{a}_{N_a}\}$ with $\hat{a}_{i+1} > \hat{a}_i$, and type $j \in \{1, ..., J\}$ which determines $\left(\hat{m}_j, \hat{q}_j, \hat{z}_j, \hat{k}_j\right)$.

a determines productivity in school and at work. Normalizing $\hat{a}_1 = 0$ simplifies the notation without loss of generality. $\hat{m}_j$ is a noisy signal of a. The agent knows the probability distribution of a given $\hat{m}_j$. $\hat{q}_j$ is the net price of attending college. We think of this as capturing tuition, scholarships, grants, and other costs or payoffs associated with attending college. $\hat{z}_j$ denotes parental transfers received during the first T_c periods after high school graduation, regardless of college attendance. The distribution of endowments is specified in section 4.

3.3 Work

We now describe the solution of the household problem, starting with the last phase of the household's life, the work phase. Consider a person who starts working at age τ with assets k_τ, ability a, n_τ college courses, and schooling level $s \in \{HS, CD, CG\}$. The worker chooses a consumption path $\{c_t\}$ for the remaining periods of his life ($t = \tau, ..., T$) to solve

$$V(n_\tau, k_\tau, a, s, \tau) = \max_{\{c_t\}} \sum_{t=\tau}^{T} \beta^{t-\tau} \ln(c_t) + U_s \tag{1}$$

subject to the budget constraint

$$\exp\left(\phi_s a + \mu n_\tau + y_s\right) + R k_\tau = \sum_{t=\tau}^{T} c_t R^{\tau-t}. \tag{2}$$

Workers derive period utility $\ln(c_t)$ from consumption, discounted at $\beta > 0$. U_s captures the utility derived from job characteristics associated with school level s that is common to all agents. It includes the value of leisure. The budget constraint equates the present value of consumption spending to lifetime earnings, $\exp\left(\phi_s a + \mu n_\tau + y_s\right)$, plus the value of assets owned at age τ. R is the gross interest rate. y_s and $\phi_s > 0$ are schooling-specific constants.

Lifetime earnings are a function of ability a, schooling s and college courses n_τ. A worker with ability $a = \hat{a}_1 = 0$ and no completed courses earns $\exp(y_s)$. Each college course increases lifetime earnings by $\mu > 0$ log points. This may reflect human capital accumulation.

A unit increase in ability increases lifetime earnings by ϕ_s log points. If $\phi_{CG} > \phi_{HS}$, high ability students gain more from obtaining a college degree than do low ability students. This may be due to human capital accumulation in college or on the job, as suggested by Ben-Porath (1967). We impose $y_{CD} = y_{HS}$ and $\phi_{CD} = \phi_{HS}$ to ensure that attending college for a single period without earning courses does not increase earnings simply by placing a "college" label on the worker. The return to attending college without earning a degree is captured by μn_τ.

Even though y_s does not depend on τ, staying in school longer reduces the present value of lifetime earnings by delaying entry into the labor market. Note that all high school graduates share $\tau = 1$ and $n_\tau = 0$, but there is variation in both τ and n_τ among college dropouts and college graduates.

Before the start of work, individuals are uncertain about their abilities. Expected utility is then given by

$$V_W(n_\tau, k_\tau, j, s, \tau) = \sum_{\iota=1}^{N_a} \Pr(\hat{a}_\iota | n_\tau, j, \tau) V(n_\tau, k_\tau + Z_{j,\tau}, \hat{a}_\iota, s, \tau), \tag{3}$$

where $Z_{j,\tau}$ denotes the present value of parental transfers received after the agent starts working. Our model of credit accumulation implies that the vector (n_τ, j, τ) is a sufficient statistic for the worker's beliefs about his ability, $\Pr(\hat{a}_\iota | n_\tau, j, \tau)$, which implies that $(n_\tau, k_\tau, j, s, \tau)$ is the correct state vector.

3.4 College

We now describe a student's progress through college. Consider an individual of type j who has decided to study in period t. He enters the period with assets k_t and n_t college courses. In each period, the student attempts n_c courses and completes each with probability $\Pr_c(a)$ given by the logistic function

$$\Pr{}_c(a) = \gamma_{min} + \frac{1 - \gamma_{min}}{1 + \gamma_1 e^{-\gamma_2 a}}. \tag{4}$$

We assume $\gamma_1, \gamma_2 > 0$, so that the probability of earning courses increases with ability. Based on the number of completed courses, n_{t+1}, the student updates his beliefs about a. Since n_{t+1} is drawn from the Binomial distribution, it is a sufficient statistic for the student's entire history of course outcomes. It follows that his beliefs about a at the end

of period t are completely determined by n_{t+1} and j. The value of being in college at age t is then given by

$$V_C\left(n, k, j, t\right) = \max_{c,v,k'} u\left(c, 1-v\right) + \beta \sum_{n'} \Pr\left(n'|n, j, t\right) V_{EC}\left(n', k', j, t+1\right) \quad (5)$$

subject to the budget constraint

$$c = Rk - k' - \hat{q}_j + \hat{z}_j + y_{coll}\left(v\right) \quad (6)$$

and the borrowing constraint $k' \geq k_{min}$. Period utility is given by $u\left(c, 1-v\right)$ where $1-v$ denotes leisure. Hours worked are chosen from a set of discrete levels $\{v_1, ..., v_{N_w}\}$. $y_{coll}(v)$ denotes earnings associated with work hours v.

$\Pr\left(n'|n, j, t\right)$ denotes the probability of having earned n' courses at the end of period t. This is computed using Bayes' rule from the students' beliefs about a. V_{EC} denotes the value of entering period t before the decision whether to work or study has been made. It is determined by the discrete choice problem

$$V_{EC}\left(n, k, j, t\right) = \mathbb{E}\max\left\{V_C\left(n, k, j, t\right) - \pi p_c, V_W\left(n, k, j, s\left(n\right), t\right) - \pi p_w\right\}, \quad (7)$$

where p_c and p_w are independent draws from a demeaned standard type I extreme value distribution with scale parameter $\pi > 0$. $s\left(n\right)$ denotes the schooling level associated with n college courses (CG if $n \geq n_{grad}$ and CD otherwise). The implied choice probabilities and value functions have closed form solutions (Rust, 1987).

In evaluating V_{EC} three cases can arise:

1. If $n \geq n_{grad}$, then $s\left(n\right) = CG$ and $V_C = -\infty$: the agent graduates from college.

2. If $t = T_c$ and $n < n_{grad}$, then $s\left(n\right) = CD$ and $V_C = -\infty$: the student has exhausted the permitted time in college and must drop out.

3. Otherwise the agent chooses between working as a college dropout with $s\left(n\right) = CD$ and studying next period.

College entry decision. At high school graduation ($t = 1$), each student chooses whether to attempt college or work as a high school graduate. The agent solves

$$\max\left\{V_C(0, \hat{k}_j, j, 1) - \pi_E p_c, \ V_W(0, \hat{k}_j, j, HS, 1) - \pi_E p_w\right\}, \quad (8)$$

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where p_c and p_w are two independent draws from a demeaned standard type I extreme value distribution with scale parameter $\pi_E > 0$.

3.5 Discussion of Model Assumptions

Our model attempts to capture key features that may be important for ability selection. Following Manski (1989), we allow for the possibility that high school graduates are *uncertain about their abilities*. This could be important for ability selection because it gives low and medium ability students an incentive to try college. Modeling learning imposes restrictions on the model of credit accumulation. If a student could influence the probability of passing a course (e.g. by choosing study effort, course load, or work hours) he would have to keep track of the entire history of choices and course outcomes in order to form beliefs about his ability. This would greatly increase computational costs. The appropriate interpretation of $p(a)$ is therefore a broad one. Students differ in persistent characteristics that affect either course passing rates, course loads, or study efforts. All of these characteristics are bundled into model abilities a.

We incorporate *heterogeneity in financial assets* and in the *net cost* of attending college to capture the role of borrowing constraints for college selection. Whether borrowing constraints are important remains controversial in the literature (see Cameron and Taber 2004, Belley and Lochner 2007, among others). In our model, the vast majority of students have access to sufficient funds to pay for college tuition. However, some are subject to soft borrowing constraints which limit the amount of consumption they can afford in college. Allowing students to choose work hours while in college prevents our model from overstating the role of financial constraints on college outcomes.

The work-study decisions of model agents are subject to *preference shocks* which are similar to the "psychic costs" commonly found in models of school choice (see Heckman et al. 2006 for a discussion). The main purpose of the preference shock affecting the college entry decision is to regulate the association between agents' types and school choices. Without preference shocks, school sorting would be perfect in the sense that all agents of a given type j would make the same college entry decision. This would bias our results in favor of large ability selection (see Hendricks and Schoellman 2014). The preference shocks affecting the college dropout decision mainly improve the model's ability to account for the timing of dropout decisions and for the dropout rates of high ability students. In Appendix E we show that our main result is robust against variation in the dispersion of the preference shocks.

4   Setting Model Parameters

The model is calibrated to match data moments for men born around 1960. The model period is one year. Our main data sources are HS&B and PETS (subsection 2.1). Lifetime earnings are constructed from the National Longitudinal Surveys (NLSY79). The NLSY79 is a representative, ongoing sample of persons born between 1957 and 1964 (Bureau of Labor Statistics; US Department of Labor, 2002). Members of the supplemental samples are included. Sampling weights are used to offset the oversampling of minorities. We use data from the Current Population Surveys (King et al., 2010) to impute the earnings of older workers. Appendix B and Appendix C provide additional details.

4.1   Distributional Assumptions

Our distributional assumptions allow us to model substantial heterogeneity in assets, ability signals, and college costs in a parsimonious way. We set the number of types to $J = 200$. Each type has mass $1/J$. We assume that the marginal distributions are given by $\hat{q}_j \sim N\left(\mu_q, \sigma_q^2\right)$, $\hat{z}_j \sim \max\left\{0, N\left(\mu_z, \sigma_z^2\right)\right\}$, $\hat{k}_j \sim \max\left\{0, N\left(\mu_k, \sigma_k^2\right)\right\}$, and $m \sim N(0,1)$. To capture the fact that transfers and assets are non-negative with a mass at 0, we set negative draws of $\hat{z}_j$ and $\hat{k}_j$ to 0. Aside from this truncation, we assume that the endowments are drawn from a joint Normal distribution. The correlation coefficients are calibrated.[12]

The ability grid $\hat{a}_i$ approximates a Normal distribution with mean $\bar{a}$ and variance 1. Each of the $N_a = 9$ grid points has the same probability, $\Pr\left(\hat{a}_i\right) = 1/N_a$. We think of grid point i as containing all continuous abilities in the set $\Omega_i = \left\{a : \frac{i-1}{N_a} \leq \Phi\left(a - \bar{a}\right) < \frac{i}{N_a}\right\}$ where Φ is the standard Normal cdf. We therefore set $\hat{a}_i = \mathbb{E}\left\{a | a \in \Omega_i\right\}$. We normalize $\bar{a}$ such that $\hat{a}_1 = 0$. We model the joint distribution of abilities and signals as a discrete approximation of a joint Normal distribution given by $a = \bar{a} + \frac{\alpha_{a,m}m + \varepsilon_a}{\left(\alpha_{a,m}^2 + 1\right)^{1/2}}$, where $\varepsilon_a \sim N(0,1)$. The denominator ensures that the unconditional distribution of a has a unit variance. We set $\Pr(\hat{a}_i | j) = \Pr\left(a \in \Omega_i | m = \hat{m}_j\right)$.

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[12] We implement this by drawing independent standard Normal random vectors of length J: ε_z, ε_q, ε_m, and ε_k. Next, we set $\hat{z}_j = \max\left(0, \mu_z + \sigma_z \varepsilon_{z,j}\right)$, where $\varepsilon_{z,j}$ is the jth element of ε_z. We set $\hat{q}_j = \mu_q + \sigma_q \frac{\alpha_{q,z}\varepsilon_{z,j} + \varepsilon_{q,j}}{\left(\alpha_{q,z}^2 + 1\right)^{1/2}}$, $\hat{m}_j = \frac{\alpha_{m,z}\varepsilon_z + \alpha_{m,q}\varepsilon_{q,j} + \varepsilon_{m,j}}{\left(\alpha_{m,z}^2 + \alpha_{m,q}^2 + 1\right)^{1/2}}$, and $\hat{k}_j = \max\left(0, \frac{\alpha_{mk}\varepsilon_m + \varepsilon_{k,j}}{\left(\alpha_{m,k}^2 + 1\right)^{1/2}}\right)$. The α parameters govern the correlations of the endowments. The numerators scale the distributions to match the desired standard deviations. To conserve on parameters, we assume that assets correlate only with ε_m.

4.2 Mapping of Model and Data Objects

We discuss how we conceptually map model objects into data objects. Variables without observable counterparts include abilities, ability signals, consumption, initial assets, and preference shocks. We use the Consumer Price Index (all wage earners, all items, U.S. city average) reported by the Bureau of Labor Statistics to convert dollar figures into year 2000 prices.

College credits. Students are classified as attending college if they attempt at least 9 non-vocational credits in a given year, either at 4-year colleges or at academic 2-year colleges. Students who earn 2-year college degrees are treated as dropouts, unless they transfer to 4-year colleges where they earn bachelor's degrees.[13] The returns to earning 2-year degrees are captured by the effect of courses on lifetime earnings, μn.[14] The fact that low test score students tend to enroll in 2-year colleges is reflected in their lower average tuition costs. Students attending vocational schools (e.g., police or beauty academies) are classified as high school graduates.

Test scores. In the model, we assume that test scores are noisy measures of the ability signals observed by the agents. This implies that the agents know more about their abilities than we do. Specifically, we model test scores as signal plus Gaussian noise:

$$IQ = \frac{\alpha_{IQ,m} m + \varepsilon_{IQ}}{\left(\alpha_{IQ,m}^2 + 1\right)^{1/2}} \tag{9}$$

with $\varepsilon_{IQ} \sim N(0,1)$. If m were continuous, the distribution of test scores would be standard Normal. Since m is restricted to take on values on the grid $\hat{m}_j$, only the conditional distribution $IQ|m$ is Normal.

In the data, we divide students into quartiles either according to their high school GPAs (HS&B) or their 1989 Armed Forces Qualification Test scores (NLSY79). The AFQT aggregates a battery of aptitude test scores into a scalar measure. The tests cover numerical operations, word knowledge, paragraph comprehension, and arithmetic reasoning (see NLS User Services 1992 for details). We remove age effects by regressing AFQT scores on the age at which the test was administered (in 1980). Borghans et al. (2011) show that high

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[13]Trachter (2014) studies the role of 2-year colleges as stepping stones towards bachelor's degrees.

[14]In HS&B data, only 12% of students who enter 2-year institutions earn a 2-year degree.

school GPAs and AFQT scores are highly correlated. Sidestepping the question of what test scores measure (see Flynn 2009), we use the term "test scores" in the text and the symbol IQ in mathematical expressions.

4.3   Fixed Parameters

Table 3 summarizes the values of parameters that are fixed a priori.

1. The discount factor is $\beta = 0.98$.

2. Based on McGrattan and Prescott (2000), the gross interest rate is set to $R = 1.04$.

3. Motivated by the fact that, in our HS&B sample, 95% of college graduates finish college by their 6th year, we set the maximum duration of college to $T_c = 6$.

4. Each model course represents 2 courses (6 credits) in the data. The number of courses needed to graduate is set to $n_{grad} = 21$ (125 data credits). In each year, students attempt $n_c = 6$ courses (36 credits). This corresponds to the 90th percentile of the distribution of credits earned in the data.

5. Work time: Students can choose from $N_w = 5$ discrete work hour levels in the set $\{0, 10, 20, 30, 40\}$. In setting the choice set for v, we start from an annual time endowment of 5824 hours (52 weeks with 16 hours of discretionary time per day). Based on Babcock and Marks 2011, we remove 35.6 hours of study time for 32 weeks, covering the fall and spring semesters, arriving at a time endowment net of study time of 90 hours per week. Given that v equals work time divided by time endowment, this implies $v \in \{0.00, 0.11, 0.22, 0.33, 0.44\}$.

6. Earnings in college: We set $y_{coll}(v) = 7.60 \times 5824 \times v$. This is the product of the mean hourly wage earned by college students of \$7.60 and the work hours associated with each level of v.

7. Assets: While in college, students can choose from $N_k = 12$ discrete asset levels. For each type j, the asset grid linearly spans the interval $\left[k_{min}, \hat{k}_j \right]$.

8. Borrowing limits are set to approximate those of Stafford loans, which are the predominant form of college debt for the cohort we study (see Johnson 2013). Until 1986, students could borrow \$2,500 in each year of college up to a total of \$12,500 (\$19,750 in year 2000 prices). We therefore set $k_{min} = -\$19,750$.

Table 3: Fixed Model Parameters

Parameter	Description	Value
β	Discount factor	0.98
T_c	Maximum duration of college	6
n_{grad}	Number of credits required to graduate	21
n_c	Number of credits attempted each year	6
N_k	Size of asset grid	12
k_{min}	Borrowing limit ($)	-19,750
v	Work hours during college	0.00; 0.11; 0.22; 0.33; 0.44
$y_{coll}(v)$	Earnings during college ($)	0; 3,950; 7,900; 11,850; 15,800
J	Number of types	200
R	Gross interest rate	1.04

The period utility function in college is given by $u(c, 1-v) = \delta \ln(c) + \rho \ln(1-v)$. $\rho > 0$ determines how much the household values leisure in college. The parameter $0 < \delta < 1$ reduces the marginal utility of consumption while in college. It is needed to account for the low consumption expenditures of college students implied by the financial data.

4.4 Calibrated Parameters

The remaining 26 model parameters are jointly calibrated to match the target data moments summarized in Table 4. We show the data moments in subsection 4.5 where we compare our model with the calibration targets. Appendix E discusses which data moments are important for the calibrated values of key model parameters.

For each candidate set of parameters, the calibration algorithm simulates the life histories of $100,000$ individuals. It constructs model counterparts of the target moments and searches for the parameter vector that minimizes a weighted sum of squared deviations between model and data moments.[15]

Table 5 shows the values of the calibrated parameters. We will highlight key parameter values when we discuss the paper's findings in section 5.

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[15]Within each block of moments, such as the fraction of students who drop out of college by test score quartile and year in college, deviations are weighted by the inverse standard deviations of the data moments or, if this is not available, by the square root of the number of observations used to compute each data moment.

Table 4: Calibration Targets

Target	Value
Fraction in population, by (test score quartile, schooling)	Figure 3
Lifetime earnings, by (test score quartile, schooling)	Table 14
Dropout rate, by (test score quartile, t)	Figure 13
Average time to BA degree (years)	4.4
College credits	
Mean cumulative credits, by (graduation status, t)	Table 6
Mean cumulative credits, by (test score quartile, t)	Table 6
Persistence of credits across years	Table 7
CDF of cumulative credits, by t	Figure 9
CDF of cumulative credits, by (graduation status, t)	Figure 10, Figure 11
CDF of cumulative credits, by (test score quartile, t)	Figure 12
Financial moments	
College costs q, by test score quartile	Table 15
(mean and standard deviation)	
Parental transfers z, by test score quartile	Table 15
(mean and standard deviation)	
Mean earnings in college, by test score quartile	Table 15
Fraction of students in debt, by t	Table 16
Mean student debt, by t	Table 16

Notes: Lifetime earnings targets are based on NLSY79 data. The remaining targets are based on HS&B data.

Table 5: Calibrated Parameters

Parameter	Description	Value
Endowments		
μ_k, σ_k	Marginal distribution of k_1	$35,814; 28,846$
μ_q, σ_q	Marginal distribution of q	5,723; 4,153
μ_z, σ_z	Marginal distribution of z	2,894; 6,135
$\alpha_{m,z}, \alpha_{m,q}, \alpha_{q,z}, \alpha_{a,m}$	Endowment correlations	0.42; -0.03; -0.27; 2.85
$\alpha_{k,m}$	Correlation k_1, m	-0.21
$\alpha_{IQ,m}$	Correlation IQ, m	1.16
Lifetime earnings		
ϕ_{HS}, ϕ_{CG}	Effect of ability on lifetime earnings	0.150; 0.192
y_{HS}, y_{CG}	Lifetime earnings factors	3.92; 3.96
μ	Earnings gain for each college credit	0.010
Other parameters		
ρ	Weight on leisure	1.324
δ	Weight on consumption	0.650
π	Scale of preference shocks	1.206
π_E	Scale of preference shocks at entry	0.469
U_{CD}, U_{CG}	Preference for job of type s	-1.09; -2.49
$\gamma_1, \gamma_2, \gamma_{min}$	Credit accumulation rate $p_{(a)}$	4.73; 2.07; 0.47

4.5 Model Fit

This section compares the model implications with selected data moments. To conserve space, a more detailed comparison is relegated to Appendix D. The overall finding is that the model successfully accounts for a broad range of data moments, including the dispersion and persistence of credits earned. This success supports the model of credit accumulation that we argue is of central importance for the paper's results (see section 2).

College credits. Table 6 shows credit accumulation rates at the end of the first 4 years in college. The model replicates the large and persistent observed gap in earned credits between dropouts and graduates (panel a) as well as the relationship between earned credits and high school GPAs (panel b). Table 7 shows how the model fits the observed persistence of credit accumulation rates. While the model replicates the level of persistence, it fails to account for its decline over time. Appendix D shows that the model accounts for the large dispersion in earned credits observed in the data, also within high school GPA quartiles.

Table 6: Credit Accumulation Rates

(a) College graduates and college dropouts

| | College dropouts | | College graduates | |
Year	Model	Data	Model	Data
1	58.3	57.1 (1.0)	83.6	85.4 (0.6)
2	58.3	59.6 (1.0)	83.3	83.4 (0.5)
3	57.5	55.6 (0.9)	83.1	83.0 (0.4)
4	55.6	53.6 (1.1)	82.9	82.3 (0.4)

(b) Test score quartiles

| | Test Score Quartile | | | |
	1	2	3	4
$t = 1$	54.3 / 48.1 (2.3)	63.0 / 61.8 (1.6)	71.0 / 71.0 (1.2)	80.4 / 81.8 (0.9)
$t = 2$	55.2 / 53.7 (2.3)	65.0 / 67.6 (1.4)	72.9 / 71.5 (1.0)	81.5 / 81.6 (0.7)
$t = 3$	56.9 / 58.1 (2.3)	67.4 / 69.5 (1.4)	74.6 / 72.4 (0.9)	82.6 / 81.7 (0.6)
$t = 4$	59.1 / 62.3 (2.8)	69.7 / 71.8 (1.5)	76.1 / 75.3 (0.8)	83.4 / 82.0 (0.5)

Notes: The credit accumulation rate is the number of college credits completed at the end of each year divided by a full course load (36 credits per year). Standard errors are in parentheses. Panel (b) divides students into test score (GPA) quartiles. Each cell shows model / data values. Source: High School & Beyond.

Table 7: Persistence of Credit Accumulation Rates

	Year $1 - 2$	Year $2 - 3$	Year $3 - 4$
Correlations, model	0.45	0.44	0.44
data	0.48	0.42	0.39
Eigenvalues, model	0.46	0.46	0.46
data	0.51	0.47	0.41
N	1665	1378	1196

Notes: The table compares the persistence of the number of college credits earned implied by the model with the data. "Correlations" refers to the correlation coefficients of credits earned in adjacent years. "Eigenvalues" shows the second largest eigenvalues of quartile transition matrices. Source: High School & Beyond.

Schooling and test scores. Figure 3 shows that test scores are strong predictors of college entry and college completion. 81% of students in the top test score quartile attempt college and 74% of them earn college degrees. In the lowest test score quartile, only 22% of students enter college and only 11% of them earn degrees.[16] One question our model answers is why low ability students attempt college, even though their graduation chances are small (see subsection 5.2).

5 Results

5.1 Ability Selection

This section presents our main finding. Part of the lifetime earnings gap between college graduates and high school graduates represents ability differences between the two groups rather than returns to schooling. We use our calibrated model to measure this part.

In the model, the mean log lifetime earnings of school group s, discounted to age 1, are given by

$$\mathbb{E}[\phi_s a + \mu n_\tau + y_s + \ln(R^{-\tau})|s], \tag{10}$$

where $\tau = 1$ and $n_\tau = 0$ for high school graduates. The mean log lifetime earnings gap between school group s and high school graduates may then be decomposed into four terms:

1. prices: $y_s - y_{HS} + (\phi_s - \phi_{HS})\mathbb{E}(a|s)$;

2. credits: $\mathbb{E}(\mu n_\tau|s)$;

3. delayed labor market entry: $\mathbb{E}\{\ln R^\tau|s\} - \ln R^{-1} = \mathbb{E}\{\ln R^{1-\tau}|s\}$;

4. ability selection: $\phi_{HS}[\mathbb{E}(a|s) - \mathbb{E}(a|HS)]$.

For a student of given ability, earning a college degree has three effects on lifetime earnings. (i) It changes the skill prices earned in the labor market (y_s and ϕ_s). (ii) It requires a certain number of earned college credits. (iii) Earning these credits delays entry into the labor market, which reduces lifetime earnings. Taken together, these three effects represent the return to college graduation. As in much of the recent related literature, the return to

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[16]Bound et al. (2010)'s Figure 2 documents similar patterns in NLS72 and NELS:88 data.

Figure 3: Schooling and Test Scores

(a) Test score quartile 1

(b) Test score quartile 2

(c) Test score quartile 3

(d) Test score quartile 4
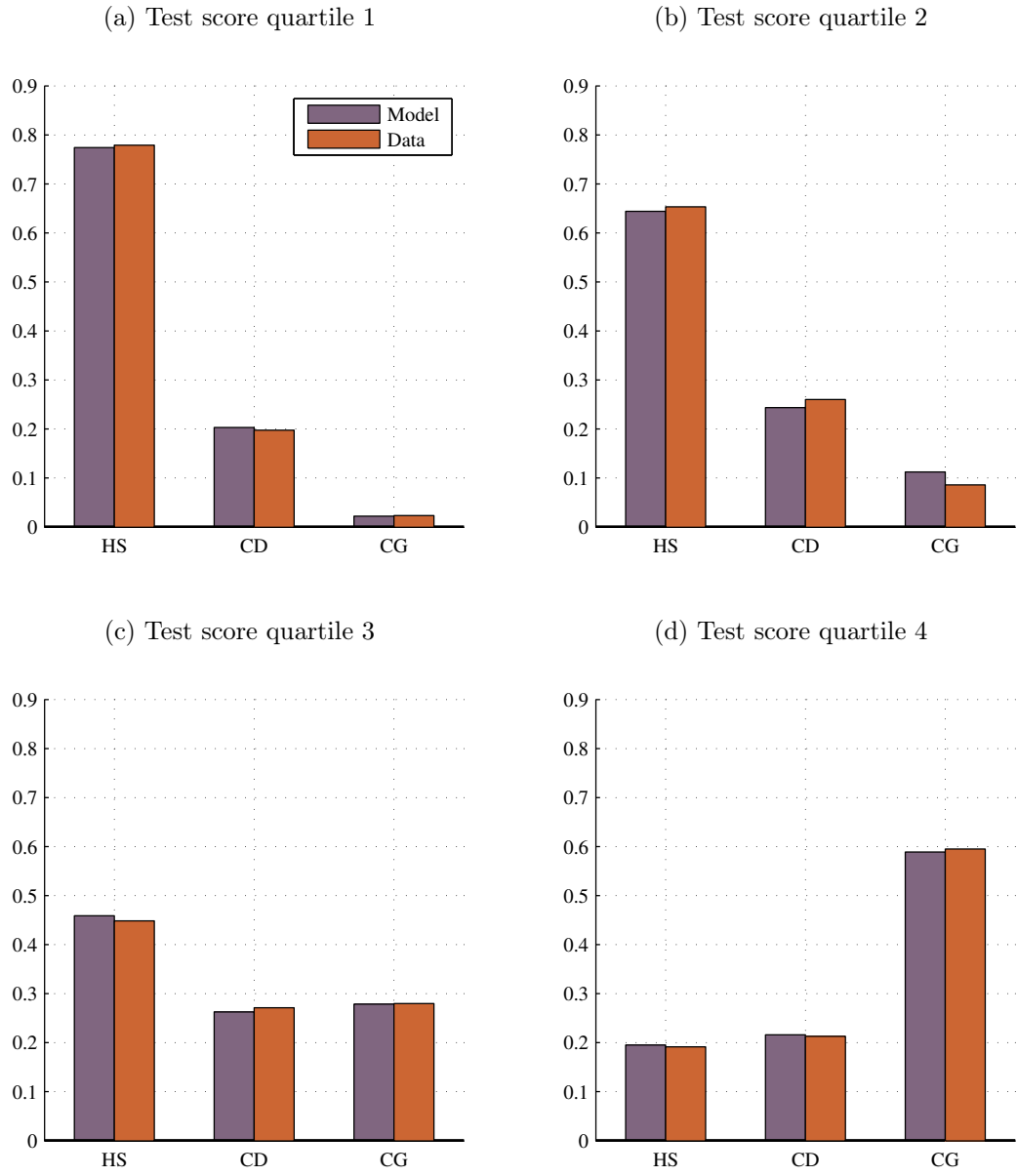
Notes: For each test score quartile, the figure shows the fraction of persons who attain each schooling level.
Source: High School & Beyond.

Table 8: Ability Selection

| Gap relative to HS | College dropouts | | College graduates | |
(in log points)	Gap	Fraction	Gap	Fraction
Total gap	6	–	45	–
Delayed labor market entry	-10	-165	-18	-40
Prices: y_s and ϕ_s	0	0	16	36
Credits	8	143	23	50
Ability selection	7	122	24	54

Notes: Row 1 shows mean log lifetime earnings of college dropouts and college graduates relative to high school graduates. The remaining rows decompose these lifetime earnings gaps into the contributions of various factors defined in the text. "Fraction" denotes the fraction of the lifetime earnings gap due to each factor.

schooling varies across individuals (see Card 2001). The remaining gap between the mean log earnings of college graduates and high school graduates represents ability selection.

Table 8 shows the decomposition implied by the model. College graduates earn 45 log points more than high school graduates. Since postponing entry into the labor force reduces lifetime earnings by 18 log points, it follows that completing college increases lifetime earnings, discounted to age τ, by 63 log points. Of this increase, 23 log points are due to credit accumulation, 16 log points are due to prices (y_s and ϕ_s), and the remaining 24 log points (54% of the college lifetime earnings premium) are due to ability selection. The finding that ability selection accounts for roughly half of the college earnings premium is quite robust, as we show in Appendix F.

For college dropouts, the mean log earnings gap relative to high school graduates is much smaller (6 log points). By assumption, the effect of prices is zero. The effect of earned credits roughly offsets the cost of delayed labor market entry, implying that most of the earnings gap relative to high school graduates is due to ability selection.

We next explain why the model implies a large role of ability selection. From (10), ability selection is determined by the ability gap between college graduates and high school graduates, $\mathbb{E}(a|CG) - \mathbb{E}(a|HS)$, and by the effect of ability on lifetime earnings, ϕ_{HS}. We discuss both in turn.

The ability gap between college graduates and high school graduates. The structural model implies an ability gap between college graduates and dropouts of 1.63. To

understand why the gap is large, recall the discussion of subsection 2.3. The model must account for the observation that, during their first 2 years in college, dropouts earn only 60% of the credits they attempt, compared with 83% for college graduates (see Table 6). Given the process by which credits are accumulated, this requires large heterogeneity in credit accumulation rates $p(a)$. While high ability students pass 94% of their attempted credits, low ability students pass only 48% (see Figure 4a).

As in the reduced form model, and for the same logic, graduation prospects rise sharply with p. As a result, high ability students are virtually guaranteed to graduate from college, if they persist for 6 years (see Figure 4a). As shown in Figure 4b, 99% of students in the highest ability group attempt college and 93% of these entrants manage to graduate. By contrast, low ability students have little chance of graduating and rarely attempt college. Students with abilities around the median constitute most of the college dropouts. These students face genuine uncertainty about their graduation prospects. While 36% of median ability students attempt college, only 14% of these entrants eventually graduate.

Note that the graduation probability rises even more sharply with ability than graduation prospects. In particular, virtually no students in the lowest ability quartile manage to graduate from college. The reason is that only students with strong graduation prospects can expect to earn large financial gains by staying in college. Moreover, since $\phi_{CG} > \phi_{HS}$, the lifetime earnings gains associated with college graduation increase with student abilities. For low ability students, the fact that y_{CG} is close to y_{HS} implies that graduating has little effect on earnings (beyond the gains due to earned credits). Students with low graduation prospects are therefore easily persuaded to drop out of college before earning a degree (see subsection 5.3).

Since students' ability signals are quite precise, the main features of Figure 4 remain unchanged when students are sorted according to their signals rather than their abilities.[17] To understand why the model implies that signals are very precise, we calibrate the model while fixing signal noise (via the parameter $\alpha_{a,m}$) at higher levels. The model then implies that students in different test score quartiles are too similar in terms of their credit accumulation rates, schooling, and lifetime earnings. The reason is that test scores are less precise signals of ability than in the baseline model. After all, test scores cannot be more precise than the ability signals they are based on. More signal noise also increases the option value of college. Students then avoid dropping out until they have formed sufficiently precise
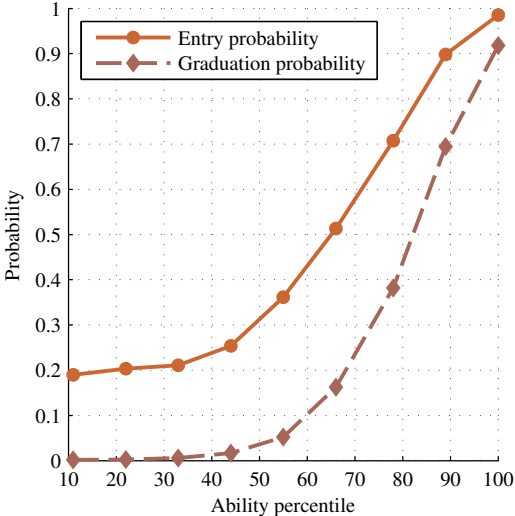
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[17]We do not show these graphs in order to conserve space. Nevertheless, learning about abilities is not irrelevant. It helps the model account for the timing of college dropouts (see Appendix E).

Figure 4: Graduation Prospects and Abilities

(a) Graduation prospects
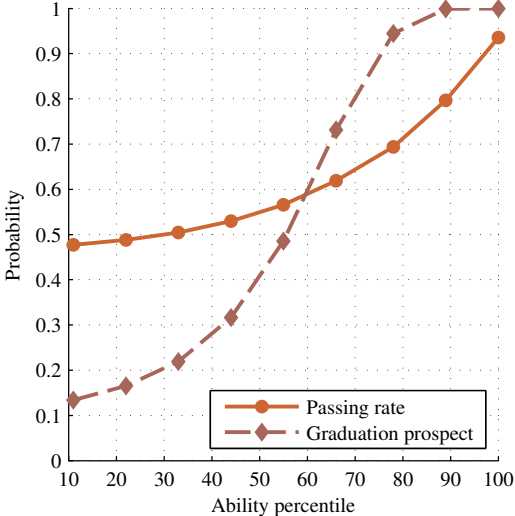
(b) College outcomes

Notes: Panel (a) shows the course passing rate $p(a)$ and the implied graduation prospect (the probability of earning 21 credits in 6 years) for each ability level. Panel (b) shows the fraction of students who attempt college and who graduate from college.

beliefs about their abilities. As a result, college dropouts remain in college longer than in the data.

Abilities and lifetime earnings. How strongly lifetime earnings vary with abilities within a school group is governed by the value of ϕ_s. If test scores measured abilities without noise, its value could be estimated by regressing log lifetime earnings on test scores, with school dummies controlling for y_s.[18] When test scores are noisy measures of abilities, the resulting estimates suffer from attenuation bias. Noisier test scores therefore imply higher values of ϕ_s and larger contributions of selection to the college earnings premium.

To understand how the noise of test scores is identified, recall the discussion of the reduced form model. Since controlling for test scores does not substantially reduce the dispersion of earned credits, test scores must contain substantial noise. In the calibrated model, the correlation between test scores and abilities is 0.66. Accounting for the observed relationship between lifetime earnings and test scores then requires large values of ϕ_s. A one standard deviation increase in ability raises lifetime earnings by 0.15 for high school graduates and by 0.19 college graduates.[19]

We now return to the question of ability selection. Our model implies a large ability gap between college graduates and high school graduates that accounts for 54% of the college lifetime earnings premium. The main reason why this ability gap is large and robust is the large gap in graduation prospects between high and low ability students our model generates in order to match the observed credit accumulation rates. Ability selection then occurs not only at college entry, but also in college, where low ability students fail to earn the credits required for graduation. Selection at college entry accounts for 66% of the ability gap between college graduates and high school graduates.[20] Selection in college accounts for the remaining 34%.[21]

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[18] In practice, this would be complicated by measurement error in schooling and by the effect of earned credits on earnings.

[19] These values are larger than the estimates obtained from regressing log wages on test scores and school dummies. The mean of such estimates collected by Bowles et al. (2001) is 0.07. Given the noise in test scores implied by our model, we would expect these regressions to suffer from substantial attenuation bias. The sensitivity analysis in Appendix E shows that larger values of ϕ_{HS} are associated with a larger contribution of ability selection to the measured college premium.

[20] $\mathbb{E}\{a|CD \vee CG\} - \mathbb{E}\{a|HS\} = 0.66\ (\mathbb{E}\{a|CG\} - \mathbb{E}\{a|HS\})$.

[21] Of course, school outcomes are also correlated with financial endowments. Students who face lower college costs or who have more assets are more likely to enter college and more likely to graduate, conditional on entry. These correlations are, in part, due to the correlation between abilities and financial endowments. To conserve space, we do not show the details.

One contribution of our analysis is to highlight how the two levels of selection interact. At college entry, low ability students recognize that their graduation prospects are poor. This deters them from attempting college. This interaction is absent in models that abstract from college completion risk.

5.2 Understanding College Entry

A puzzling feature of the data is that significant numbers of students in the lowest test score quartile attempt college (22%), even though very few (11%) of these entrants manage to earn a bachelor's degree (see Figure 3). Why do these students enter college? In short, the answer is that, for these students, the average financial gains or losses associated with attempting college are small.

Figure 5 shows how mean log lifetime earnings vary with schooling and ability (Panel 5a) or ability signal (Panel 5b). Only those who manage to graduate can expect large financial gains. For students in the highest ability group, graduating from college increases lifetime earnings by 26 log points. The gains are smaller for students of lower abilities. There are two reasons for this: (i) it takes low ability students longer to graduate, and (ii) the complementarity between ability and college education implied by $\phi_{CG} > \phi_{HS}$.

College dropouts enjoy much smaller earnings gains. On average, working as a high school graduate yields almost the same expected lifetime earnings as attempting college. Our model therefore implies that the expected payoff from attempting college increases sharply with ability.

We can now understand why low ability students enter college, even though their graduation prospects are poor. Attending college for a few years without earning a degree has little impact on expected lifetime earnings.[22] The potential losses from attempting college are limited by the option of dropping out. Low or medium ability students may then try college for the unlikely, but potentially large, earnings gains from graduation, especially if the direct costs of college are small.

One reason why the model implies such small earnings gains from dropping out is the small mean lifetime earnings gap between college dropouts and high school graduates observed in the data (6 log points). The model implies that part of this gap is due to selection.

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[22]Subtracting the direct cost of college does not change this conclusion much because the mean of college costs net of college earnings is close to 0. These small earnings gains could explain why college students spend little time studying while at the same time working for modest wages (Babcock and Marks, 2011).

Figure 5: Schooling and Lifetime Earnings

(a) Abilities and lifetime earnings

(b) Signals and lifetime earnings
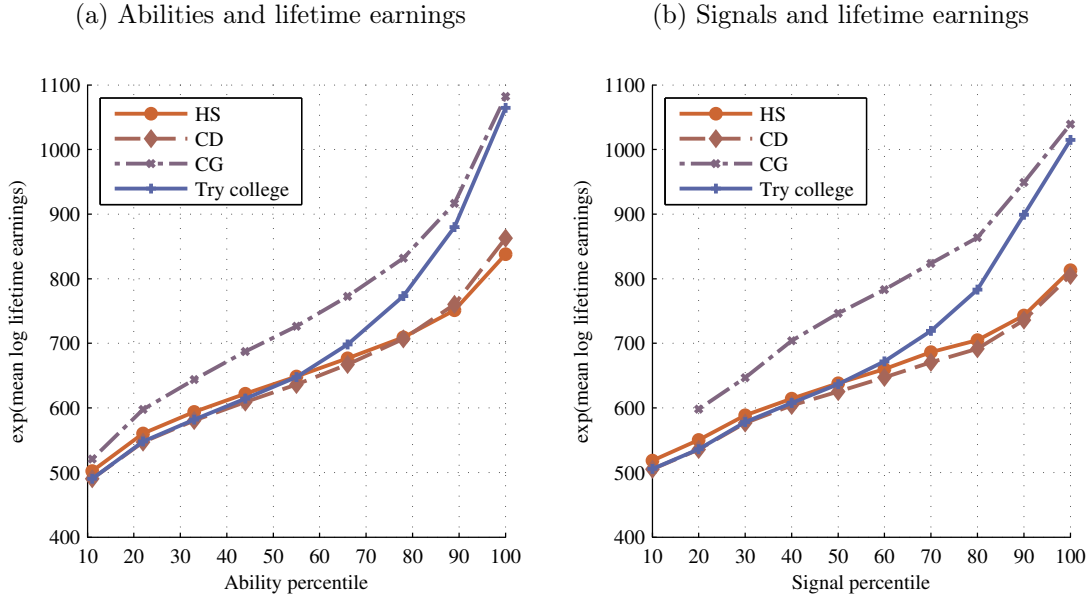
Notes: The figure shows the exponential of mean log lifetime earnings of students who attain each school level in thousands of year 2000 dollars. Calculations are based on simulated model histories. "Try college" combines college dropouts and college graduates. Since the model generates very few college graduates with low ability signals, their lifetime earnings are not shown.

Therefore, holding ability constant, the gain from attending college without earning a degree must be small. This feature is also important for the model's ability to generate dropouts in every year of college (see subsection 5.3).

An important implication of the model is that low and high ability students respond to different incentives when deciding whether or not to enter college. High ability students typically attempt college in order to graduate and increase their lifetime earnings. Since college costs represent only a small fraction of lifetime earnings, these students are not sensitive to tuition changes. Low ability students, on the other hand, understand that their graduation prospects are poor. They only enter college if it is sufficiently cheap, and their entry decisions are highly sensitive to tuition costs. We return to this insight when we perform comparative statics experiments in subsection 5.4.

5.3 Understanding College Dropouts

This section examines why nearly half of all students drop out of college. Our model offers three main reasons: money, luck, and preference shocks.

Money. Given that model agents face substantial heterogeneity in financial resources and college costs, some lack the funds to pay for several years in college. However, this is not a major reason for dropping out. To show this, we compute a counterfactual experiment that doubles students' borrowing limits. While this change does not alter the financial costs or benefits of attending college, it improves consumption smoothing between college and work periods. Relaxing students' financial constraints reduces the dropout rate from 48.0% to 47.2%.[23]

These results suggest that financial constraints are not a major obstacle to college graduation. One reason is that students can earn substantial amounts while working in college. A full time working student earns $15,800 per year. Since, for the typical student, parental transfers nearly offset college costs, college earnings can be used entirely to finance consumption.[24]

Luck. The second reason for dropping out is bad luck. Consistent with the data, our model implies that college dropouts have low credit completion rates (see Table 6). In response, these students update their beliefs about their graduation prospects and some drop out.

For dropouts in each signal decile, Figure 6 shows students' graduation prospects at the time of college entry and at the time of dropping out. Dropouts receive bad news during their college careers that lead to a substantial downward revision in their graduation probabilities.

To quantify how many students drop out because they earn fewer credits than expected, we compute a counterfactual experiment that sets the realizations of earned credits to the expected number of credits given a student's type j (rounded to the nearest integer). This change does not alter students' decision rules. However, it implies that students do not receive new information about their abilities after entering college. The resulting change

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[23]For ease of interpretation, this and the following counterfactual experiments fix college entry decisions as in the baseline model. Allowing entry decision to adjust makes little difference as none of the experiments change them significantly.

[24]Limiting students' maximum work time to 30 hours per week does not substantially change our findings.

Figure 6: Beliefs about Graduation Prospects Among Dropouts
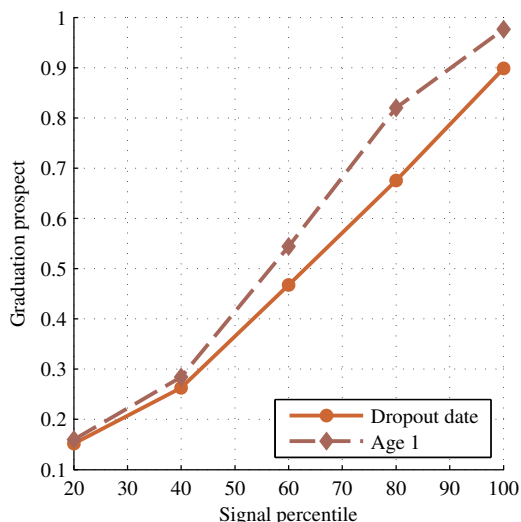
Notes: The figure shows the probability of earning n_{grad} credits by the end of year T_c among college dropouts. The probabilities are computed as of college entry (age 1) and at the time of dropping out of college.

in the dropout rate is small; it falls to 45.5%. One reason is that random grades not only lead unlucky students to drop out; they also allow lucky students to graduate.

Preference shocks. The last reason for dropping out is preference shocks. To isolate their effects, we recompute the model setting the realizations of preference shocks during college to zero. Students follow the same decision rules as in the baseline model. This reduces the dropout rate to 25.8%. Without preference shocks, most students stay in college for at least 4 years. At this point, they either graduate or realize that graduation is not feasible.

Planned dropouts. We quantify the combined effect of money, luck, and preference shocks by computing a counterfactual experiment that doubles borrowing limits and sets the realizations of earned credits and preferences shocks to their expected values (given type j). Even in that case, 19.8% of all college entrants drop out. These students enter college *planning* to drop out. Many lack the ability to earn a college degree and enter college to earn some credits and increase their future earnings. Others attempt college to enjoy the option of receiving favorable shocks. When this option fails to materialize, they drop out.

5.4 Changing College Costs and Payoffs

We study two counterfactual experiments that illustrate a key feature of our model: High ability agents mainly view college as an investment, while low ability agents mainly view it as a consumption good. The two groups therefore respond very differently to changes in college costs and returns.

The *low tuition* experiment reduces the mean of q by \$1,000. This amount is chosen so that the model's implications can be compared with empirical estimates. The *high return* experiment increases y_{CG} by 3 log points. This amount is chosen to yield roughly the same change in college enrollment as the low tuition experiment. For each case, we simulate individual life histories, holding all other parameters constant.

Consider first the low tuition experiment. College enrollment rises by 3.3 percentage points. The model's implications can be compared with a sizable empirical literature which estimates the effects of reducing tuition on college attendance. Dynarski (2003) summarizes this literature as well as her own estimates as follows: a \$1,000 reduction in the cost of attending college (in year 2000 prices) leads to a 3 to 4 percentage point increase in attendance. The model's implication is near the lower range of these estimates.

Figure 7 breaks down the change in college attendance by ability. Students of all abilities respond to tuition changes, with the largest responses occurring for low and median abilities. Since most of these students drop out, the fraction of college graduates rises by only 1.1 percentage points. Many of the new college entrants drop out.

The implications of the high return experiment are very different. Overall college enrollment rises by a very similar amount, 3.2 percentage points, but the fraction of college graduates rises by 4.6 percentage points. The students that respond most to higher returns to college are drawn from the upper tail of the ability distribution (Figure 7). Most of these students graduate from college, so that the dropout rate declines.

From the perspective of the commonly used Roy model, it would seem surprising that college attendance responds so much to a change in tuition that represents a small fraction of lifetime earnings. On a per dollar basis, changing tuition has a much larger effect on college enrollment than changing lifetime earnings. A 3% increase in lifetime earnings of the average college graduate is worth about \$30,000. Yet the implied changes in enrollment are similar to those implied by a \$1,000 change in tuition, which is worth less than \$5,000 for the typical college graduate who stays in college for less than 5 years. Dropout risk is key for understanding this result. While the tuition change affects the incentives for all

Figure 7: Changing College Costs and Payoffs
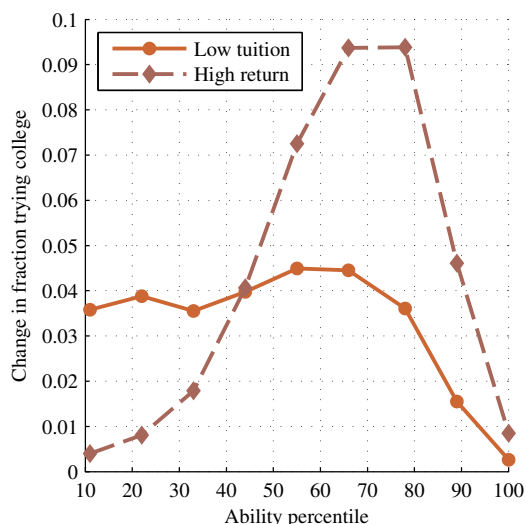
Notes: The figure shows the effects of reducing the mean of q and of raising y_{CG} on the fraction of high school graduates that enters college.

students, the college premium is mainly relevant for high ability students who expect to graduate from college.[25]

6 Conclusion

We conclude by considering potential avenues for future research. A key challenge is the identification of school sorting by ability and of human capital production in college. Modeling two additional decisions that can be observed for college students could help to address this problem.

The first decision is the allocation of time between study effort, work, and leisure. Babcock and Marks (2011) show that college students spend little time attending classes and studying, while at the same time working for low wages, especially in recent years. This suggests a low marginal value of study effort and could be used to help identify human capital production in college.

The second decision is the quality and cost of the college attended. Admission to better

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[25]Based on similar intuition, Athreya and Eberly (2013) argue that college enrollment is not very sensitive to changes in the college wage premium.

colleges may account for part of the higher returns to college enjoyed by high ability students (Dale and Krueger, 2002; Hoekstra, 2009). Observing how wages vary with test scores and college qualities may help disentangle the effects of ability selection and human capital production.

Additional progress could be made by modeling the work phase in more detail. How wage dispersion changes with age contains information about the joint distribution of abilities and human capital endowments (see Huggett et al. 2006, 2011). This idea is pursued in Hendricks (2013) in the context of a stochastic Ben-Porath model that abstracts from college completion risk.

References

Akyol, A. and K. Athreya (2005). Risky higher education and subsidies. *Journal of Economic Dynamics and Control 29*(6), 979 – 1023.

Altonji, J. G. (1993). The demand for and return to education when education outcomes are uncertain. *Journal of Labor Economics 11*(1), pp. 48–83.

Arcidiacono, P. (2004). Ability sorting and the returns to college major. *Journal of Econometrics 121*(1), 343–375.

Arcidiacono, P., E. Aucejo, A. Maurel, and T. Ransom (2012). College attrition and the dynamics of information revelation. Mimeo. Duke University.

Athreya, K. and J. Eberly (2013). The College Premium, Risk, and Human Capital Investment. Mimeo, Federal Reserve Bank of Richmond.

Babcock, P. and M. Marks (2011, May). The Falling Time Cost of College: Evidence from Half a Century of Time Use Data. *Review of Economics and Statistics 93*(2), 468–478.

Belley, P. and L. Lochner (2007). The changing role of family income and ability in determining educational achievement. *Journal of Human Capital 1*(1), 37–89.

Belzil, C. and J. Hansen (2002, September). Unobserved ability and the return to schooling. *Econometrica 70*(5), 2075–2091.

Ben-Porath, Y. (1967). The production of human capital and the life cycle of earnings. *Journal of Political Economy 75*(4), pp. 352–365.

Borghans, L., B. H. H. Golsteyn, J. Heckman, and J. E. Humphries (2011). Identification problems in personality psychology. *Personality and Individual Differences*.

Bound, J., M. F. Lovenheim, and S. Turner (2010). Why have college completion rates declined? an analysis of changing student preparation and collegiate resources. *American Economic Journal: Applied Economics 2*(3), 129–57.

Bowen, W. G., M. M. Chingos, and M. S. McPherson (2009). *Crossing the Finish Line: Completing College at America's Public Universities*. Princeton University Press.

Bowles, S., H. Gintis, and M. Osborne (2001). The determinants of earnings: A behavioral approach. *Journal of Economic Literature 39*(4), pp. 1137–1176.

Bureau of Labor Statistics; US Department of Labor (2002). National longitudinal survey of youth 1979 cohort. Produced and distributed by the Center for Human Resource Research, The Ohio State University. Columbus, OH.

Cameron, S. V. and C. Taber (2004). Estimation of educational borrowing constraints using returns to schooling. *The Journal of Political Economy 112*(1), pp. 132–182.

Card, D. (1999). The causal effect of education on earnings. Volume 3, Part A of *Handbook of Labor Economics*, Chapter 30, pp. 1801 – 1863. Elsevier.

Card, D. (2001). Estimating the return to schooling: Progress on some persistent econometric problems. *Econometrica 69*(5), pp. 1127–1160.

Caucutt, E. M. and K. B. Kumar (2003). Higher education subsidies and heterogeneity: a dynamic analysis. *Journal of Economic Dynamics and Control 27*(8), 1459–1502.

Chatterjee, S. and F. Ionescu (2012). Insuring student loans against the financial risk of failing to complete college. *Quantitative Economics 3*(3), 393–420.

Cunha, F., J. J. Heckman, and S. Navarro (2005). Separating uncertainty from heterogeneity in life cycle earnings. *Oxford Economic Papers 57*, 191–261.

Dale, S. B. and A. B. Krueger (2002). Estimating the payoff to attending a more selective college: An application of selection on observables and unobservables. *The Quarterly Journal of Economics 117*(4), pp. 1491–1527.

Dynarski, S. M. (2003). Does aid matter? measuring the effect of student aid on college attendance and completion. *American Economic Review 93*(1), 279–288.

Eckstein, Z. and K. I. Wolpin (1999, November). Why Youths Drop Out of High School: The Impact of Preferences, Opportunities, and Abilities. *Econometrica 67*(6), 1295–1339.

Flynn, J. R. (2009). *What Is Intelligence? Beyond the Flynn Effect*. Cambridge University Press.

Garriga, C. and M. P. Keightley (2007). A general equilibrium theory of college with education subsidies, in-school labor supply, and borrowing constraints. Mimeo. Federal Reserve Bank of St Louis.

Heckman, J. J., L. Lochner, and C. Taber (1998). Explaining rising wage inequality: Explorations with a dynamic general equilibrium model of labor earnings with heterogeneous agents. *Review of Economic Dynamics 1*(1), 1–58.

Heckman, J. J., L. J. Lochner, and P. E. Todd (2006). Earnings functions, rates of return and treatment effects: The mincer equation and beyond. In E. Hanushek and F. Welch (Eds.), *Handbook of the Economics of Education*, Volume 1, Chapter 7, pp. 307–458. Elsevier.

Heckman, J. J. and S. Urzua (2008). The option value of educational choices and the rate the option value of educational choices and the rate of return to educational choices. Manuscript. University of Chicago.

Hendricks, L. (2013). Accounting for the evolution of u.s. wage inequality. Manuscript. University of North Carolina.

Hendricks, L. and T. Schoellman (2014). Student abilities during the expansion of u.s. education. *Journal of Monetary Economics 63*, 19–36.

Hoekstra, M. (2009, 2013/09/17). The effect of attending the flagship state university on earnings: A discontinuity-based approach. *Review of Economics and Statistics 91*(4), 717–724.

Huggett, M., G. Ventura, and A. Yaron (2006). Human capital and earnings distribution dynamics. *Journal of Monetary Economics 53*(2), 265–290.

Huggett, M., G. Ventura, and A. Yaron (2011). Sources of lifetime inequality. *American Economic Review 101*, 2923–54.

Johnson, M. T. (2013). Borrowing constraints, college enrollment, and delayed entry. *Journal of Labor Economics 31*(4), pp. 669–725.

Keane, M. P. and K. I. Wolpin (1997). The career decisions of young men. *Journal of Political Economy 105*(3), 473–522.

Keane, M. P. and K. I. Wolpin (2001). The effect of parental transfers and borrowing constraints on educational attainment. *International Economic Review 42*(4), 1051–1103.

King, M., S. Ruggles, J. T. Alexander, S. Flood, K. Genadek, M. B. Schroeder, B. Trampe, and R. Vick (2010). Integrated public use microdata series, current population survey: Version 3.0. [machine-readable database]. Minneapolis: University of Minnesota.

MaCurdy, T., T. Mroz, and R. M. Gritz (1998). An evaluation of the national longitudinal survey on youth. *The Journal of Human Resources 33*(2), pp. 345–436.

Manski, C. F. (1989). Schooling as experimentation: a reappraisal of the postsecondary dropout phenomenon. *Economics of Education Review 8*(4), 305–312.

Manski, C. F. and D. A. Wise (1983). *College choice in America*. Harvard University Press.

McGrattan, E. R. and E. C. Prescott (2000). Is the stock market overvalued? *Federal Reserve Bank of Minneapolis Quarterly Review 24*(4).

Navarro, S. (2008). Using observed choices to infer agent's information: Reconsidering the importance of borrowing constraints, uncertainty and preferences in college attendance. Mimeo: University of Wisconsin.

NLS User Services (1992). Nls79 profiles of american youth. addendum to attachment 106. http://www.nlsinfo.org/ordering/display_db.php3.

Oreopoulos, P. and U. Petronijevic (2013). Making college worth it: A review of research on the returns to higher education. *The Future of Children 23*(1), 41–65.

Rust, J. (1987). Optimal replacement of gmc bus engines: An empirical model of harold zurcher. *Econometrica: Journal of the Econometric Society*, 999–1033.

Stange, K. M. (2012, January). An empirical investigation of the option value of college enrollment. *American Economic Journal: Applied Economics 4*(1), 49–84.

Stinebrickner, T. R. and R. Stinebrickner (2012). Learning about academic ability and the college drop-out decision. *Journal of Labor Economics 30*(4), 707–748.

Trachter, N. (2014). Stepping stone and option value in a model of postsecondary education. *Quantitative Economics forthcoming*.

United States Department of Education. National Center for Education Statistics (1988). High school and beyond, 1980: Sophomore and senior cohort third follow-up (1986).

Willis, R. J. and S. Rosen (1979). Education and self-selection. *Journal of Political Economy 87*(5), pp. S7–S36.

Online Appendix

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).[26] 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 high school GPA, which is available for 90% of our sample. For the remaining 10%, we impute high school GPA by estimating a linear regression with self-reported high school 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,

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

Table 9: 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 high school GPA quartile that drops out of college at the end of each year. N is the number of observations.

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.[27]

For each high school GPA quartile, Table 9 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 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 10 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,

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[27]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 10: 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.

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 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.

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.[28] 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.

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[28]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 11: 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 11 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

Table 12: 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.

observations after age 35 or whose reported earnings account for less than 30% of lifetime earnings according to the CPS profile. Table 12 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.

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:

$$g_{CPS}(t|s) = \exp\left(1960 \text{ cohort dummy} + \text{age dummy}(t) + \text{year effect}(1960 + t)\right) f(t|s) \quad (11)$$

For years after 2010, we impose the average year effect. Figure 8 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.

Figure 8: Age-earnings Profiles
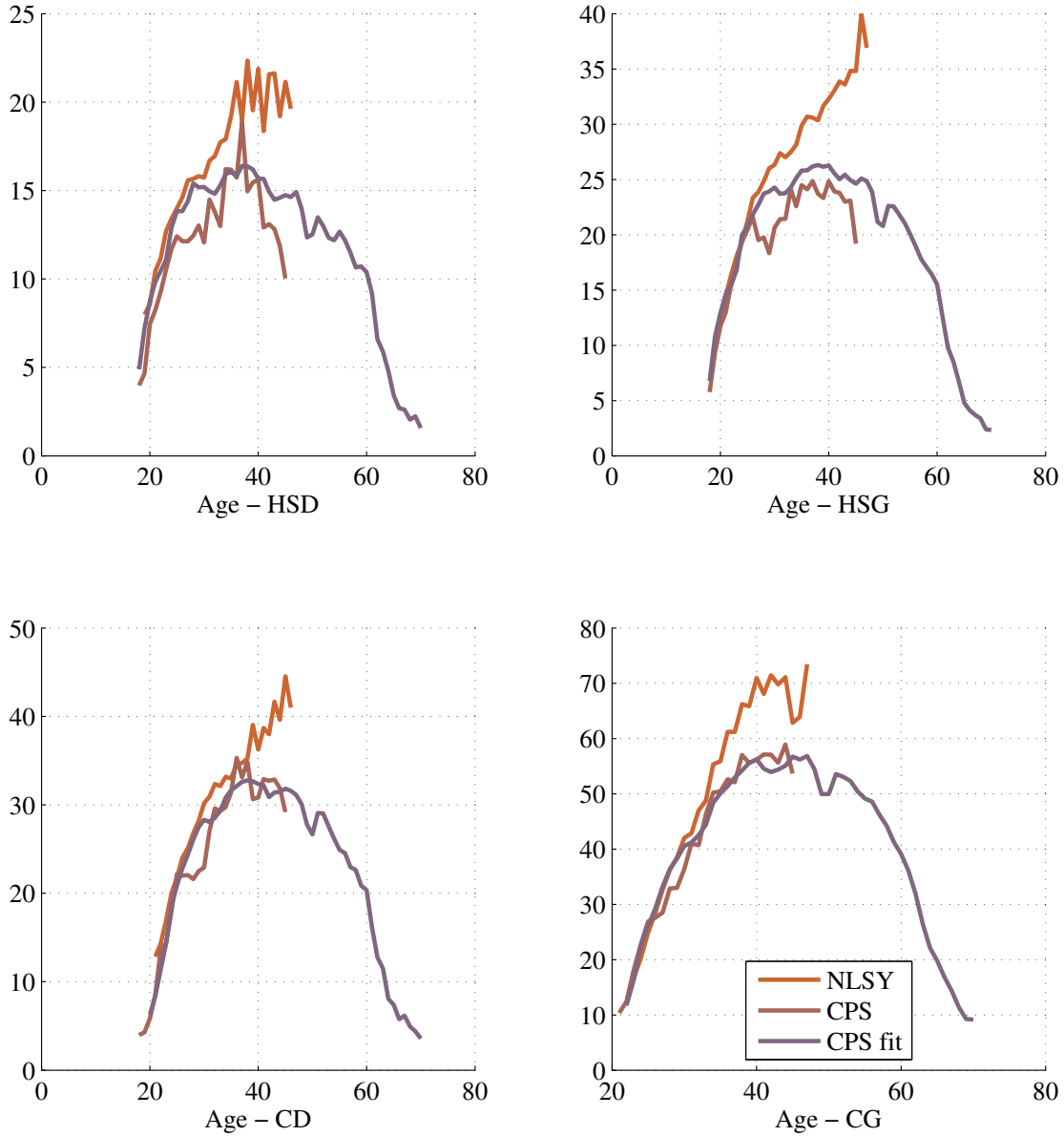
Notes: The figures show the exponential of mean log earnings by schooling and age in thousands of year 2000 dollars. Earnings are adjusted for the fraction of persons working at each age as described in the text.

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 9 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 10 and Figure 11 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 12 shows the distribution of credits broken down by year and test score quartile. The model replicates the fact that controlling for test scores does not substantially reduce the dispersion of credits. The main discrepancies between model and data occur among students in the lowest test score quartile, who make up a small fraction of college students.

Schooling and lifetime earnings.   Table 13 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 14 shows mean log lifetime earnings by school group and test score quartile. The model broadly matches the data cells with large numbers of observations. The largest discrepancy occurs for college graduates in the lowest test score quartile, which are quite rare (32 observations).
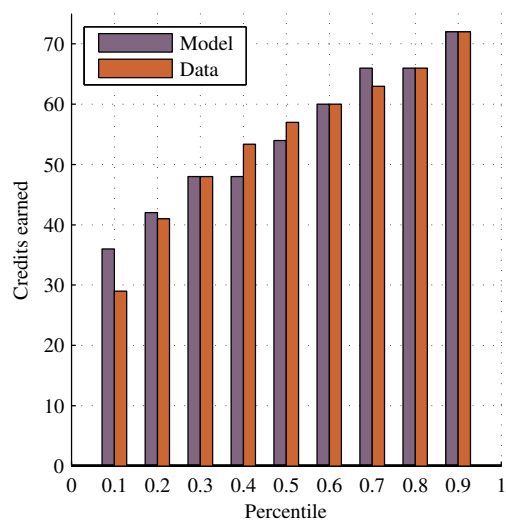
Dropout rates.   Figure 13 shows college dropout rates, defined as the number of persons dropping out at the end of each year divided by the number of college entrants in year
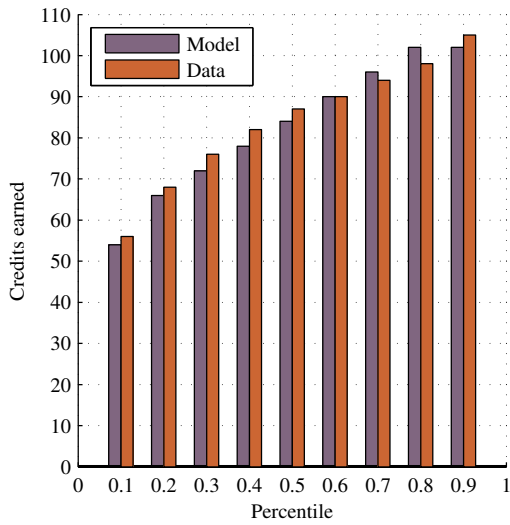
Figure 9: Distribution of Credits by Year
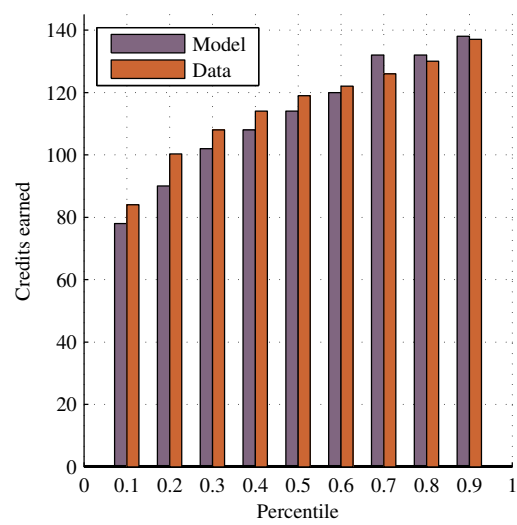
(a) Year 1
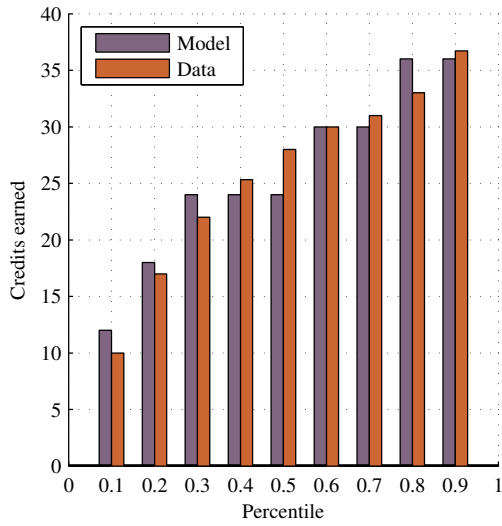
(b) Year 2
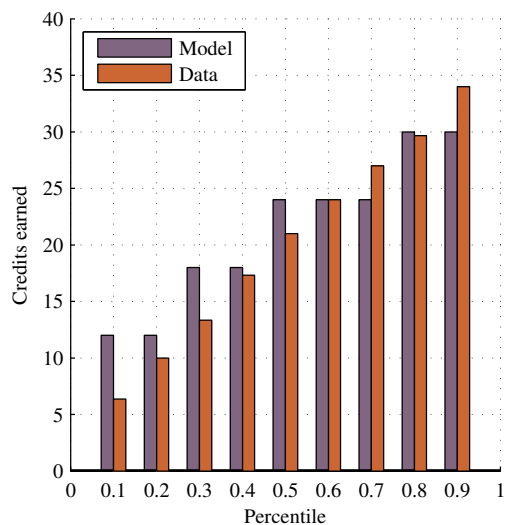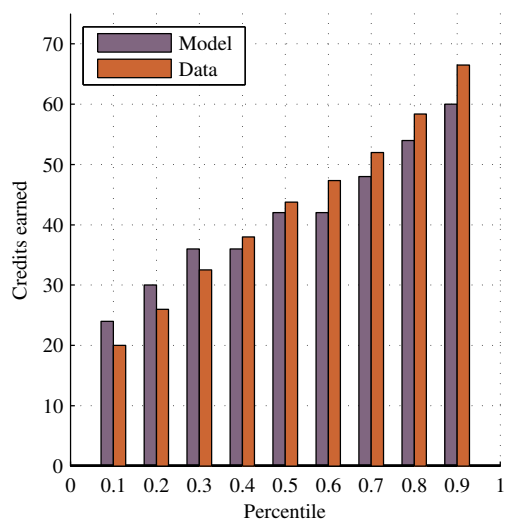
(c) Year 3

(d) Year 4

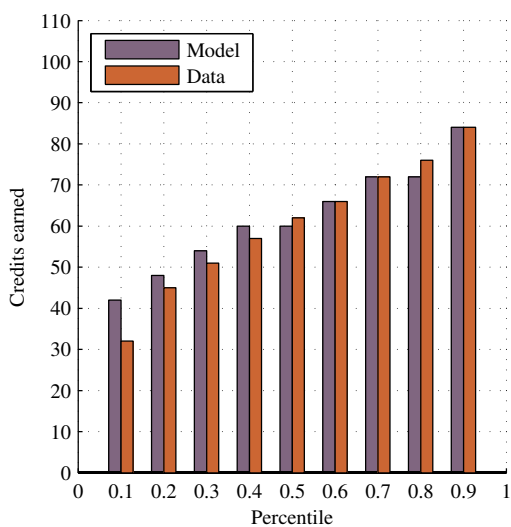Figure 10: Distribution of Credits among Dropouts
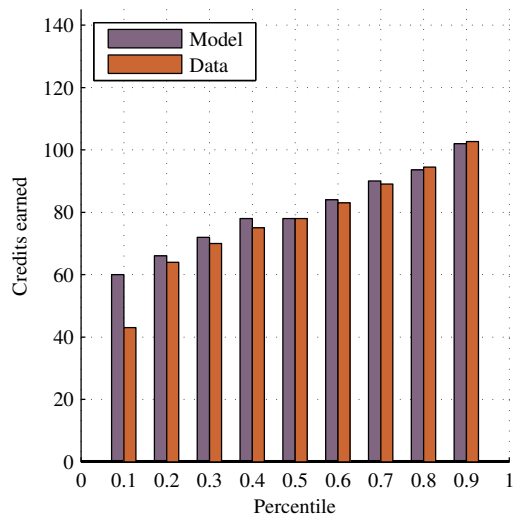
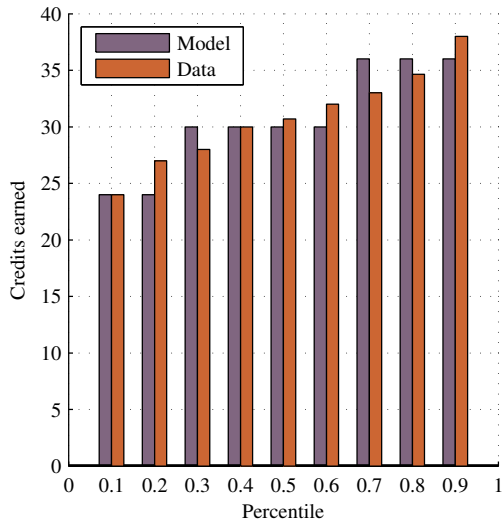(a) Year 1

(b) Year 2
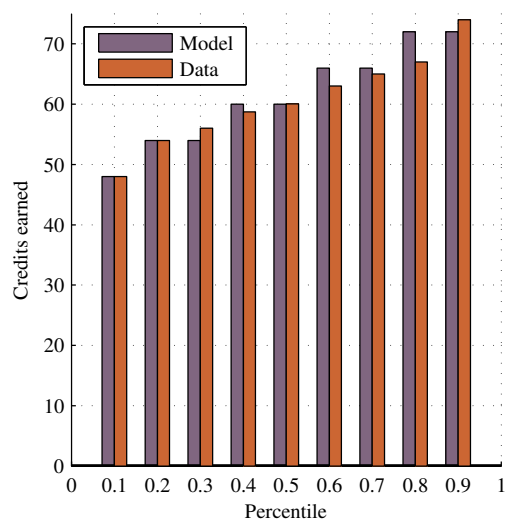
(c) Year 3

(d) Year 4
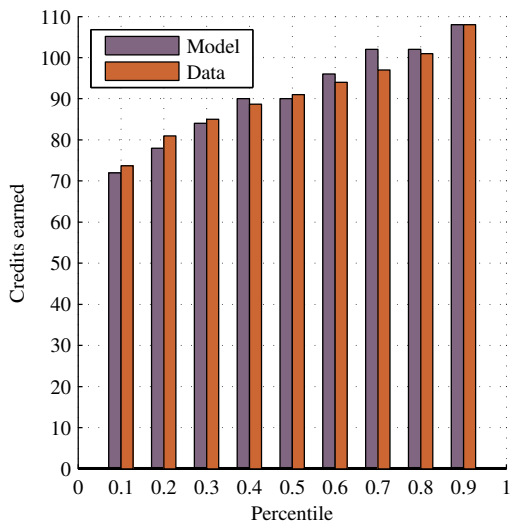
Figure 11: Distribution of Credits among Graduates

(a) Year 1

(b) Year 2

(c) Year 3

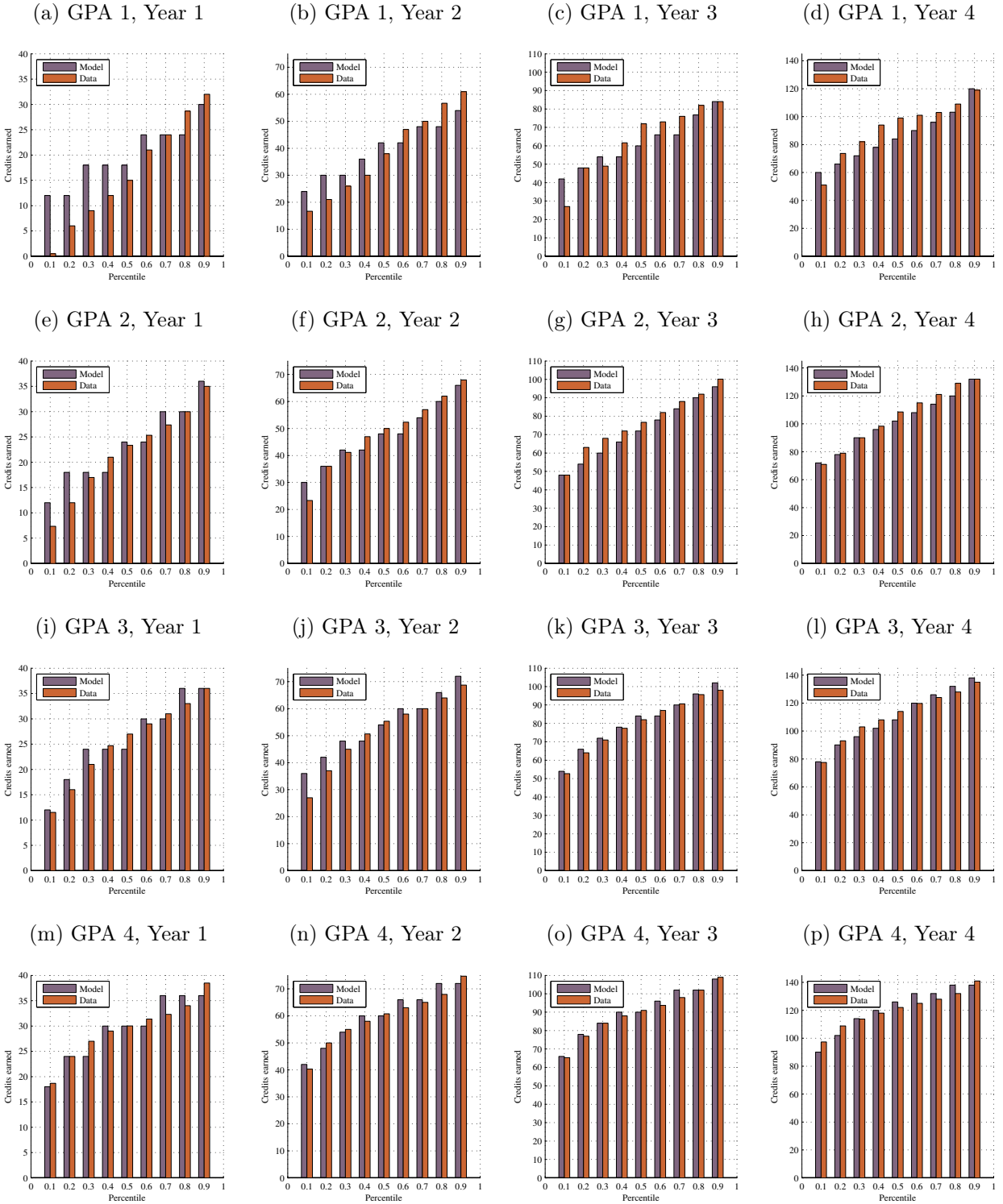(d) Year 4
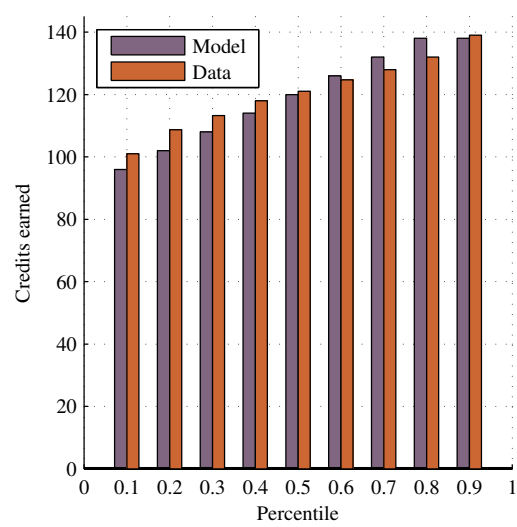
Figure 12: Distribution of Credits by GPA Quartile

Table 13: Schooling and Lifetime Earnings

| | School group | | |
	HS	CD	CG
Fraction			
Data	51.9	22.9	25.2
Model	51.8	23.1	25.0
Gap (pct)	-0.1	1.2	-0.9
Lifetime earnings			
Data	600	643	944
Model	601	637	944
Gap (pct)	0.1	-1.0	0.0

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.

Table 14: Lifetime Earnings

| | Test score quartile | | | |
	1	2	3	4
HS, model	4.03	4.11	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	4.42	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 test score quartile. Standard errors in parentheses.
Source: NLSY79.

Table 15: Financial Moments

	Test score quartile				Percentile		
	1	2	3	4	25	50	75
q, model	3,449	3,065	3,320	4,113	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	1940	1940	1940
z, model	3,567	5,115	5,544	5,585	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	854	854	854
y_{coll}, model	8,522	5,942	4,992	5,242			
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 test score (high school GPA) quartile. Percentile values are shown for all college students. 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.

1. Dropout rates decline strongly with test scores and with time spent in college. They help identify the rate at which students learn about their graduation prospect as they move through college.
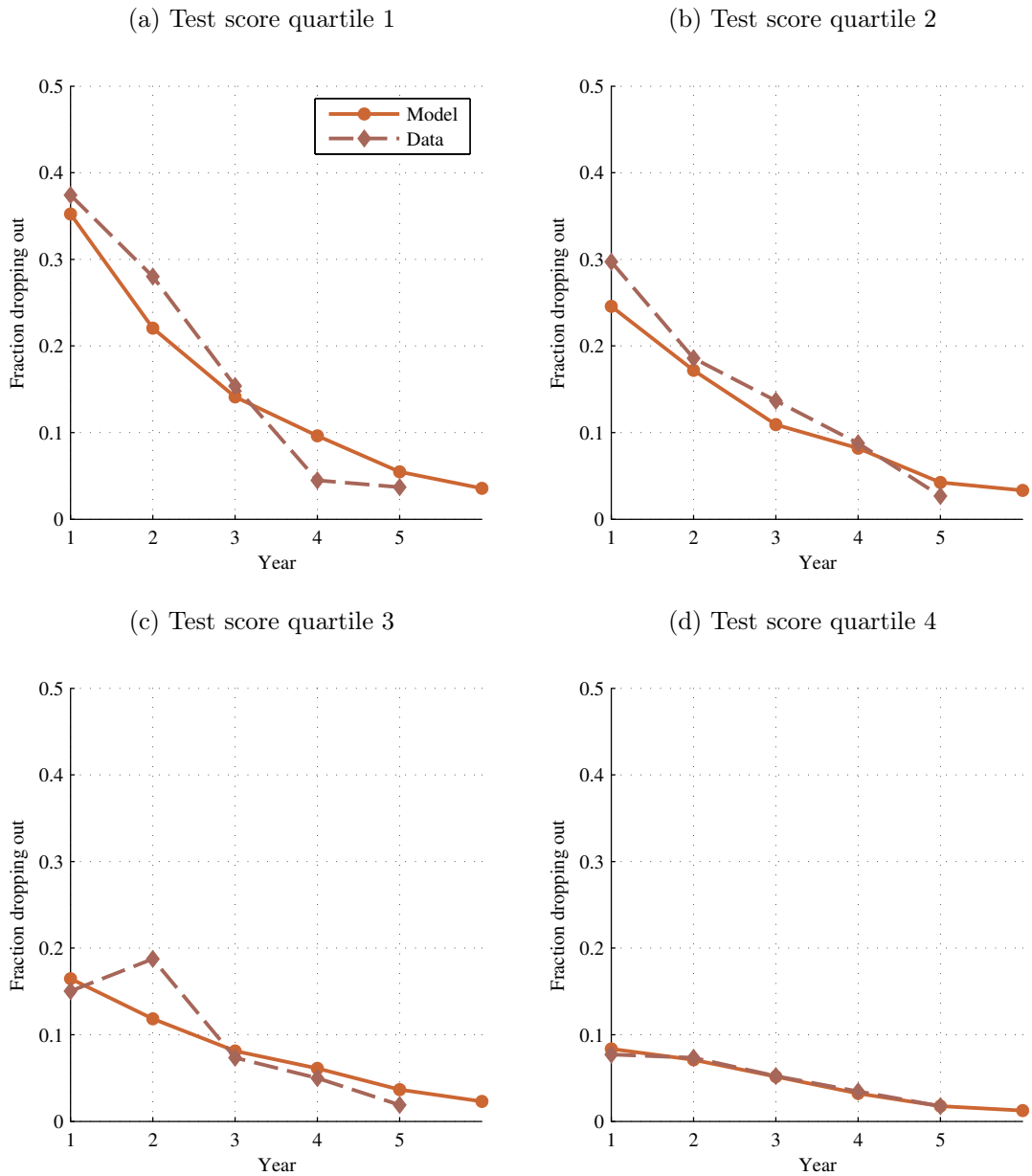
Financial resources. Table 15 shows the means of college costs, parental transfers, and college earnings for students in each test score quartile. In the data, higher ability students face slightly higher college costs, but they also receive larger parental transfers. This allows them to work less. The average net cost of attending college, $q - y_{coll}$, is negative, especially for low test score students.[29] As a measure of dispersion, the table also shows the 25th, 50th and 75th percentile values of each variable.[30]

Table 16 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

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[29]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.

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

Figure 13: Dropout Rates

(a) Test score quartile 1

(b) Test score quartile 2

(c) Test score quartile 3

(d) Test score quartile 4

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 16: 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.

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 test scores 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 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 test scores and lifetime earnings (Table 14).

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 13).

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 17 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 subsection 5.1. The remaining rows of Table 17 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.[31]

Across all parameter values covered in Table 17, 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 or extended models. For example, we explored alternative functional forms for the probability of passing

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

Table 17: 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.

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.