The Return to College: Selection and Dropout Risk*

Lutz Hendricks† Oksana Leukhina‡

January 23, 2017

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 59% of the college lifetime earnings premium.

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

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

*For helpful comments we thank the Editor (Dirk Krueger) and three anonymous referees. We also thank David Blau, V. V. Chari, Larry Jones, Patrick Kehoe, Rodolfo Manuelli, Luigi Pistaferri, José-Victor Rios-Rull, Gianluca Violante, Christoph Winter as well as seminar participants at IFS, Indiana University, Ohio State, University of Minnesota, University of Washington, Western University, Simon Fraser University, Tel Aviv University, Washington State University, York University, the Federal Reserve Bank of Minneapolis, the 2011 Midwest Macro Meetings, the 2011 SED Meetings, the 2011 Cologne Macro Workshop, the 2011 CASEE Human Capital Conference, the 2011 Barcelona Growth Workshop, the 2011 USC-Marshall mini macro labor conference, and the 2013 QSPS Summer Workshop.

†University of North Carolina, Chapel Hill; lutz@lhendricks.org

‡University of Washington; oml@u.washington.edu

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.

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

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 or HS GPAs, transcripts provide *repeated* observations for the same individual. This helps to estimate how precisely HS GPAs measure abilities. It is then possible to correct for the biases introduced when HS GPAs are used in lieu of abilities.

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

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

retirement. At high school graduation, agents are endowed with heterogeneous financial resources and abilities. Following Manski (1989), we assume that students observe only noisy signals of their abilities.[2] 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.[3] 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 the required 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.

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 59% (27 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:

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

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

[2] Based on surveys that elicit student expectations, Stinebrickner and Stinebrickner (2012a; 2014) find that learning about academic ability accounts for 45% of students' dropout decisions during the first two years at Berea College.

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

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 HS GPAs 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 HS GPAs does not greatly reduce credit dispersion implies that HS GPAs must be noisy measures of ability. Given these estimates of HS GPA noise and the ability gap, we can use the observed joint distribution of lifetime earnings and HS GPAs to estimate ϕ. The structural model then interprets the strong association between HS GPAs 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 accumulation 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. 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 (see the survey by Card 1999). The returns to schooling implied by IV methods are typically larger than those implied by OLS regression, suggesting that selection bias may be weak. However, Heckman et al. (2006) argue that IV estimates do not identify readily interpretable treatment effects.

A more recent literature has developed structural discrete choice models of schooling decisions. A large share of this work is based on Roy models which abstract from college completion risk.[4] The implied role of ability selection varies widely across studies. For example, in Cunha et al. (2005), selection accounts for 14% of the lifetime earnings gap between college graduates and high school graduates. In Carneiro et al. (2003), the fraction is 53%. 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 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] Es-

[4] A seminal contribution is Willis and Rosen (1979). More recent work includes Heckman et al. (1998), Carneiro et al. (2003), 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).

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

timated rates of return to schooling vary widely, ranging from near zero to over 10% per year (see Belzil 2007, Table 1).[7] In models based on Keane and Wolpin (1997), 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.

Other studies of risky college completion that use transcript data include Arcidiacono (2004; 2012) and Stange (2012). In these models, college grades affect either earnings or the utility derived from attending college. In our model, students must pass courses in order to graduate from college. A student's ability affects the the rate at which he progresses towards graduation. Heterogeneity in abilities therefore generates dispersion in the incentives to attempt or persist in 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.

2 Transcript Data

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

[7] Based on the results reported in these studies, it is not possible to calculate the contribution of ability selection to the college lifetime earnings premium. We are therefore unable to compare our findings with those of previous research.

Table 1: College Credits

GPA quartile	Credit distribution 20th	50th	80th	Median credits CD	CG	Fraction 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.

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.[8]

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.[9]

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.[10]

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

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

The data admit two interpretations.

[8] The supplementary appendices are available online.

[9] 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.

[10] Stinebrickner and Stinebrickner (2012b) 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.

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 why conditioning on HS GPA does not reduce credit dispersion much, even if HS 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 HS GPA does not reduce credit dispersion much implies that HS 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.

2.3 Implications for Ability Selection

In order to quantify what the transcript evidence implies for ability selection, we develop a structural model of credit accumulation (see section 3). Before presenting this model, we summarize our identification strategy.

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 HS 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.

The identification strategy proceeds as follows. We posit a specific model of credit accumulation that decomposes the observed dispersion in credit accumulation rates into the contributions of ability heterogeneity and luck. Given an estimate of the role of luck, we can back out the ability gap between college graduates and college dropouts from the observed difference in credit accumulation rates between the two groups.

Next, we estimate how precisely HS GPAs measure abilities. The idea is that the noise in HS GPA determines by how much controlling for HS GPAs reduces the dispersion of credit accumulation rates. Given an estimate of HS GPA noise, we can back out ϕ from the observed relationship between HS GPA and lifetime earnings (correcting for the attenuation bias implied by the noise in HS GPA).

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.

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 baseline 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 $z_t = f(\hat{z}_j, t, \mathbb{I}_{coll})$, and decides how much to work v_t, consume c_t, and save k_{t+1}. Transfers depend on the baseline transfer $\hat{z}_j$, on the year since high school graduation t, and on college attendance $\mathbb{I}_{coll}$.

2. He attempts n_c college courses and succeeds in a random subset, which yields n_{t+1}. More able students accumulate courses faster.[11]

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.

[11] Garriga and Keightley (2007) and Trachter (2015) model students' progress through college in a similar way. However, their models are not well suited to measure ability selection.

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. Parental transfers are received during the first T_c periods after high school graduation. Their level depends on $\hat{z}_j$. 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, $\exp(\phi_s a + \mu n_\tau + y_s)$, 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.[12] 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.

[12] Relaxing the assumption that lifetime earnings are a linear function of ability does not significantly affect our results.

In each period, the student attempts n_c courses and completes each with probability $p(a)$ given by the logistic function

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

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

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

subject to the budget constraint

$$c = Rk - k' - \hat{q}_j + f(\hat{z}_j, t, \mathbb{I}_{coll}) + y_{coll}(v) \tag{6}$$

and the borrowing constraint $k' \geq k_{min}$. Period utility is given by $u(c, 1-v)$ 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.

$\Pr(n'|n,j,t)$ 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

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

where p_c and p_w are independent draws from a demeaned standard type I extreme value distribution with scale parameter $\pi > 0$. $s(n)$ 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 $s(n) = CG$ and $V_C = -\infty$: the agent graduates from college.

2. If $t = T_c$ and $n < n_{grad}$, then $s(n) = CD$ 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 $s(n) = CD$ 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

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

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.[13]

Learning about student abilities imposes restrictions on the modeling 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), the model's state space would increase massively. Students would have to keep track of their entire history of choices and course outcomes in order to form beliefs about their abilities. 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 credit accumulation rates, course loads, or study efforts. All of these characteristics are bundled into model abilities a.

Given that tractability concerns force us to abstract from potentially interesting model features, it is useful to consider how this affects our results. We comment on a number of potential concerns:

1. If low income students must work long hours in order to pay for college, this, rather than low ability, may account for their poor course outcomes. In an Online Appendix,

[13] Other recent models with learning about student abilities include Arcidiacono et al. (2012), Stange (2012), Stinebrickner and Stinebrickner (2012b), and Trachter (2015)

we summarize an empirical literature and our own empirical results that attempt to quantify these effects. The central findings may be summarized as follows.

(a) Differences in hours worked between high and low income students are modest. In our sample, students in the top quartile of socioeconomic status work about 1.2 hours per week less than students in the bottom quartile. In NLSY79 data, the gap is of similar size (Hendricks et al., 2015). More generally, we find that little of the variation in hours worked across students is explained by observable financial characteristics (parental transfers, college costs, or student debt).

(b) Much of the literature finds that working in college has small effects on course outcomes (e.g., DeSimone 2008; Kalenkoski and Pabilonia 2010). In our sample, an extra hour of work per week is associated with a 0.001 point reduction in GPA. By contrast, Stinebrickner and Stinebrickner (2003) find that working has large negative effects on grades for students at Berea College. Their estimation uses work assignments as a source of exogenous variation in hours. This identification strategy is arguably more compelling than what is found in most of the literature.

(c) Much of the literature finds that study time has little effect on course outcomes (see the literature surveys by Plant et al. 2005 and Nonis and Hudson 2006). However, Stinebrickner and Stinebrickner (2008) find large effects of study time on student grade point averages for Berea College. Once gain, their identification strategy appears compelling. The characteristics of randomly assigned roommates provide exogenous variation in study time.

Our reading of the literature leads us to abstract from the effect of hours worked on course outcomes. Whether working in college negatively impacts grades remains controversial. Moreover, it is not clear how a strong causal effect of working in college could be reconciled with the weak correlation between hours worked and course outcomes that is commonly seen in the data.

2. Suppose that some students choose more difficult courses than others for reasons that are not related to their abilities. Our identification strategy may then overstate the role of abilities for course outcomes. In subsection F.1, we study an extension of our model where students are endowed with an additional persistent trait that affects their course outcomes. We find that our results remain valid.

3. Two-year colleges may play a fundamentally different role from 4-year colleges.

(a) One possibility is that 2-year college students study "on the side" while working full time. However, Carroll and Chan-Kopka (1988) find that 2-year college students work only about 1 hour per week more during the academic year than students enrolled in public 4-year colleges.

(b) Students may learn more in 4-year colleges than in 2-year colleges. However, Kane and Rouse (1995) find that the wage returns to credits earned in both types of colleges are similar. Moreover, Rouse (1995) finds that starting at a 2-year college does not lower a student's likelihood of earning a BA degree.

(c) Our model features heterogeneity in college costs and thus captures the fact that 2-year colleges are cheaper than 4-year colleges.

We incorporate *heterogeneity in financial assets* and in the *net cost* of attending college to capture the role of borrowing constraints for college selection. Consistent with much of the empirical literature that studies the same time period, we find that borrowing constraints are not an important barrier to college entry or graduation.[14] 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.

[14] The literature is surveyed by Lochner and Monge-Naranjo (2012). Some studies, such as Brown et al. (2012) and Winter (2014), find that borrowing constraints do bind for significant numbers of students in the 1980s.

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.[15]

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 $\Pr(\hat{a}_i | j) = \Pr\left(a \in \Omega_i | m = \hat{m}_j\right)$.

[15] 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 j^{th} 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. The returns to earning 2-year degrees are captured by the effect of courses on lifetime earnings, μn.[16] The fact that low HS GPA 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.

HS GPAs. In the model, we assume that HS GPAs 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 HS GPAs as signal plus Gaussian noise:

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

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

In the data, we divide students into quartiles either according to their HS 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 HS GPAs and AFQT scores are highly correlated. Sidestepping the question of what test scores measure, we use the term "HS GPAs" in the text and the symbol GPA in mathematical expressions.

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

Financial variables. The cost of attending college (q) is measured as the sum of tuition and fees net of scholarships and grants. Parental transfers are measured as the annual average of all transfer payments that parents make to their children within the first two years after high school graduation, regardless of whether these payments are labeled as college related. Parental transfers are observed for all high school graduates, including those who never attend college.

4.3 Fixed Parameters and Functional Forms

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 6^{th} 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 90^{th} 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 $\left[k_{min}, \hat{k}_j\right]$.

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

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 $k_{min} = -\$19,750$.

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.

The transfer function is of the form

$$f(\hat{z}_j, t, \mathbb{I}_{coll}) = \hat{z}_j \times (1 + \mathbb{I}_{coll}\bar{z}_c) \times (1 + \bar{z}_t). \tag{10}$$

Parents top up $\hat{z}_j$ by the factor $\bar{z}_c$ while a student attends college. $\bar{z}_t$ determines how transfers vary over time (we assume that transfers are constant after four years). How transfers depend on student abilities and college costs is captured by the correlation of $\hat{z}_j$ with the other endowments.

4.4 Calibrated Parameters

30 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.

Table 4: Calibration Targets

Target	Value
Fraction in population, by (hs gpa quartile, schooling)	Figure 1
Lifetime earnings, by (hs gpa quartile, schooling)	Table D.1
Dropout rate, by (hs gpa quartile, t)	Figure D.5
Average time to BA degree (years)	4.4
College credits	
Mean cumulative credits, by (graduation status, t)	Table 6
– by (hs gpa quartile, t)	Table 6
Persistence of credits across years	Table 7
CDF of cumulative credits, by t	Figure D.1
– by (graduation status, t)	Figure D.2, Figure D.3
– by (hs gpa quartile, t)	Figure D.4
Financial moments	
College costs q	Table D.3
(mean by hs gpa quartile, dispersion)	
Parental transfer regressions	Table D.4
Earnings in college	Table D.3
(mean by hs gpa quartile)	
Fraction of students in debt, by t	Table D.5
Mean student debt, by t	Table D.5

Notes: Lifetime earnings targets are based on NLSY79 data. The remaining targets are based on HS&B data. With the exception of parental transfers, the financial moments are only observed for college students.

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.[17]

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.

[17]Within each block of moments, such as the fraction of students who drop out of college by HS GPA 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 5: Calibrated Parameters

Parameter	Description	Value
Endowments		
μ_k, σ_k	Marginal distribution of k_1	$39,974; 29,768$
μ_q, σ_q	Marginal distribution of q	4,619; 3,244
μ_z, σ_z	Marginal distribution of z	1,973; 3,989
$\alpha_{m,z}, \alpha_{m,q}, \alpha_{q,z}, \alpha_{a,m}$	Endowment correlations	0.32; -0.23; 0.77; 2.98
$\alpha_{k,m}$	Correlation k_1, m	-0.18
$\alpha_{IQ,m}$	Correlation IQ, m	1.19
Shocks		
π	Scale of preference shocks	1.406
π_E	Scale of preference shocks at entry	0.490
Lifetime earnings		
ϕ_{HS}, ϕ_{CG}	Effect of ability on lifetime earnings	0.165; 0.212
y_{HS}, y_{CG}	Lifetime earnings factors	3.90; 3.97
μ	Earnings gain for each college credit	0.008
Other parameters		
ρ	Weight on leisure	1.553
δ	Weight on consumption	0.833
U_{CD}, U_{CG}	Preference for job of type s	-1.20; -2.46
$\gamma_1, \gamma_2, \gamma_{min}$	Credit accumulation rate $p_(a)$	4.88; 2.13; 0.49
$\bar{z}_c$	Transfer top-up for college students	0.66
$\bar{z}$	Transfer factor by year	-0.11; -0.01; -0.29

Table 6: Credit Accumulation Rates

(a) College graduates and college dropouts

	College dropouts		College graduates	
Year	Model	Data	Model	Data
1	58.9	57.1 (1.0)	84.2	85.4 (0.6)
2	58.6	59.6 (1.0)	83.8	83.4 (0.5)
3	57.8	55.6 (0.9)	83.6	83.0 (0.4)
4	55.7	53.6 (1.1)	83.4	82.3 (0.4)

(b) Test score quartiles

	HS GPA Quartile			
	1	2	3	4
$t = 1$	53.8 / 48.1 (2.3)	62.5 / 61.8 (1.6)	71.1 / 71.0 (1.2)	81.2 / 81.8 (0.9)
$t = 2$	54.4 / 53.7 (2.3)	64.5 / 67.6 (1.4)	73.2 / 71.5 (1.0)	82.5 / 81.6 (0.7)
$t = 3$	55.9 / 58.1 (2.3)	67.0 / 69.5 (1.4)	75.1 / 72.4 (0.9)	83.5 / 81.7 (0.6)
$t = 4$	58.0 / 62.3 (2.8)	69.8 / 71.8 (1.5)	76.6 / 75.3 (0.8)	84.2 / 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 HS GPA quartiles. Each cell shows model / data values.
Source: High School & Beyond.

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 HS GPAs (panel b). Table 7 shows how the model fits the observed persistence of credit accumulation rates. Appendix D shows that the model accounts for the large dispersion in earned credits observed in the data, also within HS GPA quartiles.

Table 7: Persistence of Credit Accumulation Rates

	Year $1-2$	Year $2-3$	Year $3-4$
Correlations, model	0.46	0.45	0.43
data	0.48	0.42	0.39
Eigenvalues, model	0.53	0.46	0.43
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 HS GPAs. Figure 1 shows that HS GPAs are strong predictors of college entry and college completion. 81% of students in the top HS GPA quartile attempt college and 74% of them earn college degrees. In the lowest HS GPA quartile, only 22% of students enter college and only 11% of them earn degrees.[18] 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

$$\mathbb{E}[\phi_s a + \mu n_\tau + y_s + \ln(R^{-\tau})|s], \tag{11}$$

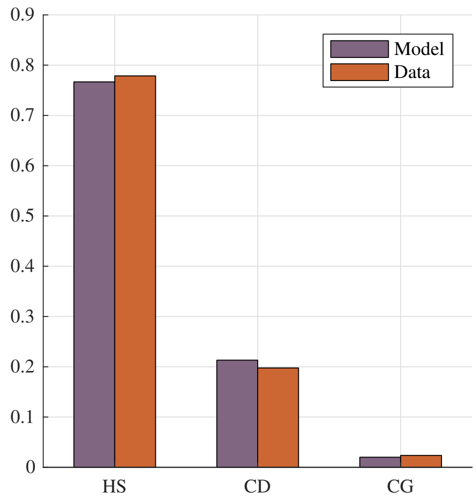
where $\tau = 1$ and $n_\tau = 0$ for high school graduates. The mean log lifetime earnings gap between school group s and high school graduates may then be decomposed into four terms:

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

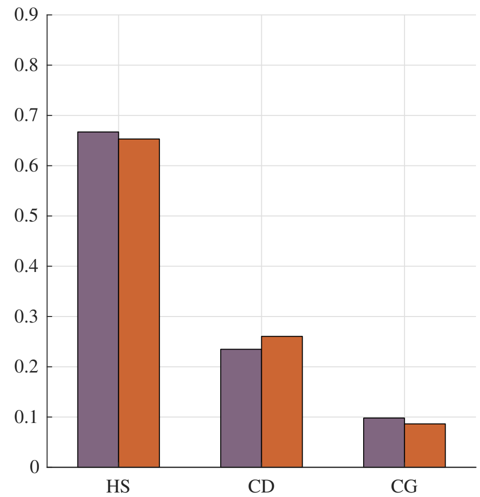
[18] Bound et al. (2010)'s Figure 2 documents similar patterns in NLS72 and NELS:88 data.

Figure 1: Schooling and Test Scores

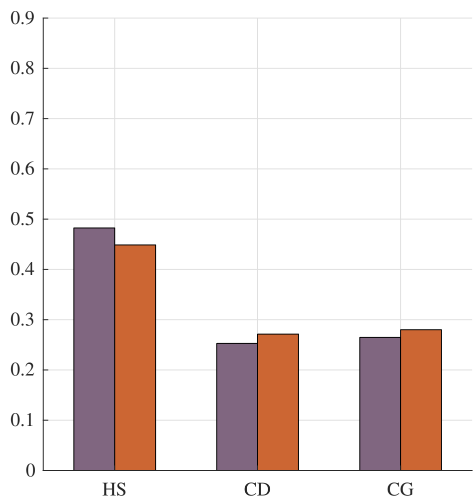
(a) HS GPA quartile 1



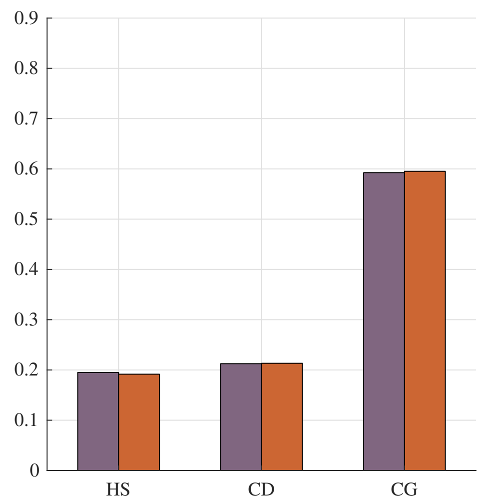
(b) HS GPA quartile 2



(c) HS GPA quartile 3



(d) HS GPA quartile 4



Notes: For each HS GPA quartile, the figure shows the fraction of persons who attain each schooling level.
Source: High School & Beyond.

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 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, 17 log points are due to credit accumulation, 20 log points are due to prices (y_s and ϕ_s), and the remaining 27 log points (59% 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 (4 log points). By assumption, the effect of prices is zero. The effect of earned credits is not enough to offset the cost of delayed labor market entry, implying that more than the entire 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 (11), 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 high school graduates of 1.61 standard deviations. To understand why this gap is large, recall the discussion of our identification strategy in subsection 2.3.

Accounting for the observed dispersion in credit accumulation rates requires substantial heterogeneity in credit accumulation rates. Figure 2a shows how the probability of passing

Table 8: Ability Selection

Gap relative to HS (in log points)	College dropouts Gap	Fraction	College graduates Gap	Fraction
Total gap	4	–	45	–
Delayed labor market entry	-9	-214	-18	-40
Prices: y_s and ϕ_s	0	0	20	43
Credits	6	141	17	38
Ability selection	7	172	27	59

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.

a course varies with student abilities, $p(a)$. While high ability students pass 94% of their attempted credits, low ability students pass only 49%.

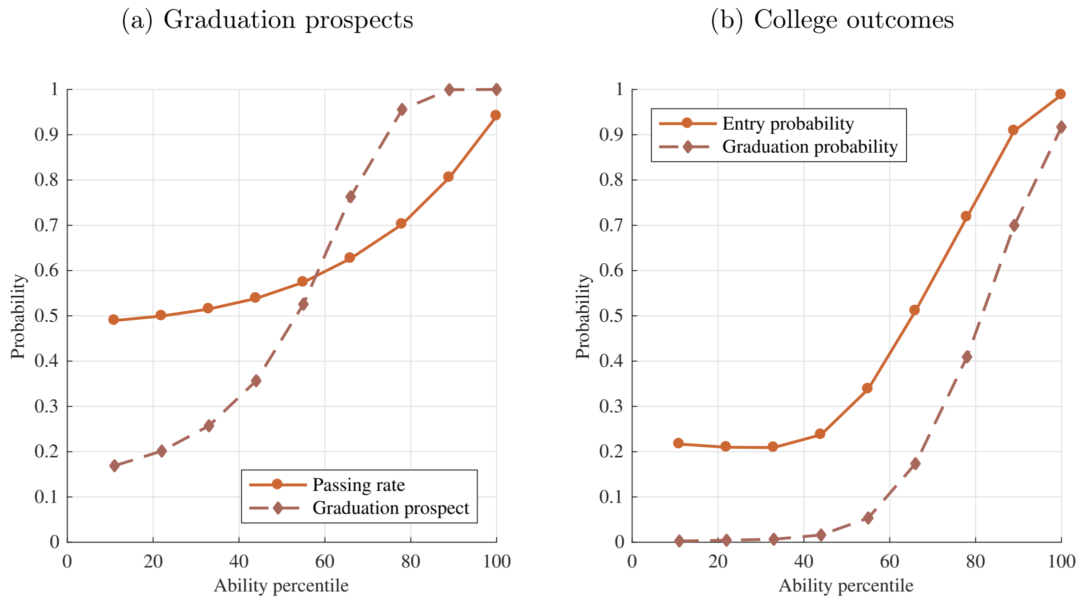
To see why this much heterogeneity in $p(a)$ is needed, consider what would happen if all students shared the same p, given by the average credit accumulation rate at the end of the second year in college (75%). The binomial distribution of courses passed would then imply that students in the 80^{th} percentile pass 83% of their courses, compared with 67% for students in the 20^{th} percentile (a gap of 17%). In the data, the corresponding gap is 52% (see Table 1). The difference must be accounted for by heterogeneity in $p(a)$.

Recall from Table 1 that students who eventually graduate earn 40% more credits by the end of the second year in college than students who eventually drop out. Accounting for this difference requires a large ability gap between the two groups.

The economic mechanism that generates the ability gap is as follows. Define a student's graduation prospect as the probability of earning enough credits for graduation in 6 years. Figure 2a shows that graduation prospects increase sharply with student abilities. While high ability students are virtually guaranteed to graduate from college, if they persist for 6 years, low ability students have little chance of graduating.

This has implications for students' incentives to enter college and to persist when faced with negative shocks. High ability college entrants can expect to earn large financial rewards if they persist through 6 years of college. Not only are they virtually guaranteed to graduate, they also face larger wage gains when they do compared with low ability students (because $\phi_{CG} > \phi_{HS}$). As a result, 99% of students in the highest ability group attempt college and 93% of these entrants manage to graduate (see Figure 2b).

Figure 2: Graduation Prospects and Abilities



Notes: Panel (a) shows the credit accumulation 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.

Low ability students face very different incentives. Even if they persist, their chances of graduating are slim. 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). As a result, they rarely even attempt college. If they do, they almost never graduate.

Only students with intermediate abilities face genuine uncertainty about their graduation prospects. They also constitute most of the college dropouts. While 34% of median ability students attempt college, only 16% of these entrants eventually graduate.

Since students' ability signals are quite precise, the main features of Figure 2 remain unchanged when students are sorted according to their signals rather than their abilities.[19] 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 HS GPA quartiles are too similar in terms of their credit accumulation rates, schooling, and lifetime earnings. The reason is that HS GPAs are less precise

[19] 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).

signals of ability than in the baseline model. After all, HS GPAs 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 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 HS GPAs measured abilities without noise, its value could be estimated by regressing log lifetime earnings on HS GPAs, with school dummies controlling for y_s. When HS GPAs are noisy measures of abilities, the resulting estimates suffer from attenuation bias. Noisier HS GPAs therefore imply higher values of ϕ_s and larger contributions of selection to the college earnings premium.

To estimate how precisely HS GPAs measure abilities, we exploit the observation that controlling for HS GPAs does not substantially reduce the dispersion of earned credits (see Table 1).[20] Viewed through the lens of our model of credit accumulation, this fact implies that HS GPAs must contain substantial noise. In the calibrated model, the correlation between HS GPAs and abilities is 0.68. Accounting for the observed relationship between lifetime earnings and HS GPAs then requires large values of ϕ_s. A one standard deviation increase in ability raises lifetime earnings by 0.16 for high school graduates and by 0.21 college graduates.[21]

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 59% 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.[22] Selection in college accounts

[20] 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.

[21] 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.

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

for the remaining 34%.[23]

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 HS GPA quartile attempt college (22%), even though very few (11%) of these entrants manage to earn a bachelor's degree (see Figure 1). 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 3 shows how mean log lifetime earnings vary with schooling and ability (Figure 3a) or ability signal (Figure 3b). 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 24 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 $\phi_{CG} > \phi_{HS}$.

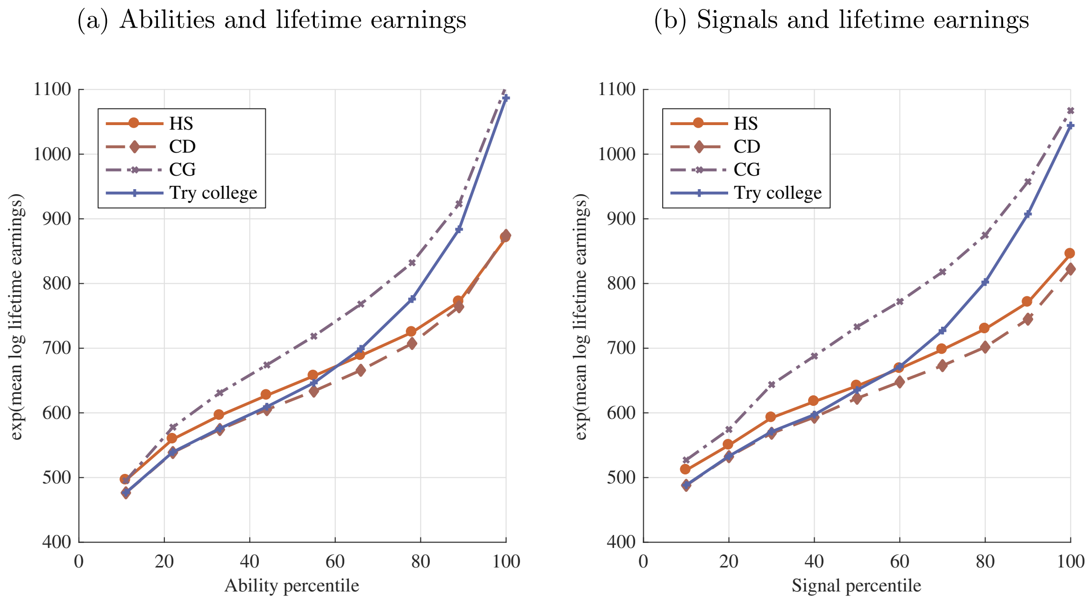
College dropouts enjoy much smaller earnings gains. On average, working as a high school graduate yields almost the same expected lifetime earnings as attempting college. Our model therefore implies that the expected payoff from attempting college increases sharply with ability.

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.[24] The potential losses from attempting college are limited by the option of dropping out. Low or medium ability students may then try college

[23] 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.

[24] The earnings gains due to earned credits roughly offset the losses due to foregone earnings. 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 3: Schooling 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.

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 (4 log points). The model implies that part of this gap is due to selection. 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.[25] 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 47.1% to 45.7%.[26]

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.[27]

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.

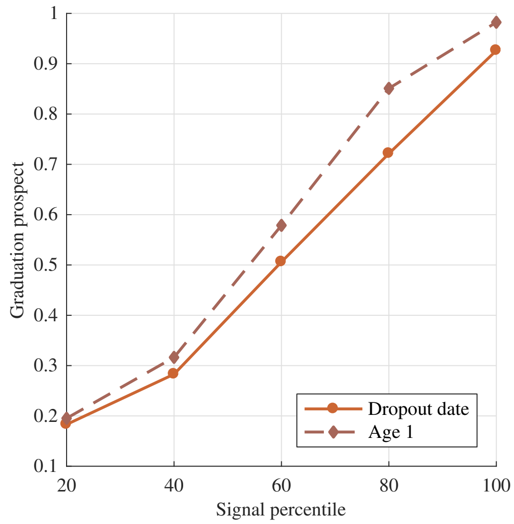
For dropouts in each signal decile, Figure 4 shows students' graduation prospects at the time of college entry and at the time of dropping out. Dropouts receive bad news during their college careers that lead to a substantial downward revision in their graduation prospects.

[25] The purpose of this experiment is diagnostic. We ask how dropout decisions change when financial constraints are relaxed. Analyzing the equilibrium effects of changing borrowing limits requires a structural model of parental transfers (see Winter 2014).

[26] 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.

[27] Limiting students' maximum work time to 30 hours per week does not substantially change our findings. Our conclusion that borrowing constraints are not a major concern for the time period that we study is consistent with a sizable empirical literature (see Cameron and Heckman 1998; Carneiro and Heckman 2002; Cameron and Taber 2004)

Figure 4: 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.

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 in the dropout rate is small; it falls to 44.7%. 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 23.6%. 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. Since the lifetime earnings of low to medium ability students do not depend much on when these students drop out of college (see Figure 3b), even small preference shocks can have large effects on the timing of college dropout decisions.

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, 18.6% 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.

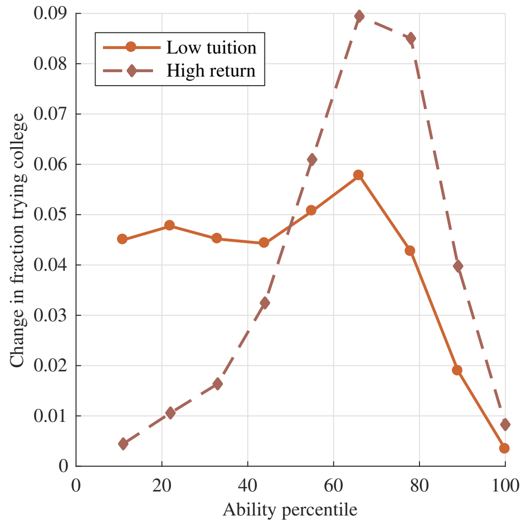
The *low tuition* experiment reduces the mean of q by \$1,000. This amount is chosen so that the model's implications can be compared with empirical estimates. The *high return* experiment increases y_{CG} by 3 log points. This amount is chosen to yield roughly the same change in college enrollment as 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 3.9 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 falls within the range of these estimates.

Figure 5 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 1.3 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, 3.9 percentage points, but the fraction of college graduates rises by 4.5 percentage points. The students that respond most to higher returns to college are drawn from the upper tail of the ability distribution (Figure 5). Most of these students graduate from college, so that the dropout rate declines.

Figure 5: 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.

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 students, the college premium is mainly relevant for high ability students who expect to graduate from college.[28]

6 Conclusion

This paper argues that a large fraction of the lifetime earnings gap between college graduates and high school graduates is due to ability selection. Our empirical innovation is to obtain repeated indicators of student abilities from their college transcripts. Transcript data also provide information about students' incentives to persist in college. Our theoretical

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

innovation is to model in detail how students progress through college towards fulfilling the requirements for college graduation. The calibrated model implies that 59% of the college lifetime earnings premium is due to ability selection.

We conclude by considering potential avenues for future research. Allowing students to choose between colleges of different qualities may refine our understanding of the returns to college. Admission to better 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 HS GPAs and college qualities may help disentangle the effects of ability selection and human capital production.

It would be of interest to extend our analysis to other time periods. We expect that our findings extend to cohorts that entered college in the early 1990s. These cohorts still faced fairly generous loan limits relative to tuition costs. As late as 1992-93, the Stafford/SLS loan limit of (at least) $17,250 easily covered tuition and fees at public 4-year colleges ($3,000 per year, on average). Only 23% of all undergraduates enrolled at such institutions received any Stafford or SLS loans. The average loan amount of $2,900 was less than 20% of the loan limit (Berkner and Bobbitt, 2000). These figures suggest that workers who are currently in their forties faced colleges finances that were not very different from what we observe in the NLSY79. However, in recent years, college college costs have increased relative to student debt limits (Belley and Lochner, 2007). Tighter financial constraints may have affected ability selection in college. Before the early 1960s, student loans were largely unavailable. Empirical estimates by Hendricks et al. (2015) suggest that student ability was less important for college entry compared with later time periods, while parental income was more important. Whether these changes are related is an open question.

Finally, our findings suggest that policies that encourage college attendance, such as tuition subsidies, may attract mainly low ability students who are unlikely to graduate. These students' entry decisions are especially sensitive to financial incentives because their lifetime earnings are not strongly affected by their college attendance. Future research should formally investigate the implications of such policies.

References

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

Altonji, J. G. (1993): “The Demand for and Return to Education When Education Outcomes are Uncertain,” *Journal of Labor Economics*, 11, pp. 48–83.

Arcidiacono, P. (2004): “Ability sorting and the returns to college major,” *Journal of Econometrics*, 121, 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): “The Falling Time Cost of College: Evidence from Half a Century of Time Use Data,” *Review of Economics and Statistics*, 93, 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, 37–89.

Belzil, C. (2007): “The return to schooling in structural dynamic models: a survey,” *European Economic Review*, 51, 1059–1105.

Belzil, C. and J. Hansen (2002): “Unobserved Ability and the Return to Schooling,” *Econometrica*, 70, 2075–2091.

Ben-Porath, Y. (1967): “The Production of Human Capital and the Life Cycle of Earnings,” *Journal of Political Economy*, 75, pp. 352–365.

Berkner, L. and L. Bobbitt (2000): “Trends in undergraduate borrowing: Federal student loans in 1989-90, 1992-93, and 1995-96 (NCES 2000-151). Washington, DC: US Department of Education,” *National Center for Education Statistics*, bibtex: berkner_trends_2000.

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, 129–57.

Bowles, S., H. Gintis, and M. Osborne (2001): "The Determinants of Earnings: A Behavioral Approach," *Journal of Economic Literature*, 39, pp. 1137–1176.

Brown, M., J. K. Scholz, and A. Seshadri (2012): "A New Test of Borrowing Constraints for Education," *Review of Economic Studies*, 79, 511–538.

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 J. J. Heckman (1998): "Life cycle schooling and dynamic selection bias: Models and evidence for five cohorts of American males," *The Journal of Political Economy*, 106, 262.

Cameron, S. V. and C. Taber (2004): "Estimation of Educational Borrowing Constraints Using Returns to Schooling," *The Journal of Political Economy*, 112, pp. 132–182.

Card, D. (1999): "The causal effect of education on earnings," Elsevier, vol. 3, Part A of *Handbook of Labor Economics*, chap. 30, 1801 – 1863.

——— (2001): "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems," *Econometrica*, 69, pp. 1127–1160.

Carneiro, P., K. T. Hansen, and J. J. Heckman (2003): "2001 Lawrence R. Klein Lecture: Estimating Distributions of Treatment Effects with an Application to the Returns to Schooling and Measurement of the Effects of Uncertainty on College Choice," *International Economic Review*, 44, 361–422.

Carneiro, P. and J. J. Heckman (2002): "The Evidence on Credit Constraints in Post-Secondary Schooling*," *The Economic Journal*, 112, 705–734.

Carroll, C. D. and T. Chan-Kopka (1988): "College Students Who Work: 1980-1984 Analysis Findings From High School and Beyond," *Washington, DC: National Center for Education Statistics.*

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

Chatterjee, S. and F. Ionescu (2012): “Insuring Student Loans Against the Financial Risk of Failing to Complete College,” *Quantitative Economics*, 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, pp. 1491–1527.

DeSimone, J. S. (2008): “The impact of employment during school on college student academic performance,” Tech. rep., National Bureau of Economic Research.

Dynarski, S. M. (2003): “Does Aid Matter? Measuring the Effect of Student Aid on College Attendance and Completion,” *American Economic Review*, 93, 279–288.

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

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, 1–58.

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 *Handbook of the Economics of Education*, ed. by E. Hanushek and F. Welch, Elsevier, vol. 1, chap. 7, 307–458.

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., C. Herrington, and T. Schoellman (2015): "Family Background, Academic Ability, and College Decisions in the 20th Century U.S." Mimeo. 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): "The Effect of Attending the Flagship State University on Earnings: A Discontinuity-Based Approach," *Review of Economics and Statistics*, 91, 717–724.

Johnson, M. T. (2013): "Borrowing Constraints, College Enrollment, and Delayed Entry," *Journal of Labor Economics*, 31, pp. 669–725.

Kalenkoski, C. M. and S. W. Pabilonia (2010): "Parental transfers, student achievement, and the labor supply of college students," *Journal of Population Economics*, 23, 469–496.

Kane, T. J. and C. E. Rouse (1995): "Labor-market returns to two-and four-year college," *The American Economic Review*, 85, 600–614.

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

——— (2001): "The effect of parental transfers and borrowing constraints on educational attainment," *International Economic Review*, 42, 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.

Lochner, L. and A. Monge-Naranjo (2012): "Credit Constraints in Education," *Annual Review of Economics*, 4, 225–256.

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

McGrattan, E. R. and E. C. Prescott (2000): "Is the Stock Market Overvalued?" *Federal Reserve Bank of Minneapolis Quarterly Review*, 24.

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.

Nonis, S. A. and G. I. Hudson (2006): "Academic performance of college students: Influence of time spent studying and working," *Journal of Education for Business*, 81, 151–159.

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, 41–65.

Plant, E. A., K. A. Ericsson, L. Hill, and K. Asberg (2005): "Why study time does not predict grade point average across college students: Implications of deliberate practice for academic performance," *Contemporary Educational Psychology*, 30, 96–116.

Rouse, C. E. (1995): "Democratization or diversion? The effect of community colleges on educational attainment," *Journal of Business & Economic Statistics*, 13, 217–224.

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): "An Empirical Investigation of the Option Value of College Enrollment," *American Economic Journal: Applied Economics*, 4, 49–84.

Stinebrickner, R. and T. Stinebrickner (2014): "Academic Performance and College Dropout: Using Longitudinal Expectations Data to Estimate a Learning Model," *Journal of Labor Economics*, 32, 601–644.

Stinebrickner, R. and T. R. Stinebrickner (2003): "Understanding Educational Outcomes of Students from Low-Income Families: Evidence from a Liberal Arts College with a Full Tuition Subsidy Program," *The Journal of Human Resources*, 38, pp. 591–617.

——— (2008): "The causal effect of studying on academic performance," *The BE Journal of Economic Analysis & Policy*, 8.

Stinebrickner, T. and R. Stinebrickner (2012a): "Learning about Academic Ability and the College Dropout Decision," *Journal of Labor Economics*, 30, 707–748.

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

Trachter, N. (2015): "Stepping stone and option value in a model of postsecondary education," *Quantitative Economics*, 6, 223–256.

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, pp. S7–S36.

Winter, C. (2014): "Accounting for the changing role of family income in determining college entry," *The Scandinavian Journal of Economics*, 116, 909–963.

A High School & Beyond Data

B NLSY79 Data

C CPS Data

D Model Fit

E Varying Selected Model Parameters

F Robustness

F.1 Two Abilities

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