

How Risky Is College Investment?

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March 9, 2017

Abstract

This paper is motivated by the fact that nearly half of U.S. college students drop out without earning a bachelor's degree. Its objective is to quantify how much uncertainty college entrants face about their graduation outcomes. To do so, we develop a quantitative model of college choice. The innovation is to model in detail how students progress towards a college degree. The model is calibrated using transcript and financial data. We find that more than half of college entrants can predict whether they will graduate with at least 80% probability. As a result, stylized policies that insure students against the financial risks associated with uncertain graduation have little value for the majority of college entrants.

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

Keywords: Education. College dropout risk.

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1 Introduction

A growing literature emphasizes that college is a risky investment.¹ This is motivated by the empirical finding that nearly half of all U.S. college students drop out before earning a bachelor's degree (Bound and Turner, 2011). A separate branch of the literature points out that college choices are strongly related to student characteristics, especially their cognitive skills (Belley and Lochner, 2007). These findings suggest that college dropouts may lack the abilities or preparation required for earning a college degree.

Whether students drop out of college mainly because of endowments (heterogeneity) or shocks (uncertainty) has important policy implications. If graduation outcomes are highly uncertain, policies that insure students against failure, such as income contingent loans (Chapman, 2006), may increase welfare. On the other hand, if dropping out is mainly due to students' inability to satisfy the requirements for a college degree, policies that improve student preparation, such as remedial coursework (Bettinger and Long, 2009), may be called for.

The main purpose of this paper is to quantify the relative importance of heterogeneity and uncertainty for college dropout decisions. Put differently, we ask: how predictable or risky is graduation from the point of view of college entrants?

Transcript data. To address this question, we develop a structural model of college choice. We depart from much of the literature by modeling in detail how students progress towards satisfying the requirements for a college degree. This allows us to introduce *transcript data*, which we argue are key for measuring the distribution of college preparation among freshmen and, therefore, their graduation probabilities. Transcripts reveal how rapidly students progress towards a college degree, which is directly related to their graduation chances. Moreover, transcripts provide *repeated* indicators of college preparation for the same individual. This enables the model to decompose the observed dispersion in college outcomes into the contributions of persistent heterogeneity and transitory shocks.

We obtain college transcripts for a representative sample of high school sophomores in 1980 from the Postsecondary Education Transcript Study (PETS, section 2). We focus on how rapidly students accumulate college credits. The data also contain information about high

¹ Recent work includes Arcidiacono et al. (2012), Athreya and Eberly (2013), Stange (2012), and Trachter (2015).

school GPAs, financial resources, college costs, and degrees earned. This information is used to calibrate the structural model.

The transcripts reveal large and persistent heterogeneity in individual credit accumulation rates. In their freshmen year, students in the 80th percentile of the credit distribution earn twice as many credits as do students in the 20th percentile. The correlation between credit accumulation rates across years is 0.43. Credit accumulation is strongly related to high school GPAs and to college graduation. College graduates earn about 50% more credits than do college dropouts. After 3 years in college, dropouts have earned fewer than half of the 125 credits that students have earned, on average, when they graduate.

Structural model. To recover what the transcript data imply for the predictability of college graduation, we develop a structural model of college choice (section 3).² The model follows one cohort of high school graduates through their college and work careers. At high school graduation, students are endowed with heterogeneous “abilities” and financial resources.³ Following Manski (1989), we assume that high school graduates only observe a noisy signal of their abilities. They choose whether to attempt college or work as high school graduates. While in college, students make consumption-savings and work-leisure decisions subject to a borrowing constraint. Students face financial shocks that affect college costs and wages, as well as preference shocks.

Our main departure from the literature is to model students’ progress through college in detail.⁴ This allows us to map transcript data directly into model objects. We model credit accumulation as follows. In each period, a college student attempts a fixed number of courses. He passes each course with a probability that increases with his ability. At the end of each year, students who have earned a given number of courses graduate. The remaining students update their beliefs about their abilities based on the information contained in their course outcomes. Then they decide whether to drop out or continue their studies in the next period. Students must drop out if they lack the means to pay for college, or if they fail to earn a degree after 6 years in college.

² The model extends Hendricks and Leukhina (2014), mainly by incorporating financial shocks while in college.

³ We interpret the term “ability” to mean any persistent characteristic that affects the rate at which a student accumulates college credits (see subsection 3.5).

⁴ In much of the literature, college is a black box. Exceptions include Arcidiacono et al. (2012), Garriga and Keightley (2007), and Stange (2012).

Results. We calibrate the model to match a rich set of observations that we construct from PETS, High School & Beyond (HS&B) and NLSY79 data (section 4). The calibrated model successfully accounts for students’ credit accumulation, college entry and dropout decisions, both across years and across high school GPA quartiles, as well as for financial statistics.

The model allows us to compute the distribution of individual *graduation probabilities*, based on the information available to high school graduates at the time of college entry. Our main finding is that college graduation is highly predictable for a large fraction of college entrants (section 5). At the time of college entry, 29% of students face graduation probabilities above 80% while 24% face graduation probabilities below 20%. Among high school graduates who do not enter college, graduation probabilities are far worse. 91% of these students face graduation probabilities below 20%.

We show that the high predictability of graduation outcomes has three causes.

1. The model implies substantial heterogeneity in students’ *graduation prospects*. By this, we mean the probability of completing the required number of courses within the 6 years that students may be enrolled in college. Among college entrants, 61% face graduation prospects above 80% and 9% face graduation prospects below 20%.
2. Students can accurately predict their abilities, and thus their graduation prospects, before they make college entry decisions. In other words, their ability signals are quite precise.
3. Students’ graduation probabilities are closely linked to their graduation prospects.

Financial heterogeneity plays a minor role for the predictability of college outcomes. One reason is that most model students are not close to their borrowing limits.⁵ A second reason is that students can increase work hours to finance additional time in college.

We now discuss how the model recovers the distribution of graduation prospects, mainly from transcript data. The key data feature is the large dispersion of credit accumulation rates. According to our model, the number of courses passed is drawn from a Binomial distribution. Accounting for the observed dispersion in credit accumulation rates then requires substantial heterogeneity in the probabilities with which students pass courses. The

⁵ This finding is in line with other research based on NLSY79 data (Carneiro and Heckman, 2002).

Binomial distribution further implies that graduation prospects, the probabilities of passing enough courses for graduation, increase sharply in the course passing probability. Hence, the model implies that a large fraction of students face very high or very low graduation prospects (subsection 5.2).

The large heterogeneity in graduation prospects implies that many students' graduation probabilities are highly predictable (subsection 5.3). The reason is that the financial incentives for persisting in college depend strongly on students' graduation prospects. For students with weak graduation prospects, staying in college until graduation (or for the permitted 6 years) reduces lifetime earnings relative to their optimal dropout decisions. As a result, many low ability students drop out of college, even though they could graduate. High ability students, on the other hand, progress rapidly towards graduation and can expect large earnings gains if they persist in college. These students rarely drop out, even if they suffer adverse course outcomes or financial shocks while in college.

We investigate why the model implies that students' ability signals are very precise (see subsection 5.4). To do so, we recalibrate the model while fixing the precision of the ability signal at a lower level. Since we assume that high school GPAs are part of students' information sets, this also lowers the correlation between abilities and GPAs. The model then implies that high GPA students are too similar to low GPA students in terms of their credit accumulation rates, their college outcomes, and their lifetime earnings. Increasing signal noise also raises the option value of enrolling in college (the value of learning increases). As a result, students remain in college longer than in the data.

Our main finding that graduation outcomes are highly predictable for the majority of college freshmen is based on model outcomes. Two modeling assumptions are central for this result. First, we assume that students use all available information to form their expectations about college outcomes. Second, how we model credit accumulation is central for decomposing variation in earned credits into the contributions of student endowments and luck. Unfortunately, we cannot draw on much prior research to motivate our modeling of credit accumulation.⁶ We also lack direct evidence that students in the data make predictions that are as accurate as those of students in the model. We view the finding that our model accounts for a broad range of college related observations, including the

⁶ Eckstein and Wolpin (1999) model credit accumulation in high school. Garriga and Keightley (2007) postulate a credit production function that is multiplicative in ability, registered credits, and effort. However, they lack the transcript data needed to validate the assumed functional form.

dispersion and persistence of credits, as providing indirect support.

Policy implications. We take a first step towards exploring the policy implications of highly predictable college outcomes (section 6). We study the welfare gains generated by two stylized policy interventions. The first intervention provides insurance against the consumption risks associated with either dropping out of college or taking a long time to earn a degree. The second intervention provides students with information about their abilities and the associated graduation prospects before the college entry decision is made.⁷ In both cases, we find that the welfare gains are small for a large fraction of college entrants, especially for those who face little uncertainty about their graduation outcomes.

1.1 Related Literature

This paper relates to a large literature that studies which individual characteristics predict whether a student will be successful in college. Most studies estimate probit or logit models, based on administrative data for a single college.⁸ The focus of this literature is very different from ours. Its goal is to inform the design of college policies aimed at improving retention rates.

A growing literature studies structural models of college choice with dropout risk.⁹ Our main departure from this literature is to model in more detail how students progress through college. In this respect our approach resembles Garriga and Keightley (2007) and Trachter (2015). Both study models where graduating from college requires a fixed number of earned credits. We add to their analyses by introducing transcript data, which we argue are central for measuring students' graduation chances (section 2). Compared with most previous studies, we also have access to more detailed data on college costs, scholarships, loans, parental transfers, and earnings in college.

⁷ Actual policies that pursue these goals include income contingent student loans (Chapman, 2006) and dual enrollment programs (Stephanie Marken et al., 2013).

⁸ Recent examples include Glynn et al. (2011) and Lin et al. (2012). Astin (1997) and Light and Strayer (2000) use data for many colleges. See Reason (2009) for a survey.

⁹ Examples include Akyol and Athreya (2005), Altonji (1993), Athreya and Eberly (2013), Castex (2016), Caucutt and Kumar (2003), Chatterjee and Ionescu (2012), Johnson (2013), and Keane and Wolpin (1997). Since we are unable to determine how much college completion risk these papers imply, we cannot compare our findings with theirs.

Stange (2012) also uses transcript data to estimate a model of risky college completion. However, in his model, the transcript data play a very different role. College grades affect the utility derived from studying, rather than the students' chances of completing the requirements for earning a degree. As in much of the literature, all students in Stange's model can earn a degree by staying in college for 4 years. By contrast, our model highlights that students differ in their abilities to satisfy the requirements for earnings a college degree. We use transcript data to measure student abilities that affect their progress through college and thus their chances of graduation.

2 Transcript Data and Graduation Prospects

In this section, we explain how transcript data help to identify the distribution of students' graduation probabilities. First, we describe the 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](#)).¹⁰ The data cover a representative sample of high school sophomores in 1980. Participants were interviewed bi-annually until 1986. In 1992, postsecondary transcripts from all institutions attended since high school graduation were collected.

We retain all students who report sufficient information to determine the number of college credits attempted and earned, the dates of college attendance, and whether a bachelor's degree was earned. HS&B also contains information on college tuition, financial resources, parental transfers, earnings in college, and student debt, which we use to calibrate the structural model presented in [section 3](#). [Appendix A](#) provides additional details.

2.2 Credit Accumulation Rates

To measure students' progress towards earning a college degree, we focus on the number of completed college credits. Since the data we present are not commonly used in economics,

¹⁰The data construction follows [Hendricks and Leukhina \(2014\)](#).

Table 1: College Credits by Year

Group	Year 1	Year 2	Year 3	Year 4
20th percentile	17	41	68	100
50th percentile	28	57	87	119
80th percentile	33	66	98	130
College dropouts	21	43	60	77
College graduates	31	60	90	119
Fraction dropping out	16.6	14.5	8.3	4.9

Notes: The table shows the number of credits earned at the end of each year in college by students in the 20th, 50th, and 80th percentile of the credit distribution. The bottom panel shows the average number of credits earned by students who eventually drop out or graduate from college. “Fraction dropping out” refers to the fraction of college entrants that drop out at the end of each year.

Source: High School & Beyond.

we first present summary statistics.

Table 1 shows the distribution of earned credits at the end of each of the first four years in college. The median student earns around 30 credits in each year. Given that students graduate, on average, with 125 credits, the median student is on track to graduate in 4 or 5 years.

A key feature of the data is substantial *heterogeneity* in credit accumulation rates. In the first year, students in the 80th percentile earn nearly twice as many credits compared with students in the 20th percentile. Over time, this ratio declines. One likely reason is that the least successful students drop out.

The bottom panel of **Table 1** shows that credit accumulation rates are strongly associated with college outcomes. Students who eventually graduate from college earn around 50% more credits than do college dropouts. The gap is fairly stable over time. After three years in college, dropouts have earned fewer than half of the roughly 125 credits required for graduation.

Our subsequent analysis focuses on student abilities, measured by HS GPAs, as the main determinant of credit accumulation rates. To motivate this focus, we present evidence consistent with the notion that student abilities are indeed the main predictor of college

outcomes, while financial resources are less important.

[Table 2](#) reports measures of college success for students who enroll in college for at least two years. Students are divided into quartiles according to their HS GPAs and according to two measures of their financial situation: financial resources, and average hours worked while in college.¹¹ For each quartile, [Table 2](#) reports three measures of college success: the average number of credits earned (panel a), the fraction of students that graduate from college (panel b), and the fraction of students who persist from the second to the third year in college (panel c).

For all measures of college success, we observe large gaps between students with high versus low HS GPAs. The gaps between students with more or less generous financial endowments are much smaller. For example, students in the top HS GPA quartile earn 15.6 more credits compared with students in the bottom quartile. By contrast, the gap in credits earned across financial resource quartiles is only 5.9. Across hours worked quartiles, the gaps are consistently the smallest. These findings are consistent with a large literature on college persistence which finds that academic ability (measured by test scores or HS GPAs) is the main determinant of students' success in college (see [Astin and Oseguera, 2005](#); [Bound et al., 2010](#); [Bowen et al., 2009](#)).

Also consistent with the literature, we find a weak association between hours worked and college outcomes ([Stern and Nakata, 1991](#); [Kalenkoski and Pabilonia, 2010](#); [Scott-Clayton, 2011](#)). The structural model developed in [section 3](#) therefore abstracts from the possibility that hours worked affect credit accumulation rates.

[Table 3](#) studies the relationship between credit accumulation and HS GPAs in more detail. The table shows the distribution of credits earned at the end of the second year in college across HS GPA quartiles. The data reveal that credit accumulation rates and college graduation rates are strongly related to high school GPAs. Students in the top GPA quartile earns 60% more credits than do students in the bottom quartile. They are also 7 times more likely to earn a bachelor's degree.¹²

¹¹Financial resources are defined as the mean of parental transfers minus the net cost of college (tuition and fees net of scholarships and grants). Financial resources and hours worked are averaged over the first two years in college. Quartiles are defined for the universe of students who are enrolled in college for at least two years.

¹²These gaps are larger than those reported in [Table 2](#) because HS GPA quartiles are defined over the universe of high school graduates rather than second year college students.

Table 2: Student Characteristics and College Outcomes

(a) Mean credits					
	Q1	Q2	Q3	Q4	Gap
By GPA	46.3	52.9	56.3	61.9	15.6
	(0.8)	(0.7)	(0.7)	(0.6)	
By hours worked	56.0	56.6	51.9	52.2	-3.8
	(0.7)	(0.7)	(0.8)	(0.8)	
By fin. resources	53.2	53.0	55.4	59.1	5.9
	(0.9)	(0.9)	(1.0)	(0.7)	
(b) Fraction graduating					
	Q1	Q2	Q3	Q4	Gap
By GPA	36.3	69.0	78.8	88.6	52.3
	(2.4)	(2.3)	(2.1)	(1.7)	
By hours worked	70.8	77.9	62.3	59.6	-11.2
	(2.1)	(2.2)	(2.5)	(2.6)	
By fin. resources	66.4	70.2	69.8	83.4	17.0
	(2.8)	(2.9)	(2.9)	(2.3)	
(c) Fraction persisting to year 3					
	Q1	Q2	Q3	Q4	Gap
By GPA	68.8	84.8	91.2	94.6	25.8
	(2.3)	(1.8)	(1.4)	(1.2)	
By hours worked	85.2	92.4	80.7	80.6	-4.6
	(1.7)	(1.4)	(2.1)	(2.1)	
By fin. resources	82.9	83.4	87.2	93.6	10.7
	(2.3)	(2.3)	(2.1)	(1.5)	

Notes: The table relates college outcomes to student characteristics. Students enrolled in year two are divided into quartiles according to HS GPAs, average hours worked, or financial resources (defined as average parental transfers minus the net cost of college). Panel (a) shows mean credits earned after two years in college. Panel (b) shows the fraction of students that eventually graduate. Panel (c) shows the fraction of students that persist into the third year in college. Standard errors are in parenthesis. “Gap” refers to the difference between the fourth and the first quartile.

Table 3: College Credits at the End of Year 2

GPA quartile	Credit distribution			Median credits		Fraction graduating
	20th	50th	80th	CD	CG	
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. “Fraction graduating” is the fraction of college entrants that earns a bachelor’s degree.

Source: High School & Beyond.

Even within GPA quartiles there is substantial heterogeneity in credit accumulation rates. In the lower quartiles, the 80th percentile of credits earned is around double that of the 20th percentile. This suggests either that GPAs are noisy measures of student abilities or that passing courses requires not only skills but also luck.

One observation that points towards an important role of skills rather than luck is the substantial *persistence* of individual credit accumulation rates 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.

2.3 A Reduced Form Model

We now discuss how data on credit accumulation help to estimate the distribution of students’ graduation probabilities. The central idea of this paper is that credit accumulation rates contain information about students’ abilities or college preparation. These in turn affect their chances of completing requirements for a degree. The structural model of [section 3](#) formalizes this idea and quantifies its implications.

To gain intuition, we study the relationship between credit accumulation rates and graduation chances in the context of a simple model. The model elements are as follows:

1. There is a population of college freshmen. At the start of year $t = 1$, each student is endowed with $n_1 = 0$ completed courses, with a random ability $a \sim N(0, 1)$, and with a noisy signal of ability given by $GPA = a + \varepsilon$ where $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. In the data, we observe high school GPAs, which we assume are an arbitrarily scaled increasing function of GPA .
2. In each year, a college student tries $n_c = 12$ courses. Passing a course yields 3 credits. The value of n_c is chosen such that passing all courses yields the number of credits earned per year by students in the 90th percentile of the credit distribution (the number is the same in years 1 through 3).
3. A student of ability a passes each course with probability $p(a) = \gamma_{min} + \frac{1 - \gamma_{min}}{1 + \gamma_1 e^{-\gamma_2 a}}$. $p(a)$ is a generalized logistic function.
4. A student graduates when he passes $n_{grad} = 42$ courses (earns 125 credits).
5. If a student fails to pass n_{grad} courses by the end of year $T_c = 6$, he drops out of college. In HS&B data, only 5% of students remain in college for more than 6 years.

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

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

To estimate the dispersion of p , we calibrate the parameters of the $p(a)$ function to minimize the sum of squared deviation between the following model-implied and observed moments:

(i) the number of earned credits for the 1st through 9th decile of the credit distribution after two years in college; and (ii) the correlation of earned credits between the first and the second year in college.

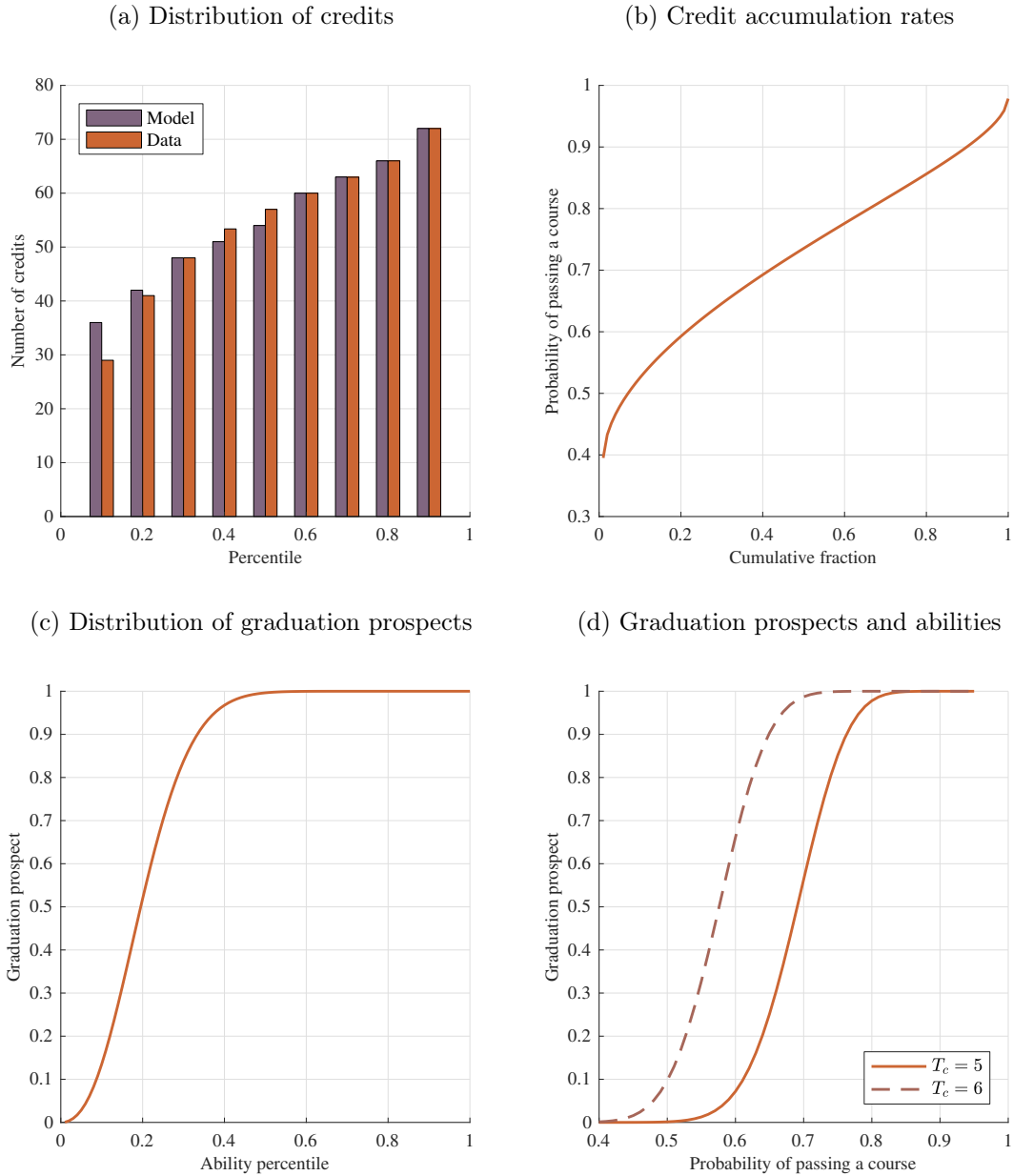
Figure 1 shows the implications of the calibrated model. Figure 1a compares the distribution of credits implied by the model with the data. The correlation of credits implied by the model of 0.56 is higher than in the data. One reason is that, in the data, the students with the worst course performance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

The large heterogeneity in p has an implication that is central for the structural model. The binomial distribution of credits implies that the probability of earning enough credits for graduation in the permitted 6 years, which we call the *graduation prospect*, increases sharply in p (see Figure 1d). Together with the calibrated distribution of p , this implies that a large fraction of students face graduation prospects near 0 or 1 (Figure 1c).

Graduation probabilities. Next, we ask what the data imply for the distribution of graduation probabilities. We expect graduation probabilities to increase with student abilities. In the structural model, this is driven by the earnings gains associated with staying in college. Students with poor graduation prospects expect small earnings gains. Even if they could graduate by staying in college long enough, this would likely take a long time. These students are therefore easily persuaded to drop out when faced with adverse shocks. By contrast, students with strong graduation prospects face larger expected earnings gains and are more resilient to shocks.

We incorporate this idea into the reduced form model in a simple way. We assume that the probability of graduating from college, conditional on entering, is a logistic function of ability. It has the same functional form as $p(a)$. For simplicity, we set $\gamma_{min} = 0$. The parameters of this logistic function are calibrated to match the gap in credit accumulation rates between college graduates and dropouts after two years in college (see Table 3). Specifically, the calibration searches for parameter values that minimize the sum of squared deviations between the model-implied and the observed numbers of credits earned for each decile of the credit distribution between the 1st and the 9th. A penalty is added to the objective function when the overall graduation rate implied by the model differs from the data.

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



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

Figure 2 shows the implications of the calibrated model. The overall dropout rate among college entrants is 48.8% vs 47.5% in the data. Figure 2a and Figure 2b show how well the model fits the CDFs of earned credits for college dropouts and college graduates, respectively.

The model implies that the graduation rate increases sharply with ability (Figure 2c). This allows the model to account for the large gap in earned credits between college graduates and college dropouts. A large fraction of college entrants faces either very low or very high graduation probabilities. The model implies a striking difference in the graduation probabilities, as of high school graduation, for students that eventually graduate compared with those who eventually drop out. Most future college graduates are quite certain of their success, while most future dropouts are quite certain of their failure to graduate.

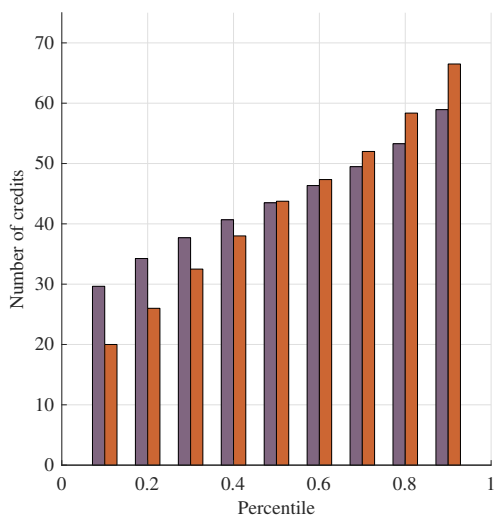
The reduced form model clarifies how transcript data help to identify distribution of graduation probabilities.

1. Replicating the large heterogeneity in earned credits observed in the data requires that credit accumulation rates p must vary significantly across students.
2. Given that students can attempt a large number of courses before they must exit college, graduation prospects increase sharply with p . It follows that graduation prospects are very poor for students with in the bottom of the p distribution and very strong for students in the top of the p distribution.
3. Replicating the large gaps in credit accumulation rates between college graduates and dropouts requires that the two groups differ significantly in their mean p 's and therefore also in their graduation prospects. This implies that both groups can predict outcomes with high probability.

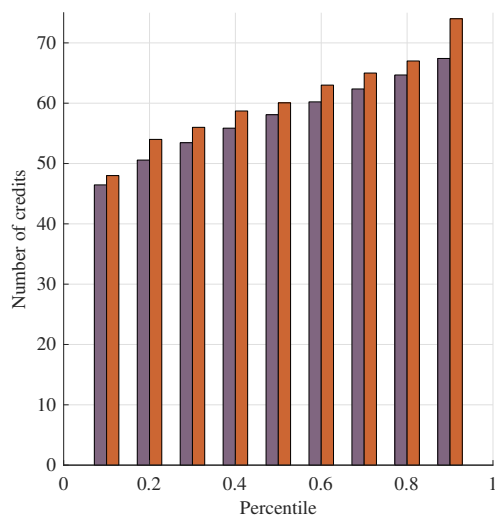
The reduced form model unfortunately does not reveal whether students know their graduation prospects (or their ps) at the time of college entry. We turn to the structural model to resolve this issue.

Figure 2: Reduced Form Model: Graduation Probabilities

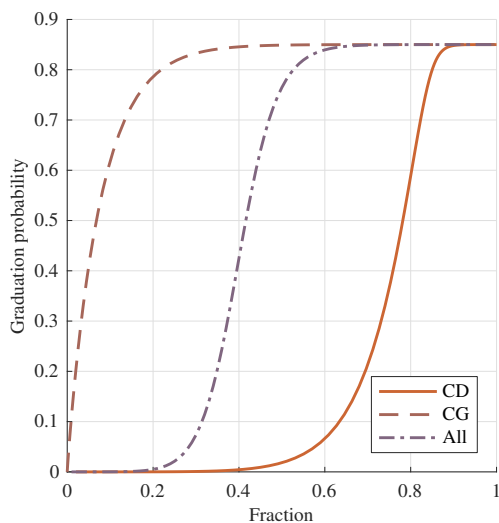
(a) Distribution of credits: Dropouts



(b) Distribution of credits: Graduates



(c) Graduation probabilities



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

3 The Model

To estimate the distribution of graduation probabilities among college entrants, we develop a structural model of college choice.¹³

3.1 Model Outline

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. Ability captures all persistent characteristics that make students more successful at school and in the labor market.
2. The student draws a type j and a persistent financial shock ζ_1 . These jointly determine his initial assets, college costs, parental transfers, and the student's beliefs about his ability.
3. The student chooses between attempting college or working as a high school graduate.

An agent who studies in period t faces the following choices:

1. He decides how much to work v_t , consume c_t , and save k_{t+1} , subject to a borrowing constraint.
2. He attempts n_c college credits and succeeds in a random subset, which yields n_{t+1} . Based on the information contained in n_{t+1} , the student updates his beliefs about a .
3. If the student has earned enough credits for graduation ($n_{t+1} \geq n_{grad}$), he must work in $t + 1$ as a college graduate. If he has exhausted the maximum number of years of study ($t = T_c$), he must work in $t + 1$ as a college dropout. Otherwise, he draws a new financial shock ζ_{t+1} and then chooses between staying in college and working in $t + 1$ as a college dropout.

¹³The model and its parameterization extend those in [Hendricks and Leukhina \(2014\)](#) where we study ability selection and the return to college.

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 credits and with random draws of ability a , type j , and financial shock ζ_1 .

Learning abilities $a \in \{\hat{a}_1, \dots, \hat{a}_{N_a}\}$ determine productivity in school and at work. We normalize $\hat{a}_1 = 0$ and order abilities such that $\hat{a}_{i+1} > \hat{a}_i$. The student's type $j \in \{1, \dots, J\}$ determines $(\hat{m}_j, \hat{k}_j, \hat{q}_j, \hat{z}_j)$. \hat{m}_j is a noisy signal of a . The agent knows the probability distribution of a given \hat{m}_j . $\hat{k}_j \geq 0$ denotes financial assets. \hat{q}_j is the permanent component of college costs. We think of this as capturing tuition, scholarships, grants, and other costs or payoffs associated with attending college. \hat{z}_j denotes parental transfers that are received during the first 6 periods after high school graduation, regardless of college attendance.

The financial shock $\zeta_t \in \{1, \dots, N_f\}$ evolves according to a Markov chain with transition matrix Π . The student's college costs, parental transfers, and college earnings in each period are jointly determined by (ζ_t, 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 credits, and schooling level $s \in \{HS, CD, CG\}$, denoting high school graduates, college dropouts, and college graduates, respectively. The worker chooses a consumption path $\{c_t\}$ for the remaining periods of his life ($t = \tau, \dots, T$) to solve

$$V(k_\tau, n_\tau, a, s, \tau) = \max_{\{c_t\}} \sum_{t=\tau}^T [\beta^{t-\tau} \bar{u}(c_t)] + U_s \quad (1)$$

subject to the budget constraint

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

Workers derive period utility $\bar{u}(c_t)$ 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 role of U_s is to allow the model to exactly match the observed fraction of students choosing each school level. U_{HS} is normalized to zero. 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 credits n_τ . A worker with ability $a = \hat{a}_1 = 0$ and no credits earns $\exp(y_s)$. Each college credit increases lifetime earnings by $\mu > 0$ log points. This may reflect human capital accumulation. A unit increase in ability raises lifetime earnings by ϕ_s . If $\phi_{CG} > \phi_{HS}$, high ability students gain more from obtaining college degrees 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 credits 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

$$VW(k_\tau, n_\tau, j, s, \tau) = \sum_{i=1}^{N_a} \Pr(\hat{a}_i | n_\tau, j, \tau) V(k_\tau + Z_{j,\tau}, n_\tau, \hat{a}_i, s, \tau), \quad (3)$$

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, $\Pr(\hat{a}_i | n_\tau, j, \tau)$, which implies that $(k_\tau, n_\tau, j, s, \tau)$ 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 , financial shock ζ_t , and n_t college credits. In each period, the student attempts n_c credits and completes each with probability

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

We assume $\gamma_1, \gamma_2 > 0$, so that the probability of earning credits increases with ability.¹⁴ Based on the number of completed credits, n_{t+1} , the student updates his beliefs about a . Since n_t 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 .

While in college, students derive utility from consumption c_t and leisure $1 - v_t$. Their sources of funds are labor earnings $w_{coll}v_t$, interest on their assets (or debts) Rk_t , and parental transfers \hat{z}_j . They purchase consumption and college related items $q(\zeta_t, j)$ (including tuition). Hence, the budget constraint is given by

$$k_{t+1} + c_t + q(\zeta_t, j) = Rk_t + \hat{z}_j + w_{coll}v_t. \quad (5)$$

Work hours v are chosen from a discrete set $\Omega_\zeta \subset \{v_1, \dots, v_{N_w}\}$ that depends on the financial shock ζ . The idea is that students receive either part time or full time work offers, which determine their feasible hours.¹⁵ Financial shocks also affect college costs. The value of being in college at age t is then given by

$$\begin{aligned} V_C(n_t, k_t, \zeta_t, j, t) = & \max_{c_t, v_t \in \Omega_\zeta, k_{t+1} \geq k_{min}} u(c_t, 1 - v_t) \\ & + \beta \sum_{n_{t+1}} \Pr(n_{t+1} | n_t, j, t) \sum_{\zeta_{t+1}} \Pi_{\zeta_t, \zeta_{t+1}} V_{EC}(n_{t+1}, k_{t+1}, \zeta_{t+1}, j, t + 1) \end{aligned}$$

subject to the budget constraint (5). k_{min} is a borrowing limit. $\Pr(n_{t+1} | n_t, j, t)$ denotes the probability of having earned n_{t+1} credits 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

¹⁴Allowing $p(a)$ to be an unrestricted function of a does not change any of our findings; see [subsection 6.3](#).

¹⁵[subsection 6.3](#) explores an alternative specification where financial shocks affects wages rather than feasible hours.

t before the decision whether to work or study has been made. It is determined by the discrete choice problem

$$V_{EC}(n_t, k_t, \zeta_t, j, t) = \mathbb{E} \max \{ V_C(n_t, k_t, j, t) - \pi\eta_c, V_W(k_t, n_t, \zeta_t, j, s(n_t), t) - \pi\eta_w \}, \quad (6)$$

where η_c and η_w are independent draws from a demeaned standard type I extreme value distribution with scale parameter $\pi > 0$.¹⁶ $s(n)$ denotes the schooling level associated with n college credits (CG if $n \geq n_{grad}$ and CD otherwise). The implied choice probabilities and value functions have closed form solutions.¹⁷

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 with continuation value $V_W(n, k, j, CG, t)$.
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 with continuation value $V_W(n, k, j, CD, t)$.
3. Otherwise the agent chooses between working as a college dropout with $s(n) = CD$ and studying next period.

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

$$\max \left\{ V_C(0, \hat{k}_j, j, 1) - \pi_E \eta_c^*, V_W(\hat{k}_j, 0, \zeta_1, j, HS, 1) - \pi_E \eta_w^* \right\}, \quad (7)$$

where η_c^* and η_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 focuses on student abilities as the main determinant of how rapidly students progress towards fulfilling the requirements for a college degree. We interpret the term

¹⁶Allowing the preference shocks to be correlated with ability signals does not materially change the results; see [subsection 6.3](#).

¹⁷See [Rust \(1987\)](#) and [Arcidiacono and Ellickson \(2011\)](#).

“ability” broadly to encompass all persistent characteristics that affect students’ credit accumulation rates. Even though we use HS GPAs as (noisy) ability measures, we do not imply that abilities are only cognitive skills. They may also include non-cognitive skills (Kautz et al., 2014) or even preferences that affect study effort.¹⁸ Our empirical approach does not depend on exactly which characteristics abilities represent. Similarly, our approach does not depend on whether abilities affect course passing rates or the number of courses attempted (both are important sources of variation in earned credits in the data). In the model, both sources of variation are captured by the probability of passing a course, $p(a)$.

We recognize that students may be endowed with other characteristics that affect dropout behavior but not course outcomes. Examples include preferences for jobs that do or do not require college degrees, or specialized skills that allow students to earn high wages without a college degree. In abstracting from these additional endowments, our model likely understates the predictability of college outcomes.

Our model allows for the possibility that students do not perfectly observe their abilities before making college entry decisions. This captures the idea that *college is experimentation* (Manski, 1989). At high school graduation, students are uncertain about their aptitudes. This information is gradually revealed by the students’ performance in college. Stinebrickner and Stinebrickner (2012) present survey evidence consistent with this idea. Abstracting from this feature would bias our results in favor of highly predictable college outcomes.

The discussion of section 2 suggests that the most important modeling choices relate to *credit accumulation*. We propose a simple model and show in subsection 4.4 that it accounts for a range of observations. The main obstacle to studying a richer model is tractability. For example, if the number of credits earned in period t depended either on study effort or on the number of credits earned in previous periods, students’ beliefs about their abilities would depend on the entire history of course outcomes. In effect, we would have to abandon Manski’s idea of college as experimentation, which would raise the question whether we biased our findings in favor of high predictability.

¹⁸The data collected by Babcock and Marks (2011, Table 6) suggest that differences in study time between students with high and low SAT scores are small.

4 Setting Model Parameters

We calibrate the model parameters to match data moments for men born around 1960.¹⁹ The model period is one year. Our main data sources are PETS and High School & Beyond (HS&B; described in [subsection 2.1](#)). We estimate lifetime earnings from National Longitudinal Surveys (NLSY79) data.

The NLSY79 is a representative, ongoing sample of persons born between 1957 and 1964 ([Bureau of Labor Statistics; US Department of Labor, 2002](#)). We collect education, earnings and cognitive test scores for all men. We include members of the supplemental samples, but use weights to offset the oversampling of minorities (see [Appendix B](#) for details). We use data from the Current Population Surveys ([King et al., 2010](#)) to impute the earnings of older workers (see [Appendix C](#) for 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. Here we summarize our modeling choices, relegating details to [Appendix D](#).

We set the number of types to $J = 200$. Each type has mass $1/J$. We assume that the marginal distributions are given by $\hat{q}_j \sim N(\mu_q, \sigma_q^2)$, $\hat{z}_j \sim \max\{0, N(\mu_z, \sigma_z^2)\}$, $\hat{k}_j \sim \max\{0, N(\mu_k, \sigma_k^2)\}$, 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 these endowments are drawn from a joint Normal distribution.

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, $\Pr(\hat{a}_i) = 1/N_a$. For notational convenience, we normalize \bar{a} such that $\hat{a}_1 = 0$. Abilities are correlated with ability signals. High school GPAs are noisy measures of students' ability signals: $GPA = (\alpha_{GPA,m} m + \varepsilon_{GPA}) / (\alpha_{GPA,m}^2 + 1)^{1/2}$ with $\varepsilon_{GPA} \sim N(0, 1)$. This implies that the agents know more about their abilities than we do. All endowment correlations are calibrated.

Financial shocks are specified as follows. In each period, students receive either part time wage offers, which allow them to work at most 20 hours per week, or full time wage offers,

¹⁹The calibration strategy extends [Hendricks and Leukhina \(2014\)](#) to incorporate financial shocks.

in which case all work states are admissible. The transition matrix for shocks to the feasible set of work hours is given by $\begin{bmatrix} p_v & 1 - p_v \\ 1 - p_v & p_v \end{bmatrix}$. In addition, students receive i.i.d. college cost shocks that are drawn from two equally likely states: $q(\zeta, j) = \hat{q}_j \pm \Delta q$. Since parental transfers are highly persistent in the data, we abstract from shocks to z . This yields $N_f = 4$ states with obvious transition probabilities. We assume that all states have equal probability at age 1.²⁰

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. 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.²¹ The returns to earning 2-year degrees are captured by the effect of credits on lifetime earnings, μn .²² The fact that low test score students tend to enroll in 2-year colleges is reflected in their lower average tuition costs. Students attending vocational schools (e.g., police or beauty academies) are classified as high school graduates.

We measure $n_{t+1}/(tn_c)$ as the number of completed college credits by the end of college year t divided by the number of credits taken, assuming a full course load, which is defined as the 90th percentile of the number of credits earned (36 credits per year). In the data, college dropouts attempt fewer credits than college graduates. Since our model abstracts from variation in course loads, we treat taking less than a full course load as failing the

²⁰If we calibrate the persistence of cost shocks, the algorithm chooses no persistence. We also experimented with shocks to the wage rate rather than admissible work hours. This does not substantially change the findings (see [subsection 6.3](#)).

²¹[Trachter \(2015\)](#) studies the role of 2-year colleges as stepping stones towards bachelor’s degrees.

²²In HS&B data, only 12% of students who enter 2-year institutions earn a 2-year degree.

courses that were not taken. This captures the fact that taking fewer courses slows a student’s progress towards graduation, which is a key element of our model.

Test scores. In the HS&B data, we divide students into quartiles according to their high school GPAs. In the NLSY79 data, we use their 1989 Armed Forces Qualification Test scores (NLSY79) instead. 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). Since [Borghans et al. \(2011\)](#) show that both measures are highly correlated, we treat GPA quartiles and AFQT quartiles as equivalent. Sidestepping the question of what test scores measure (see [Flynn 2009](#)), we use the term “test scores” in the text and the symbol GPA in mathematical expressions.

Financial variables. We interpret annual college costs q as collecting all college related payments that are *conditional* on attending college. In HS&B data, we measure tuition and fees net of scholarships and grants. We set q equal to the average of these values over the first two years in college plus \$987 for other college expenditures, such as books, supplies, and transportation.²³ q does not include room and board, which are included in consumption.

Parental transfers z represent transfers received from parents in the 6 years that follow high school graduation. While HS&B does not report initial assets k_1 , it does report student debt (negative values of k_t). w_{collv} represents labor earnings received at any time during the calendar year, including summer terms.

4.3 Model Parameters

Fixed parameters and functional forms.

1. The period utility function during work is given by $\bar{u}(c) = c^{(1-\theta)} / (1 - \theta)$.

²³Since HS&B lacks information on these expenditures, we compute them as the average cost for 1992-93 undergraduate full-time students in the National Postsecondary Student Aid Study, conducted by the U.S. Department of Education. These costs are defined as the amount student reported spending on expenses directly related to attending classes, measured in year 2000 prices.

2. Utility in college is given by $u(c, 1 - v) = \delta c^{1-\theta} / (1 - \theta) + \rho \ln(1 - v)$. The parameter $\delta \in (0, 1]$ 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 baseline model sets $\theta = 1$ (log utility). [subsection 6.3](#) explores the implications of stronger risk aversion.
3. The discount factor is $\beta = 0.98$.
4. Based on [McGrattan and Prescott \(2000\)](#), the gross interest rate is set to $R = 1.04$.
5. Motivated by the fact that, in our HS&B sample, 95% of college graduates finish college by their 6th year, we set the maximum duration of college to $T_c = 6$.
6. Each model course represents 2 courses 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 data credits).
7. 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 $v \in \{0.00; 0.11; 0.22; 0.33; 0.44\}$.
8. Earnings in college: We set w_{coll} to the mean hourly wage earned by college students of \$7.60.
9. 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 $[k_{min}, \hat{k}_j]$.
10. 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. Converting into year 2000 prices implies $k_{min} = -\$19,750$.

Calibrated parameters. The remaining 28 model parameters are jointly calibrated to match the target data moments summarized in [Table 4](#). We show the data moments in [subsection 4.4](#) where we compare our model with the calibration targets.

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.²⁴

[Table 5](#) shows the values of the calibrated parameters. The first block of the table reports the parameters governing the joint distribution of endowments. [Table 6](#) shows the implied endowment correlations. We highlight two features that are important for the predictability of college outcomes.

First, ability signals are very precise. Thus, students can accurately predict their course accumulation rates and graduation prospects before entering college. Second, test scores are noisy measures of abilities. This implies that graduation rates and graduation prospects vary even more with ability than with test scores. Both features contribute to the predictability of college outcomes. We comment on the role played by other parameter values when we present the paper’s findings in [section 5](#).

4.4 Model Fit

This section assesses how closely the model attains selected calibration targets.²⁵ We view the fact that the model accounts for a broad range of observations, including the dispersion and persistence of earned credits, as providing support for our modeling choices.

College credits. [Table 7](#) shows how the model fits the credit accumulation rates displayed earlier in [section 2](#). The model replicates the large gaps in earned credits between college graduates and dropouts and across high school GPA quartiles. [Table 8](#) shows that the

²⁴Within each block of moments, such as the fraction of students who drop out of college by test score quartile and year in college, deviations are weighted by the inverse standard deviations of the data moments or, if this is not available, by the square root of the number of observations used to compute each data moment. The numerical optimization is performed using a multi-start algorithm similar to the one proposed by [Guvenen \(2011\)](#) with Nelder-Mead as the local optimizer.

²⁵To conserve space, a more detailed assessment of the model’s fit is relegated to [Appendix E](#).

Table 4: Calibration Targets

Target	Value
Fraction in population, by (hs gpa quartile, schooling)	Figure 3
Lifetime earnings, by (hs gpa quartile, schooling)	Table 17
Dropout rate, by (hs gpa quartile, t)	Figure 12
Average time to BA degree (years)	4.4
College credits	
Mean cumulative credits, by (graduation status, t)	Table 7
– by (hs gpa quartile, t)	Table 7
Persistence of credits across years	Table 8
CDF of cumulative credits, by t	Figure 8
– by (graduation status, t)	Figure 9, Figure 10
– by (hs gpa quartile, t)	Figure 11
Financial moments	
College costs q (mean by hs gpa quartile, dispersion, autocorrelation)	Table 18
Parental transfers z (mean by hs gpa quartile, dispersion)	Table 18
Earnings in college (mean by hs gpa quartile, autocorrelation)	Table 18
Fraction of students in debt, by t	Table 19
Mean student debt, by t	Table 19

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

Table 5: Calibrated Parameters

Parameter	Description	Value
Endowments		
μ_k, σ_k	Marginal distribution of k_1	36, 620; 29, 787
μ_q, σ_q	Marginal distribution of q	5,331; 3,543
μ_z, σ_z	Marginal distribution of z	3,154; 5,542
$\alpha_{m,z}, \alpha_{m,q}, \alpha_{q,z}, \alpha_{a,m}$	Endowment correlations	0.46; -0.04; -0.12; 2.87
$\alpha_{k,m}$	Correlation k_1, m	-0.21
$\alpha_{IQ,m}$	Correlation IQ, m	1.20
Shocks		
Δ_q	q shock (\$)	1,684
p_v	Persistence of employment shock	0.51
π	Scale of preference shocks	1.197
π_E	Scale of preference shocks at entry	0.397
Lifetime earnings		
ϕ_{HS}, ϕ_{CG}	Effect of ability on lifetime earnings	0.155; 0.197
y_{HS}, y_{CG}	Lifetime earnings factors	3.91; 3.95
μ	Earnings gain for each college credit	0.010
Other parameters		
ρ	Weight on leisure	1.264
δ	Weight on consumption	0.612
U_{CD}, U_{CG}	Preference for job of type s	-1.08; -2.46
$\gamma_1, \gamma_2, \gamma_{min}$	Credit accumulation rate $p(a)$	4.58; 2.10; 0.47

Table 6: Correlation of Endowments

	GPA	a	m	q	z
GPA	1.00				
a	0.67	1.00			
m	0.72	0.92	1.00		
q	-0.13	-0.15	-0.16	1.00	
z	0.28	0.34	0.37	-0.21	1.00
k_1	-0.19	-0.25	-0.27	0.04	-0.06

Table 7: Credit Accumulation Rates (%)

Group	Year 1		Year 2		Year 3		Year 4	
	Model	Data	Model	Data	Model	Data	Model	Data
Dropouts	59.3	57.1 (1.0)	59.3	59.6 (1.0)	58.6	55.6 (0.9)	56.3	53.6 (1.1)
Graduates	84.4	85.4 (0.6)	84.1	83.4 (0.5)	84.0	83.0 (0.4)	83.7	82.3 (0.4)
GPA quartile 1	53.1	48.1 (2.3)	53.8	53.7 (2.3)	55.3	58.1 (2.3)	57.6	62.3 (2.8)
GPA quartile 2	63.1	61.8 (1.6)	65.0	67.6 (1.4)	67.3	69.5 (1.4)	70.0	71.8 (1.5)
GPA quartile 3	71.1	71.0 (1.2)	73.3	71.5 (1.0)	75.1	72.4 (0.9)	76.7	75.3 (0.8)
GPA quartile 4	80.9	81.8 (0.9)	82.0	81.6 (0.7)	83.1	81.7 (0.6)	83.9	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. Standard errors are in parentheses.

Source: High School & Beyond.

model also replicates the observed persistence of credit accumulation rates, but not its decline over time. To conserve space, the distribution of credits is relegated to [Appendix E](#).

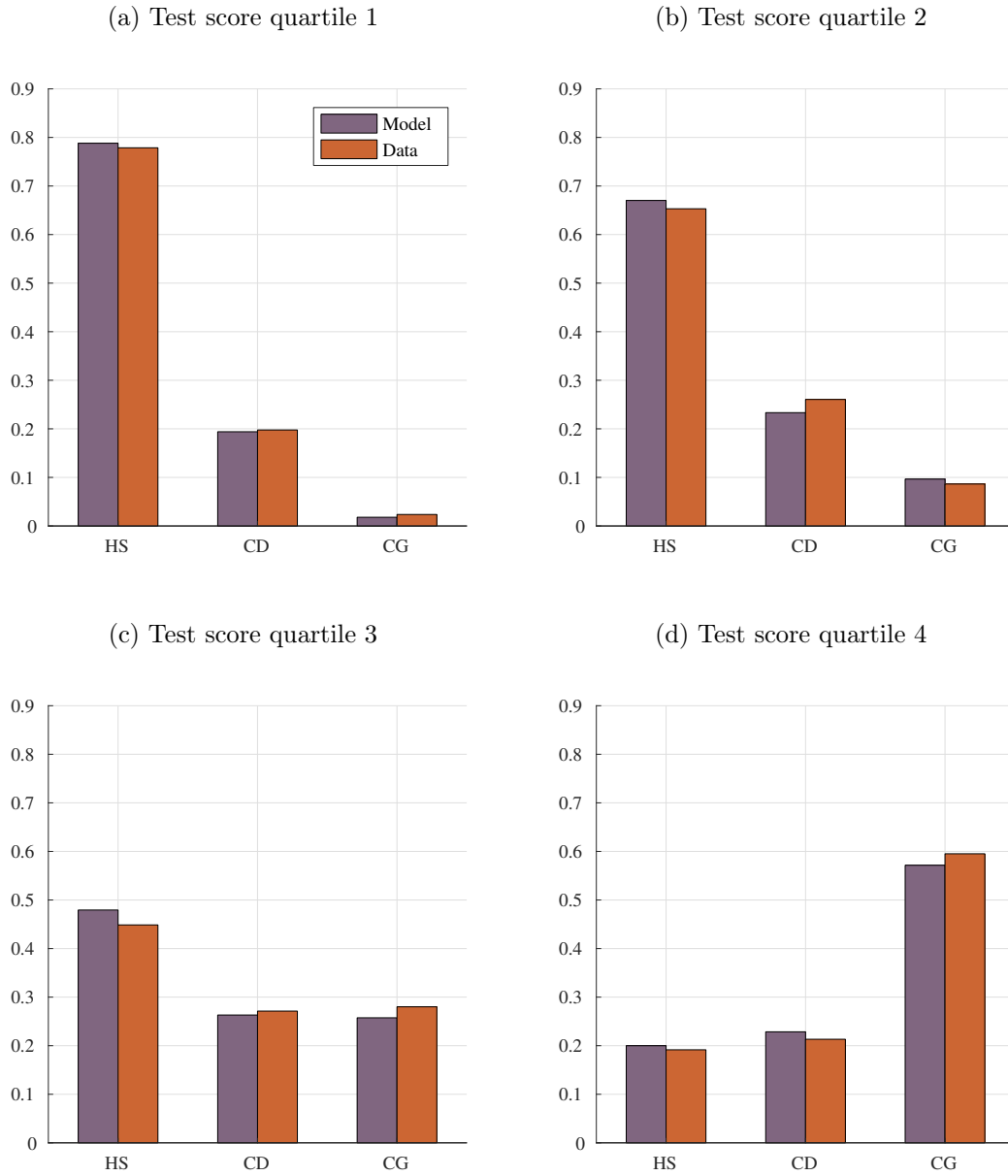
Schooling and test scores. [Figure 3](#) breaks down the schooling outcomes by test score quartiles. Test scores are strong predictors of college entry and college completion. 81% of students in the top test score quartile attempt college and 74% of them earn college degrees. In the lowest test score quartile, only 22% of students enter college and only 11% of them earn degrees.²⁶ One question our model answers is why low ability students attempt college, even though their graduation chances are small.

5 Results

This section examines what the calibrated model implies for the predictability of college outcomes. We summarize predictability by focusing on the fraction of students with graduation probabilities below 20% or above 80%. The idea is that these students can predict their graduation outcomes so well that the value of the remaining uncertainty is small. The policy experiments reported in [section 6](#) confirm this intuition.

²⁶[Bound et al. \(2010\)](#)'s [Figure 2](#) documents similar patterns in NLS72 and NELS:88 data.

Figure 3: Schooling and Test Scores



Notes: For each test score quartile, the figure shows the fraction of persons who attain each schooling level.

Source: High School & Beyond.

Table 8: Persistence of Credit Accumulation Rates

	Year 1 – 2	Year 2 – 3	Year 3 – 4
Correlations, model	0.46	0.46	0.44
data	0.48	0.42	0.39
Eigenvalues, model	0.52	0.47	0.44
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 t and $t + 1$. “Eigenvalues” shows the second largest eigenvalues of transition matrices. Each transition matrix indicates the probability that a student in a given quartile of the distribution of credits earned in year t transits to another quartile in $t + 1$. Source: High School & Beyond.

5.1 Distribution of Graduation Probabilities

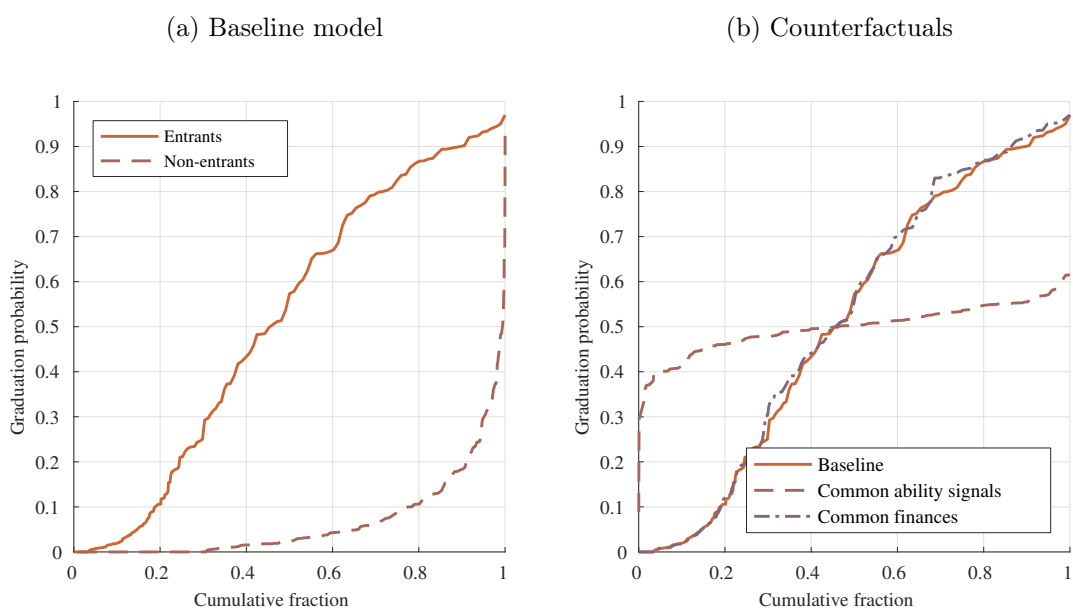
Figure 4a shows the CDF of graduation probabilities for the population of college entrants.²⁷ Graduation is highly predictable for more than half of entrants. 24% of entrants face graduation probabilities below 20% while 29% face graduation probabilities above 80%. For comparison, the figure also shows the distribution for high school graduates who do not enter college. Their graduation probabilities, were these students to enter college, are very poor. 91% of them face graduation probabilities below 20%.

To understand why the model implies high predictability for many students, we study two counterfactual experiments. At high school graduation, students differ in two types of endowments that affect their graduation probabilities: ability signals and financial resources. We quantify the role of both endowments by recomputing the model while shutting down heterogeneity in one of them.

To isolate the role of financial resources, we shut down heterogeneity in ability signals. This involves the following steps. We assign each high school graduate the distribution of abilities $\Pr(a|j)$ that corresponds to the probability distribution of a among baseline college

²⁷This is based on the simulated life histories of college entrants. For each type j , we compute the fraction of college entrants that earns a bachelor’s degree. The CDF is not smooth because there are only 200 types.

Figure 4: Distribution of Graduation Probabilities



Notes: The figure shows the CDF of graduation probabilities, conditional on student's information at the time of high school graduation. Panel (a) shows college entrants and high school graduates who do not enter college. Panel (b) shows two counterfactual experiments for students who enter college in the baseline model: (i) All students share common beliefs about their abilities. (ii) All students are endowed with the same financial endowments (k_1, q, z) .

entrants. Financial resources still differ across types. We recompute students' decision rules and simulate their life histories, drawing abilities from the counterfactual $\Pr(a|j)$. We then compute the distribution of college graduation rates in the population of students who enter college in the baseline model.

Figure 4b shows that the resulting distribution of graduation probabilities looks markedly different from the baseline model. It has almost no mass below 20% or above 80%. This shows that financial heterogeneity does not play an important role for predicting college outcomes. One reason is that very few students in the baseline model are close to their borrowing limits (Table 19) or close to the maximum number of hours they could work in college.

To isolate the role of heterogeneity in ability signals, we shut down financial heterogeneity. This involves the following steps. In the baseline model, we compute the mean financial endowments (k_1, q, z) among college entrants. In the counterfactual, we assign all students these mean financial endowments. The distribution of abilities, $\Pr(a|j)$, remains unchanged. We compute new decision rules and simulate students' life histories. Figure 4b shows that the resulting distribution of graduation probabilities is very similar to the baseline model. Shutting down financial heterogeneity alters graduation outcomes for only 3% of college entrants, compared with 32% in the case where heterogeneity in ability signals is shut down.²⁸

These findings imply that heterogeneity in ability signals and therefore graduation prospects is the main reason why graduation outcomes are highly predictable for many students. Next, we explore the link between ability signals and college outcomes. We show that the high predictability of college graduation arises for the following reasons.

1. Graduation prospects differ greatly between high and low ability students. To account for the observed dispersion in credit accumulation rates, the model implies that course passing rates $p(a)$ increase sharply in a . The Binomial distribution of earned courses then implies that graduation prospects differ greatly between high and low ability students (subsection 5.2).
2. Graduation probabilities are closely related to graduation prospects. The incentives for remaining in college until graduation increase sharply with graduation prospects.

²⁸These numbers are calculated from the simulated life histories of students who enter college in both the baseline model and in the counterfactual.

As a result, high ability students rarely drop out of college. By contrast, many low ability students drop out, even though they could have graduated by staying in college longer (subsection 5.3).

3. Students' ability signals are very precise. Students can therefore accurately predict their course passing rates and graduation prospects (subsection 5.4).

5.2 Distribution of Graduation Prospects

Figure 5a shows the distribution of graduation prospects (the probability of earning 21 courses in 6 years) among college entrants.²⁹ A large fraction of students (61%) faces graduation prospects above 80%. A much smaller fraction (9%) faces graduation prospects below 20%. The distribution of course passing rates is approximately uniform over the interval [0.50, 0.90].

Figure 5b shows the same information for students who do not enter college. It indicates strong selection into college. Few students with strong graduation prospects fail to enter college. The median graduation prospect among non-entrants is only 0.17, suggesting that the inability to graduate is the main friction that prevents college entry.

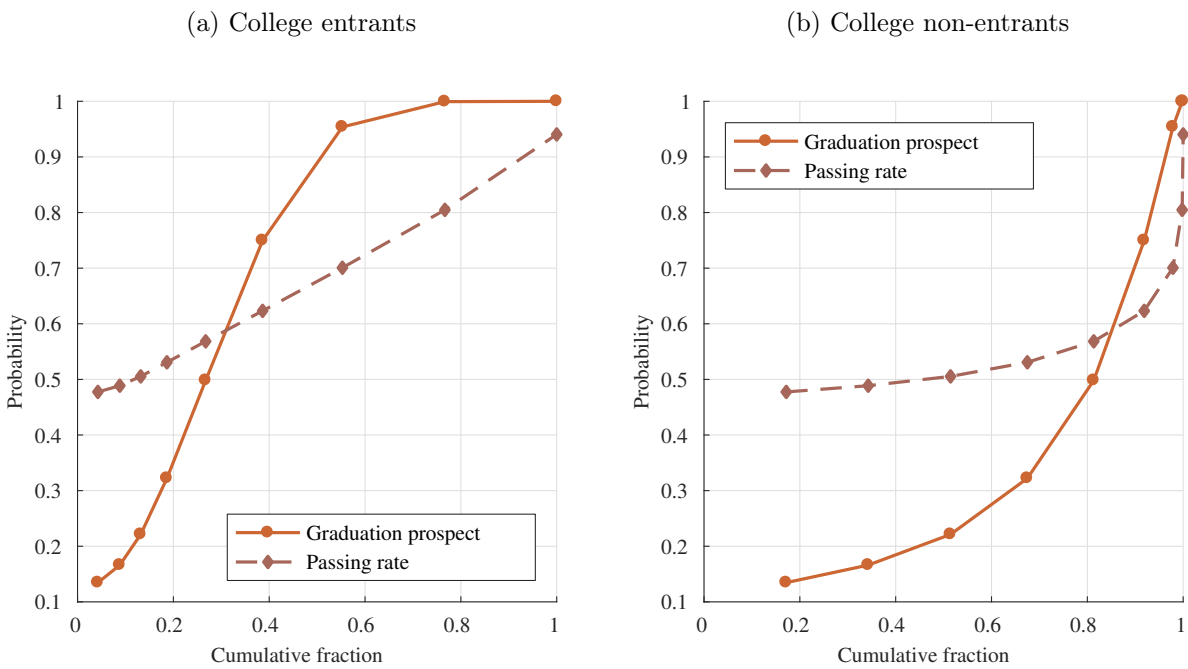
To understand why the model implies that many students face either very high or very low graduation prospects, recall the discussion of subsection 2.3. This discussion made the following points. (i) Graduation prospects increase sharply with students' credit accumulation rates. (ii) The large dispersion in observed credit accumulation rates then implies that many students face either very high or very low graduation prospects.

A similar reasoning underlies the large dispersion in the graduation prospects generated by the structural model. To gain intuition, consider the distribution of credits earned at the end of the second year in college (see Table 3). Students at the 80th percentiles of the distribution earn 66 credits, compared with only 41 credits for students at the 20th percentile. The binomial distribution of earned courses implies that only a fraction of this dispersion can be accounted for by luck (random course outcomes).

To see this, consider the case where all students share the same course passing rate, given by the mean observed in the data ($p = 0.75$). The standard deviation of earned courses is then given by $[p(1-p)2n_c]^{0.5} = 2.1$ (6.4 credits). The 20th and 80th percentiles of the

²⁹Graduation prospects are based on students' true abilities.

Figure 5: Distribution of Graduation Prospects



Notes: The figure shows the distribution of graduation prospects and course passing rates implied by the baseline model. The graduation prospect is the probability of earning at least n_{grad} courses in T_c years. Panel (a) shows college entrants. Panel (b) shows students who do not enter college.

distribution are 48 and 60 credits, respectively. Clearly, some heterogeneity in p is needed to account for the observed dispersion of credits.

To get a sense of how much dispersion in p is needed, consider the case where p is uniformly distributed over the interval $[p_L, p_H]$. The values of p_L and p_H that match the observed number of credits earned at the 20th and 80th percentiles of the distribution are 0.50 and 1.00. The implied distribution of course passing rates is therefore quite close to what the calibrated model implies (see [Figure 5a](#)).

This example clarifies how the model identifies the distribution of graduation prospects. The binomial distribution limits the dispersion of credits that is due to luck. A large part of the dispersion must therefore be generated by heterogeneity in course passing rates and thus graduation prospects. The fact that the model is consistent with the observed persistence of credit accumulation rates over time provides indirect support for the assumed binomial distribution.

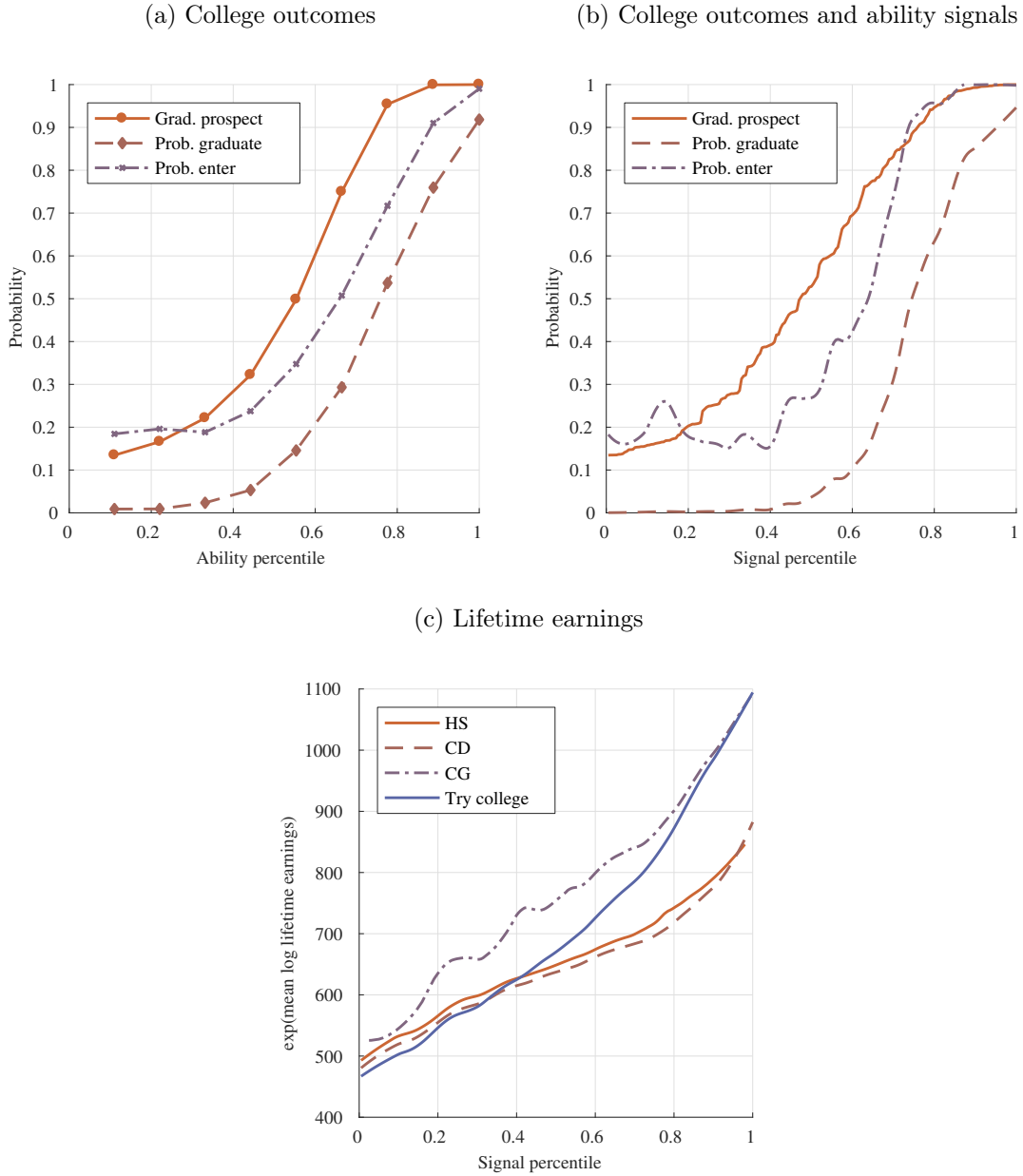
5.3 Graduation Prospects and College Outcomes

[Figure 6a](#) shows that college outcomes are closely related to graduation prospects. Both entry and graduation rates increase sharply with student abilities. While students in the lowest ability quintile have essentially no chance of graduating, students in the highest ability decile graduate with 92% probability. Only students with intermediate abilities face substantial uncertainty about their college outcomes. While 35% of students of median ability attempt college, only 15% of these entrants eventually graduate.

Except for high ability students, graduation probabilities are far lower than graduation prospects. This raises the question why so many students of low to medium abilities drop out, even though many could graduate if they remained in college. To understand this, we consider the financial rewards associated with college attendance.

This is complicated by the fact that students are uncertain about their true abilities. Fortunately, the model implies that ability signals are very precise. The correlation between signals and abilities is 0.92. It follows that inaccurate student beliefs do not play a major role for college entry and dropout decisions. To show this, [Figure 6b](#) shows the same information as [Figure 6a](#), except that all probabilities are conditional on information available at high school graduation rather than on true abilities. The similarity of both figures sug-

Figure 6: Graduation Prospects and College Outcomes



Notes: Panel (a) shows the distribution graduation prospects, the fraction of students who enter college, and the probability of graduating conditional on entry. Panel (b) shows the same data conditional on information available to students at high school graduation.

Panel (c) shows mean log lifetime earnings, discounted to age 1, by ability signal and schooling level. “Try college” shows the mean log lifetime earnings a student of given signal could expect to earn, if he remained in college as long as possible (until graduation or until year T_c). Lifetime earnings are based on simulated model histories. All lines in panels (b) and (c) are smoothed using quadratic local regressions.

gests that computing students incentives for college attendance conditional on information available at age 1 does not introduce major inaccuracies.³⁰

Figure 6c summarizes the financial rewards associated with college attendance. For each signal, the figure shows the mean log lifetime earnings associated with each possible school outcome (computed from simulated life histories). It also shows how much students can expect to earn, if they stay in college until they either graduate or are forced to drop out (at the end of year T_c). For students with below average ability signals, this counterfactual reduces their lifetime earnings relative to those resulting from their optimal dropout decision. One reason is that these students are not likely to earn enough credits for graduation. A second reason is that sheepskin effects are small for low ability students (because y_{CG} is only slightly larger than y_{HS}).

It follows that, for students of low to medium ability signals, it makes little financial difference whether they remain in college a bit longer or shorter. As a result, these students are easily persuaded to drop out, either because they lack the financial resources to pay for college without working long hours, or because they are hit by shocks while in college. This reduces their graduation probabilities far below their graduation prospects. The situation is very different for students with high ability signals, who forego large earnings gains if they drop out prematurely.

Figure 6c also sheds light on why low ability students rarely enter college. For a given ability signal, working as a high school graduate or as a college dropout yields similar lifetime earnings. The earnings gains associated with earning credits approximately offset the costs associated with postponing labor market entry (and tuition). Since low ability students rarely graduate, they have little financial incentive to enter college.

To summarize: In the data, we observe a wide dispersion in credit accumulation rates. Accounting for this requires that some model students pass so many of their courses that their graduation prospects are very strong. These students face strong financial incentives to remain in college until graduation. As a result, their graduation success is highly predictable. On the other hand, accounting for the lowest observed credit accumulation rates requires that some model students pass so few of their attempted courses that their graduation prospects are far from certain. For these students, remaining in college until graduation

³⁰Among students with low ability signals, variation in college entry rates is largely due to financial endowments (and preference shocks), not to variation in graduation prospects. This is the reason why college entry rates among low signal students are not monotone in m .

(or until year T_c) would reduce their lifetime earnings compared with dropping out earlier. Their financial incentives for remaining in college are weak. As a result, their failure to graduate is highly predictable.

5.4 Precision of Students' Ability Signals

The fact that students can accurately predict their graduation prospects plays an important role in the preceding arguments. To understand why the model implies that signals are precise, we study the model's implications when we impose more signal noise. We do so by calibrating the model while fixing the correlation between signals and abilities at 0.44, compared with 0.92 in the baseline model (i.e., we set $\alpha_{a,m} = 0.5$). Examining which data features this alternative model fails to account for reveals how the precision of the signal is identified.

Table 9 displays selected changes relative to the baseline model. More signal noise reduces the correlation between test scores and abilities from 0.67 in the baseline model to 0.36. The mechanical reason is that test scores are themselves noisy measures of ability signals. As a result, college outcomes, such as credit accumulation rates or dropout rates, vary too little across test score quartiles (see rows 1 and 2 of **Table 9**).

The calibration algorithm attempts to offset these changes by increasing the correlation between test scores and ability signals. However, given that college entry decisions depend strongly on signals, this leads the model to overstate the association between test scores and college entry decisions (row 3). These findings suggest that the values of signal noise and test score noise are mainly determined by data moments that characterize how college entry decisions and college outcomes vary across test score quartiles.

More signal noise also weakens the association between abilities and college entry rates (row 4). One mechanical reason is that students simply do not know their abilities at the time of college entry. A second reason is that the value of attempting college increases for students with low to medium ability signals. As a result, more high ability students work as high school graduates, while more low ability students enter college. This shrinks the lifetime earnings gap between college dropouts and high school graduates below its empirical value (row 5).

The predictability of college graduation declines substantially when signals are less precise (row 6). Virtually no college entrants face graduation probabilities below 20% or above 80%.

Table 9: Implications of Higher Signal Noise

	Data	Baseline	Noisy signal
Differences between high/low test score students:			
- credit accumulation rate (year 2)	0.28	0.28	0.11
- college dropout rate	0.63	0.63	0.34
- college entry rate	0.59	0.59	0.76
College entry rate, ability above/below median		0.58	0.28
Log lifetime earnings gap, CD vs HS	0.07	0.07	-0.02
Fraction with low / high graduation probabilities		24 / 29	2 / 3

Notes: The table shows the implications of increasing signal noise relative to the baseline model. Rows 1 to 3 display differences between students in the top and bottom test score quartile. Row 4 shows the difference in the college entry rate between students with abilities above and below the median. Row 5 displays the log lifetime earnings gap between college dropouts and high school graduates. Row 6 shows the fraction of college entrants with graduation probabilities below 20% and above 80%.

In part, this is a mechanical consequence of students' uncertainty about their abilities. This is reinforced by a flatter relationship between course passing rates and abilities, $p(a)$. The latter allows more low ability students to graduate and thus prevents the dropout rate from rising too much above the target value.

Summary. The main result of this section is that graduation is highly predictable for a large fraction of college entrants. The primary reason is that many students face either very strong or very poor graduation prospects. Transcript data enable the model to identify the distribution of graduation prospects. Financial heterogeneity is not a major source of predictability. The model also implies that students are able to predict their graduation prospects with high precision before entering college. We demonstrate the robustness of these findings in [subsection 6.3](#).

6 Policy Implications

This section explores policy implications. We ask how much (potential) college students value either insurance against college related risks or information about their graduation prospects (abilities).

Rather than study specific policies, we consider abstract interventions that provide *complete* insurance against college related earnings risks or *perfect* information about ability. These interventions quantify how much students value the uncertainty associated with college attendance. The main finding is that the welfare gains generated by these interventions are small for most students, especially for those facing little uncertainty about their graduation outcomes.³¹

6.1 Insuring Earnings Risk

If college is risky, welfare could potentially be raised by providing insurance against the financial risks associated with either dropping out of college or of requiring a long time to earn a degree. In this section, we ask how much potential college entrants value such insurance.

We consider idealized interventions that provide complete insurance against college related consumption risks without incurring any implementation costs or deadweight losses. In particular, we assume that students do not change their college entry or continuation behavior in response to the intervention. We thereby abstract from the moral hazard problem associated with insurance provision: students have an incentive to drop out of college early, knowing that this has no effect on their earnings.

We study two insurance arrangements. In the first case, the policy maker provides complete consumption insurance during the work phase conditional on a student's endowments a and j . It assigns each worker the average age-consumption profile of workers endowed with the

³¹We expect the welfare gains that can be generated by implementable policies to be lower than those generated by the abstract interventions we study. The main reason is that implementable policies need to guard against moral hazard (students study less or drop out earlier), adverse selection (low ability students enter college, knowing they will drop out), or deadweight losses related to financing the interventions. We leave the study of such policies for future research.

Table 10: Providing Insurance

Insurance within Welfare gains	(a, j) groups		j groups	
	median	mean	median	mean
All	0.04	0.15	0.20	0.39
Entrants	0.26	0.27	0.69	0.64
High risk entrants	0.37	0.38	0.89	0.88

Notes: The table shows the distribution of compensating differentials, expressed as percentages of baseline consumption, implied by two interventions. The interventions assign all college entrants within a type j or within an (a, j) group the group specific mean consumption.

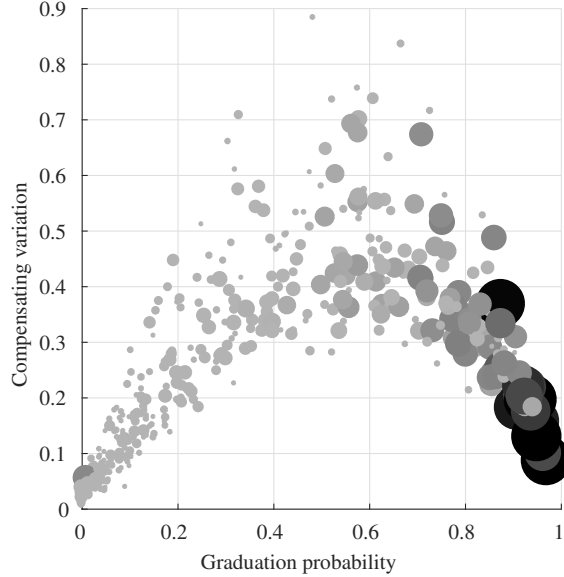
same (a, j) in the baseline model, starting at age $T_c + 1$ when all students have entered the labor market.

This policy offers insurance against uncertain credit realizations and the associated earnings and dropout risks. It also insures students against the consequences of ex-ante financial heterogeneity and financial or preference shocks that lead otherwise identical students to make different entry decisions.

The distribution of welfare gains is summarized in [Table 10](#). Welfare gains are measured by the percentage change in consumption that makes each type indifferent between the baseline model and the insurance counterfactual. The median compensating differential for this intervention amounts to only 0.04% of consumption. This is a direct consequence of the high predictability of college graduation, which limits the uncertainty students face. The average standard deviation of log consumption within (a, j) groups is only 0.04, compared with 0.24 across all types. Limiting attention to baseline college entrants increases the median welfare gain to 0.26%. This happens because the average welfare gains for types with low entry probabilities are small.

The value of college related risks is closely related to graduation risk. To illustrate this point, [Figure 7](#) plots the welfare gains for all (a, j) types against their graduation probabilities. The largest welfare gains occur for groups with intermediate graduation probabilities. Excluding those j types that face little uncertainty about college graduation (their graduation probabilities, conditional on entry, lie between 20% and 80%), increases the median welfare gain to 0.37%.

Figure 7: Welfare Gains Due to Insurance Within (a, j) Groups



Notes: Each data point is one (a, j) type. The size of each marker is proportional to the mass of college entrants of each type.

Larger welfare gains can be obtained by also insuring students against uncertainty about their true abilities. This is the second intervention shown in [Table 10](#). For each type j , the intervention replaces the random consumption stream received in the baseline model with its type specific average (again starting at age $T_c + 1$). The median welfare gains range from 0.20% (all students) to 0.89% (college entrants with significant graduation risk) of baseline consumption. Of course, part of these welfare gains arise from redistribution between students with high and low ability endowments rather than from insurance against college related risks.

When interpreting these welfare gains, the reader should keep in mind that they arise from *complete* consumption insurance during the work phase. By comparison, [Chatterjee and Ionescu \(2012\)](#) find that forgiving the college costs of dropouts increases average welfare by 2.4% of consumption. This welfare gain is much larger, even though consumption insurance is far from complete.

6.2 Providing Information

Manski and Wise (1983) argue that students enter college in part to learn about their abilities. This experimentation is costly. Students forego labor earnings and pay tuition while in college. This argument suggests that welfare could be increased by providing high school graduates with information about their abilities before they make college entry decisions. This is one motivation behind dual enrollment programs that allow high school students take college level courses (Stephanie Marken et al., 2013).

We study the welfare implications of a stylized policy intervention that costlessly informs students about their abilities before they enter college. The details are as follows. For all combinations of (a, j) , we solve for the decision rules of an agent who knows his ability. The associated value functions at high school graduations are labeled $V_{HS}^a(a, j)$. The expected value of type j before learning his ability is given by $\hat{V}_{HS}(j) = \mathbb{E}_a \{V_{HS}^a(a, j) | j\}$. The welfare gain of the intervention is the log change in annual consumption, starting at age 1, that makes each type indifferent between the baseline value $V_{HS}(j)$ and $\hat{V}_{HS}(j)$.

The average welfare gain across all high school graduates amounts to 0.15% of baseline consumption. However, for the majority of students, the gains are essentially zero. The reason is that students' ability signals are quite precise. Many high school graduates have sufficient information about their abilities to make ex post optimal college entry decisions with high probability. Large welfare gains only accrue to medium ability students who face substantial dropout risk.

Restricting attention to students who enter college in the baseline model excludes a large fraction of low ability students who do not value information about their abilities much. This increases average welfare gains to 0.22% of baseline consumption. These findings highlight the importance of targeting the proper set of students for a policy intervention to generate significant gains.

6.3 Robustness

This section explores the robustness of our findings when selected model features are modified. Specifically, we examine the following modifications:

1. $p(a)$ is an unrestricted function of ability. Since there are only 9 ability levels, $p(a)$ can be specified as a vector of length 9.

2. Financial shocks affect wages rather than feasible work hours. There are 5 financial states, ordered from worst to best. The calibrated parameters are $\Delta q, \Delta w$ and p_{stay} . College costs take on the values $q(\zeta, j) = \hat{q}_j - (\zeta - 3)\Delta q$. Wages are given by $w_{coll} + (\zeta - 3)\Delta w$. The transition probabilities are $\Pr(\zeta' = \zeta | \zeta) = p_{stay}$, $\Pr(\zeta' = 2 | \zeta = 1) = \Pr(\zeta' = 4 | \zeta = 5) = 1 - p_{stay}$, $\Pr(\zeta' = \zeta \pm 1 | \zeta) = 1 - p_{stay}/2$ for interior ζ , and $\Pr(\zeta' | \zeta) = 0$ otherwise.
3. Smaller preference shocks: $\pi = \pi_E = 0.1$.
4. Preference shocks that are correlated with ability signals: We assume that the means of the preference shocks experience in college are drawn from a joint Normal distribution together with the other student endowments (see [subsection 4.1](#)). Preferences shocks are correlated with m , but not correlated with other endowments, conditional on m .
5. Higher values of risk aversion (θ).

[Table 11](#) summarizes how the predictability of college graduation and the welfare gains of policy interventions change for each model specification. The only significant changes occur when students are more risk averse than in the baseline model. This reduces the predictability of college graduation and increases the welfare gains of interventions. However, the model's ability to replicate the calibration targets deteriorates for higher values of risk aversion (which is why the baseline model features log utility).

7 Conclusion

We conclude by considering potential avenues for future research. Since our model captures the distribution of risks and returns associated with entering college, it provides a starting point for the study of college related policies, such as income contingent loans or dual enrollment programs. However, the model abstracts from two features that may be important for policy analysis.

The first feature is study effort. Insurance arrangements distort students' incentives to study. To capture these distortions, it is necessary to model how study effort affects college outcomes. The second feature is earnings risk during the work phase. One motivation of

Table 11: Robustness

Model	Fraction with		Median welfare gain		
	graduation probability		Insurance	Known	
	< 0.20	> 0.80	within j	within (a, j)	ability
Baseline	0.24	0.29	0.20	0.04	0.15
Unrestricted $p(a)$	0.23	0.31	0.21	0.05	0.17
Wage shocks	0.26	0.28	0.21	0.07	0.14
$\pi = \pi_E = 0.1$	0.31	0.31	0.18	0.01	0.06
(η_c, m) correlated	0.25	0.31	0.22	0.05	0.15
$\theta = 1.5$	0.22	0.21	0.46	0.18	0.11
$\theta = 2.0$	0.19	0.18	0.58	0.18	0.11
$\theta = 4.0$	0.17	0.17	1.91	0.98	0.80

Notes: The table explores the robustness of the main findings. Each row shows a model version. The columns show the fraction of college entrants with low or high graduation probabilities and the median welfare gains generated by the policy interventions described in the text.

making college loans income contingent is to alleviate the tight budget constraints of young workers who may be borrowing constrained. Modeling earnings shocks would also imply that the model could be used to measure the predictability of lifetime earnings as of the age of high school graduation ([Huggett et al., 2011](#)).

8 Acknowledgements

For helpful comments we thank Philip Bond, V. V. Chari, Jonathan Heathcote, Larry Jones, José-Victor Rios-Rull, and seminar participants at the Federal Reserve Bank of Minneapolis, the University of Washington, Concordia University, Indiana University, Université Catholique de Louvain, the Federal Reserve Bank of St. Louis, University of Pittsburgh, University of Victoria, the University of Hawaii, the CIREQ Montreal Macroeconomics Conference, and the 2015 Midwest Macro Meeting.

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Online Appendix

A High School & Beyond Data

We obtain data on the academic performance of college students and on their incomes and expenditures from data collected by the National Education Longitudinal Studies (NELS) program of the National Center for Education Statistics (NCES). The High School & Beyond (HS&B) survey covers the 1980 senior and sophomore classes (see [United States Department of Education. National Center for Education Statistics 1988](#)). Both cohorts were surveyed every two years through 1986. The 1980 sophomore class was also surveyed in 1992, at which point postsecondary transcripts from all institutions attended since high school graduation were collected under the initiative of the Postsecondary Education Transcript Study (PETS).³² We restrict attention to male sophomores that are surveyed at least through 1986.

A.1 Enrollment and Dropout Statistics

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

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

We count a student as entering college if he attempts at least 9 credits in a given academic year. Using this definition, 48% of the cohort enters college immediately upon high school

³²PETS data files were obtained through a restricted license granted by the National Center for Education Statistics.

Table 12: School Attainment of College Entrants

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

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

graduation. Another 2.7% of the cohort enter in the following year. Students obtaining a bachelor’s degree within 6 years of initial enrollment are counted as college graduates, even in the presence of breaks in their enrollment. The 52.5% of immediate entrants are college graduates. Students that earn bachelor’s degrees later than 6 years after their initial enrollment are dropped from the sample.³³

For each high school GPA quartile, [Table 12](#) shows the fraction of college entrants who graduate from college and who drop out at the end of each year. These statistics are computed from 2,052 college entrants with complete transcript histories. We refer to a college entrant as a year x dropout if he/she enrolled continuously in years 1 through x , attempted fewer than 7 credits in year $x + 1$, and failed to obtain a bachelor degree within 6 years. 98.4% of the college graduates in our sample are enrolled continuously until graduation.

A.2 Financial and Work Variables

In the second and third follow-up interviews (1984 and 1986), all students reported their education expenses, various sources of financial support, and their work experience. [Table 13](#) shows the means of all financial variables for students who are enrolled in college in

³³These students typically drop out within two years of initial enrollment, experiencing a long enrollment break before returning to school. Counting these students as college graduate would raise the graduation rate to 55%.

Table 13: Financial Resources

	Year 1	Year 2	Year 3	Year 4
Net cost, q	3,750	7,831	14,773	21,985
	(1,864)	(1,572)	(1,161)	(1,028)
Tuition	4,270	8,929	16,481	24,291
	(1,875)	(1,582)	(1,226)	(1,081)
Grants, scholarships	1,430	2,892	4,433	6,097
	(1,989)	(1,687)	(1,303)	(1,157)
Earnings	5,625	10,806	15,856	20,458
	(2,042)	(1,728)	(1,444)	(1,269)
Hours worked	803	1,535	2,174	2,736
	(2,006)	(1,690)	(1,396)	(1,223)
Loans	917	2,058	3,226	4,500
	(1,997)	(1,687)	(1,320)	(1,165)
Fraction in debt	0.26	0.35	0.41	0.47
	(1,997)	(1,687)	(1,320)	(1,165)
Parental transfers	4,114	8,533	11,835	15,134
	(1,527)	(1,300)	(901)	(805)

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

a given year.

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

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

Grants refer to the total dollar value of the amount received from scholarships, fellowships, grants, or other benefits (not loans) during the academic year.

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

Table 14: Summary Statistics for the NLSY79 Sample

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

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

B NLSY79 Data

The NLSY79 sample covers men born between 1957 and 1964 who earned at least a high school diploma. We use the 1979 – 2006 waves. We drop persons who were not interviewed in 1988 or 1989 when retrospective schooling information was collected. We also drop persons who did not participate in the AFQT (about 6% of the sample). [Table 14](#) shows summary statistics for this sample.

B.1 Schooling Variables

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

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

as single year jumps in the highest grade attained. We treat all reported degrees as valid, even if years of schooling appear low.

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

B.2 Lifetime Earnings

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

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

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

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

Table 15: Lifetime Earnings

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

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

In order to limit measurement error, we drop individuals who report zero earnings for more than 30% of the observed years. We also drop persons with fewer than 5 earnings observations after age 35 or whose reported earnings account for less than 30% of lifetime earnings according to the CPS profile. [Table 15](#) shows summary statistics for the persons for which we can estimate lifetime earnings. One concern is that the NLSY79 earnings histories are truncated around age 45, which leaves 20 to 30 years of earnings to be imputed. Fortunately, the fitted CPS age profiles imply that around 70% of lifetime earnings are earned before age 45.

C CPS Data

C.1 Sample

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

C.2 Schooling Variables

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

C.3 Age Earnings Profiles

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

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

Next, we estimate the age profile of mean log earnings for those earnings more than \$2,000 per year, which we assume to be the same for all cohorts, except for its intercept. To do

so, we compute mean log earnings above \$2,000 for every [age, school group, year] cell. We then regress, separately for each school group, mean log earnings in each cell on age dummies, birth year dummies, and on the unemployment rate, which absorbs year effects. We retain the birth cohorts 1935 – 1980. We use weighted least squares to account for the different number of observations in each cell.

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

$$g_{CPS}(t|s) = \exp(1960 \text{ cohort dummy} + \text{age dummy}(t) + \text{year effect}(1960 + t))f(t|s) \quad (8)$$

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

D Calibration

Endowments and types. We randomly draw the endowments $(\hat{k}_j, \hat{q}_j, \hat{z}_j, \hat{m}_j)$ as follows.

1. We draw independent standard Normal random vectors of length J : $\varepsilon_z, \varepsilon_q, \varepsilon_m$, and ε_k .
2. We set $\hat{z}_j = \max(0, \mu_z + \sigma_z \varepsilon_{z,j})$, where $\varepsilon_{z,j}$ is the j^{th} element of ε_z .
3. We set $\hat{q}_j = \mu_q + \sigma_q \frac{\alpha_{q,z} \varepsilon_{z,j} + \varepsilon_{q,j}}{(\alpha_{q,z}^2 + 1)^{1/2}}$, $\hat{m}_j = \frac{\alpha_{m,z} \varepsilon_z + \alpha_{m,q} \varepsilon_{q,j} + \varepsilon_{m,j}}{(\alpha_{m,z}^2 + \alpha_{m,q}^2 + 1)^{1/2}}$, and $\hat{k}_j = \max\left(0, \frac{\alpha_{m,k} \varepsilon_m + \varepsilon_{k,j}}{(\alpha_{m,k}^2 + 1)^{1/2}}\right)$.

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 .

Distribution of abilities. We think of ability grid point i as containing all continuous abilities in the set $\Omega_i = \left\{a : \frac{i-1}{N_a} \leq \Phi(a - \bar{a}) < \frac{i}{N_a}\right\}$ where Φ is the standard Normal cdf. We therefore set $\hat{a}_i = \mathbb{E}\{a | a \in \Omega_i\}$. We model the joint distribution of abilities and signals as a discrete approximation of a joint Normal distribution given by

$$a = \bar{a} + \frac{\alpha_{a,m} m + \varepsilon_a}{(\alpha_{a,m}^2 + 1)^{1/2}}, \quad (9)$$

where $\varepsilon_a \sim N(0, 1)$. The denominator ensures that the unconditional distribution of a has a unit variance. We set $\Pr(\hat{a}_i | j) = \Pr(a \in \Omega_i | m = \hat{m}_j)$.

E Model Fit

This section presents additional comparison of simulated model moments with their data counterparts.

Schooling and lifetime earnings. [Table 16](#) shows that the model closely fits the observed fraction of persons attaining each school level and their mean log lifetime earnings. Key features of the data are: (i) 47.5% of those attempting college fail to attain a bachelor's degree. (ii) College graduates earn 45 log points more than high school graduates over their lifetimes. For college dropouts, the premium is only 7 log points.

Table 16: Schooling and Lifetime Earnings

	School group		
	HS	CD	CG
Fraction			
Data	51.9	22.9	25.2
Model	52.3	23.0	24.7
Gap (pct)	0.7	0.7	-2.2
Lifetime earnings			
Data	600	643	944
Model	598	640	947
Gap (pct)	-0.3	-0.5	0.3

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

Source: NLSY79.

Table 17: Lifetime Earnings

	HS GPA quartile			
	1	2	3	4
HS, model	4.02	4.10	4.15	4.18
data	3.93 (0.04)	4.12 (0.03)	4.22 (0.04)	4.22 (0.08)
CD, model	4.02	4.13	4.19	4.26
data	3.83 (0.08)	4.16 (0.05)	4.24 (0.05)	4.26 (0.06)
CG, model	4.40	4.47	4.52	4.58
data	4.11 (0.08)	4.57 (0.06)	4.46 (0.05)	4.60 (0.04)

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

Source: NLSY79.

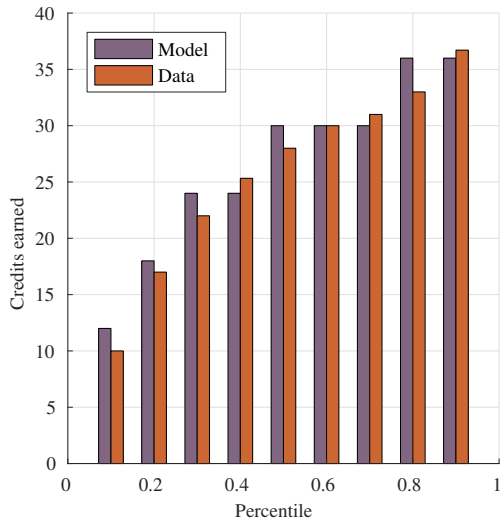
Table 17 shows mean log lifetime earnings by school group and test score quartile. The model broadly matches the data cells with large numbers of observations. The largest discrepancy occurs for college graduates in the lowest test score quartile, which are quite rare (32 observations).

College credits. Figure 8 shows the distribution of credits earned at the end of the first 4 years in college. Each bar represents a decile. While the overall fit is satisfactory, the model fails along two dimensions. First, in year 1, the model admits too few distinct values for earned credits (0 through 6) to match the finer empirical distribution. Second, the model misses the very low number of credits earned by students in the bottom decile. The gap between the first and the second decile suggests that the lowest credit realizations result from shocks that we do not model.

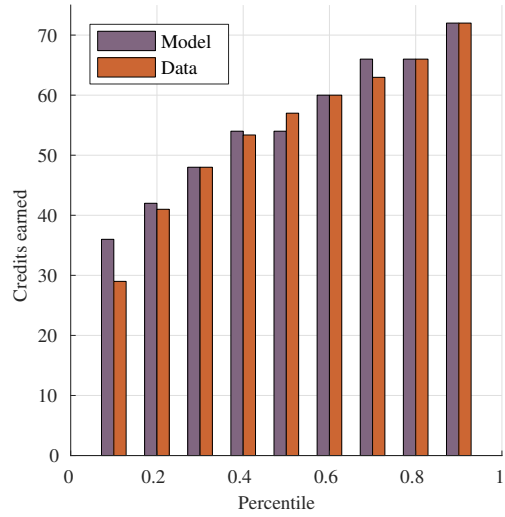
Figure 9 and Figure 10 show the distribution of credits earned at the end of the first 4 years in college broken for students who eventually drop out and who eventually graduate, respectively. Figure 11 shows the same information when students are divided into test score quartiles.

Figure 8: Distribution of Credits by Year

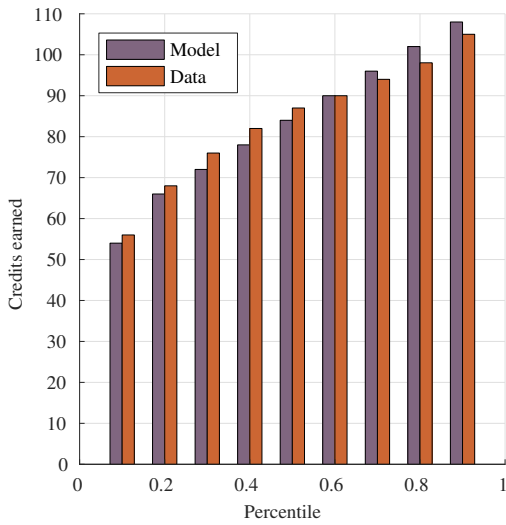
(a) Year 1



(b) Year 2



(c) Year 3



(d) Year 4

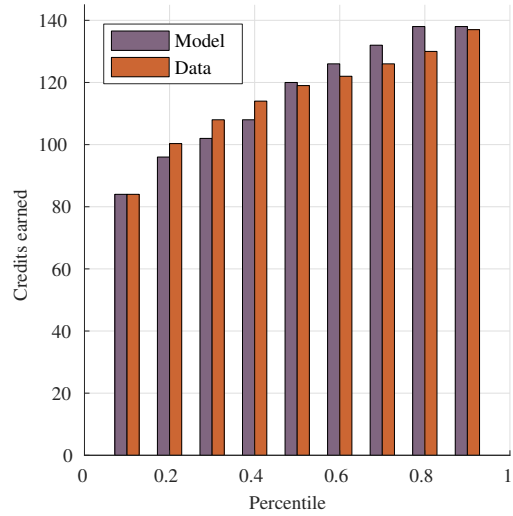
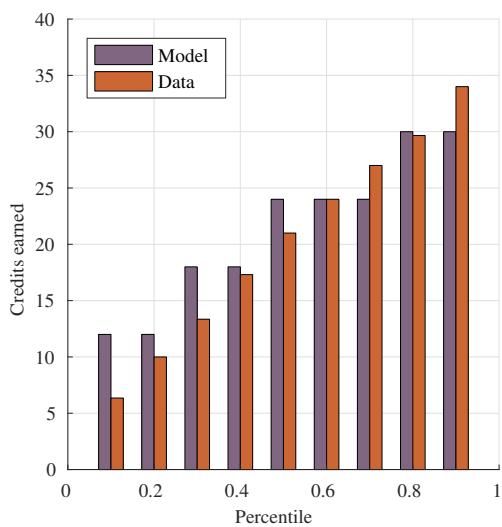
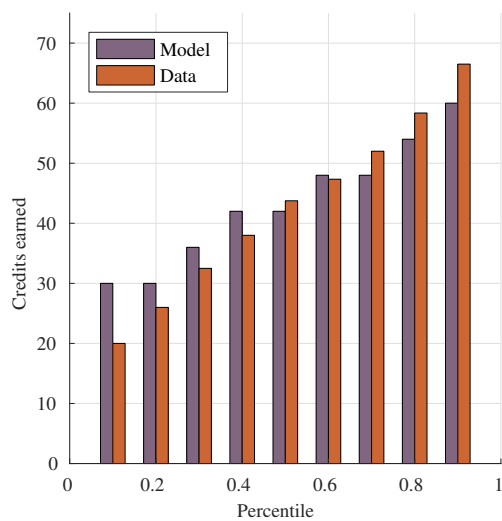


Figure 9: Distribution of Credits among Dropouts

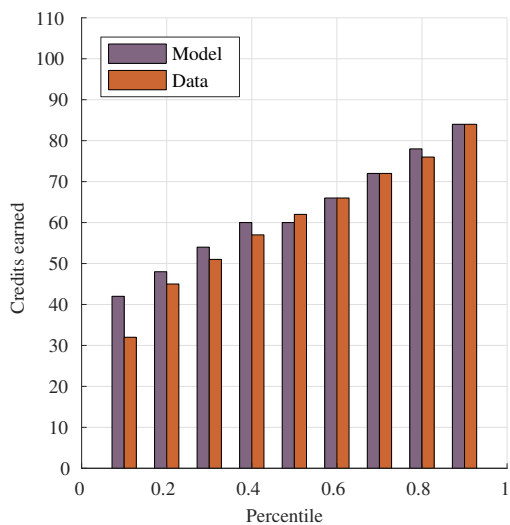
(a) Year 1



(b) Year 2



(c) Year 3



(d) Year 4

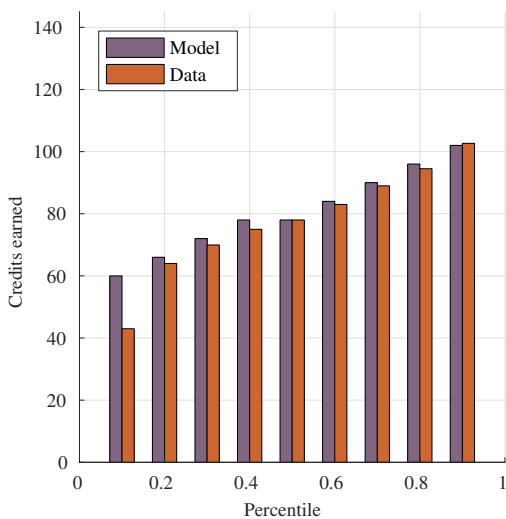
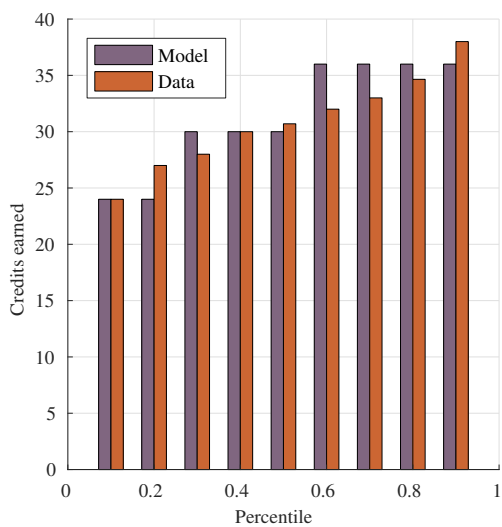
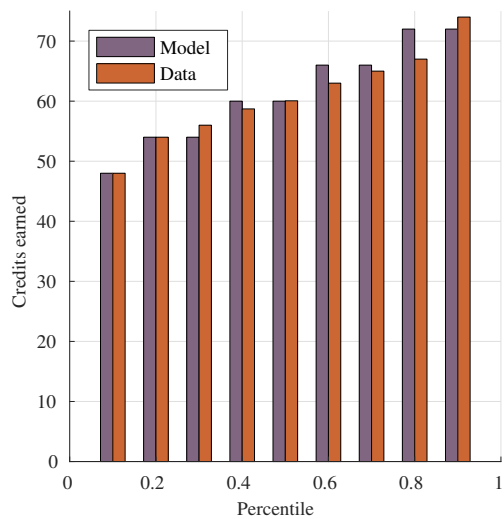


Figure 10: Distribution of Credits among Graduates

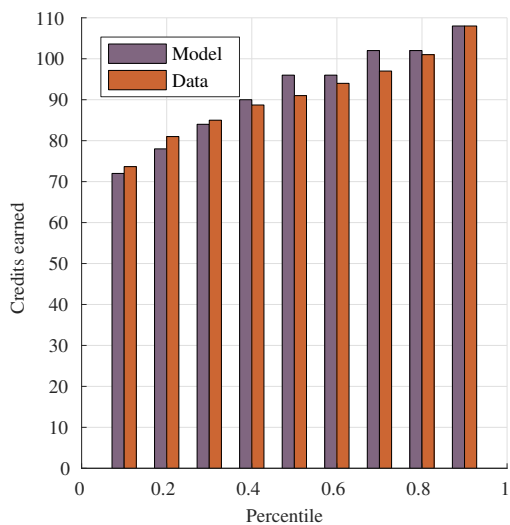
(a) Year 1



(b) Year 2



(c) Year 3



(d) Year 4

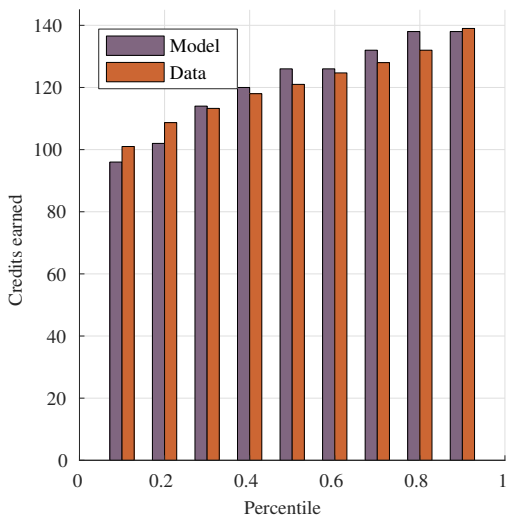
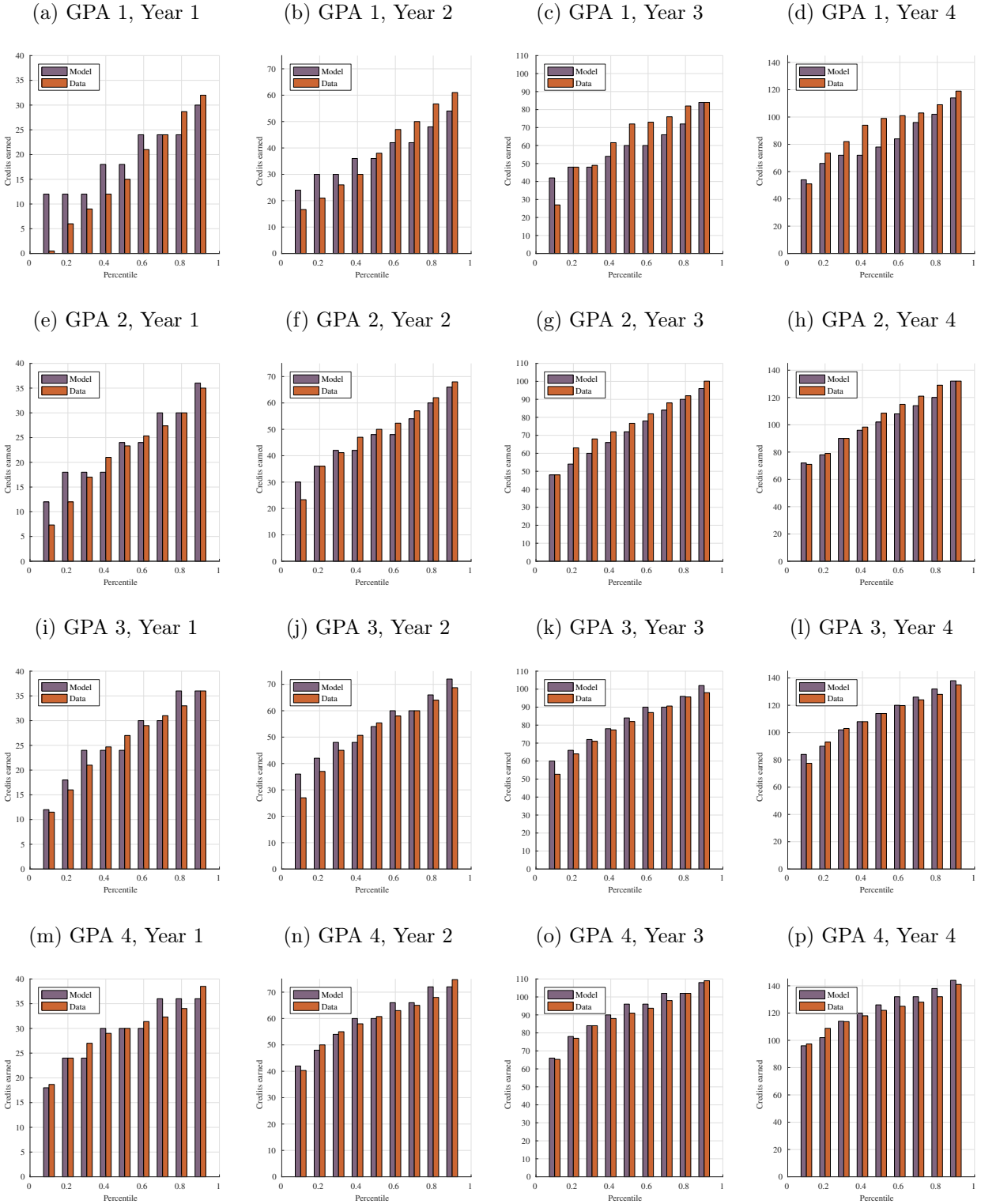


Figure 11: Distribution of Credits by GPA Quartile



Dropout rates. Figure 12 shows college dropout rates, defined as the number of persons dropping out at the end of each year divided by the number of college entrants in year 1. Dropout rates decline strongly with test scores and with time spent in college. They help identify the rate at which students learn about their graduation prospect as they move through college.

Financial resources. Table 18 shows the means of college costs, parental transfers, and college earnings, averaged over the first two years in college, for students in each test score quartile. In the data, higher ability students face slightly higher college costs, but they also receive larger parental transfers. This allows them to work less. The average net cost of attending college, $q - w_{coll}v$, is negative, especially for low test score students.³⁴ As a measure of dispersion, the table also shows the 25th, 50th and 75th percentile values of each variable.³⁵

The autocorrelations of earnings and college costs exhibit a clear time pattern in the data: they are high in years 1-2 and 3-4 but low in years 2-3. The likely reason is that students are interviewed bi-annually. Autocorrelations are high when the figures for both years are taken from the same interview and low otherwise. To circumvent this problem, the calibration targets the average autocorrelations of y and q across years 1-4. Targeting the lower autocorrelation between years 2 and 3 does not materially change the findings.

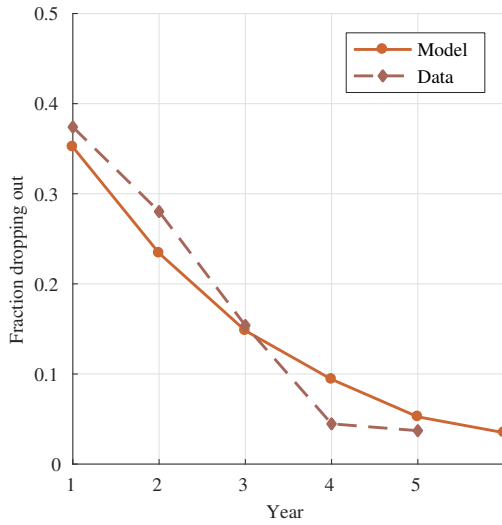
Table 19 shows student debt levels at the end of the first 4 years in college. Even after 4 years in college, only half of the students report owing any debts. Conditional on being in debt, the average debt amounts to roughly half of the borrowing limit. These results suggest that financial constraints do not bind for most of the students in our sample.

³⁴This is consistent with Bowen et al. (2009) who report that average tuition payments for public 4-year colleges roughly equal average scholarships and grants.

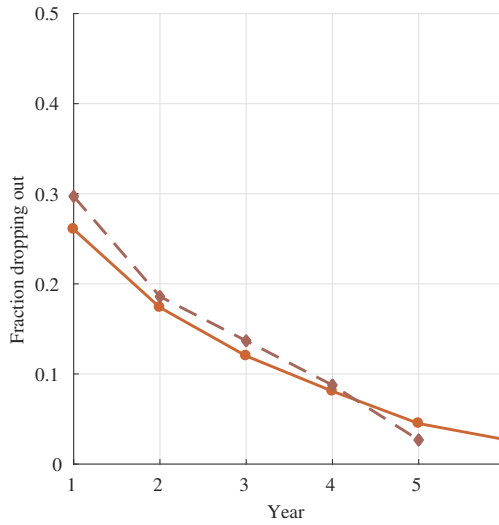
³⁵Because of potential measurement error, we do not target standard deviations of the financial moments. Doing so does not change our findings significantly.

Figure 12: Dropout Rates

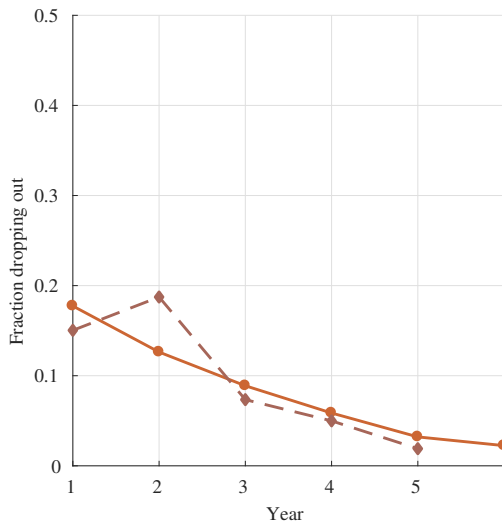
(a) Test score quartile 1



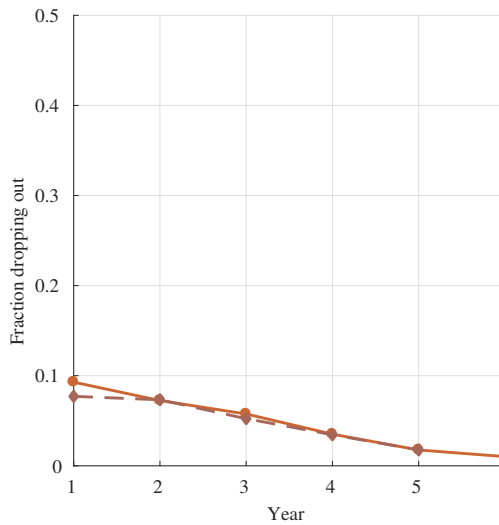
(b) Test score quartile 2



(c) Test score quartile 3



(d) Test score quartile 4



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

Source: High School & Beyond.

Table 18: Financial Moments

	HS GPA quartile				Percentile			Auto
	1	2	3	4	25	50	75	corr
q , model	3,568	3,374	3,476	4,080	1,226	3,462	6,092	0.80
data	3,122	3,097	3,828	4,280	1,354	2,705	5,378	0.80
(s.e.)	(385)	(246)	(186)	(160)	–	–	–	–
N	99	215	456	802	–	–	–	–
z , model	2,201	3,597	4,595	5,353	0	2,699	6,601	–
data	2,942	3,506	3,870	6,286	432	2,409	6,491	–
(s.e.)	(195)	(199)	(170)	(209)	–	–	–	–
N	334	499	740	990	–	–	–	–
y_{coll} , model	7,211	5,831	5,061	4,975	–	–	–	0.77
data	6,571	5,879	5,440	5,069	–	–	–	0.69
(s.e.)	(524)	(325)	(203)	(156)	–	–	–	–
N	122	255	512	839	–	–	–	–

Notes: The table shows how the model fits data on college costs q , parental transfers z , and earnings in college $w_{coll}v$. Means are shown by test score (high school GPA) quartile.

Percentile values are shown for all college students. “Std.dev.” denotes standard deviation. “Auto.corr.” denotes auto-correlation. All figures are in year 2000 dollars. “s.e.” denotes the standard deviation of the sample mean. N is the number of observations.

Source: High School & Beyond.

Table 19: Student Debt

Year	Mean debt		Fraction with debt	
	Model	Data	Model	Data
1	3,709	3,511 (42)	15.9	26.1
2	5,728	5,945 (87)	26.8	34.6
3	8,072	7,871 (137)	48.8	41.0
4	10,276	9,486 (187)	53.2	47.4

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

Source: High School & Beyond.