Factors Affecting College Completion and Student Ability in the U.S. since 1900*

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March 2013

Abstract

We develop a dynamic lifecycle model to study the increases in college completion and average IQ of college students in cohorts born from 1900 to 1972. We discipline the model by constructing historical data on real college costs from printed government reports covering this time period. We find that increases in college completion of 1900 to 1950 birth cohorts are due primarily to changes in college costs, which generate a large endogenous increase in college enrollment. Additionally, we find strong evidence that cohorts born after 1950 underpredicted sharp increases in the college earnings premium they eventually received. Combined with increasing college costs during this time period, this generates a slowdown in college completion, consistent with empirical evidence for cohorts born after 1950. Lastly, we claim that the rise in average college student IQ cannot be accounted for without a decrease in the variance of ability signals. We attribute the increased precision of ability signals primarily to the rise of standardized testing.

*The authors thank Eleanor Dillon, Todd Schoellman, and participants at the ASU Macroeconomics Workshop for helpful comments. All remaining errors are our own.

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1 Introduction

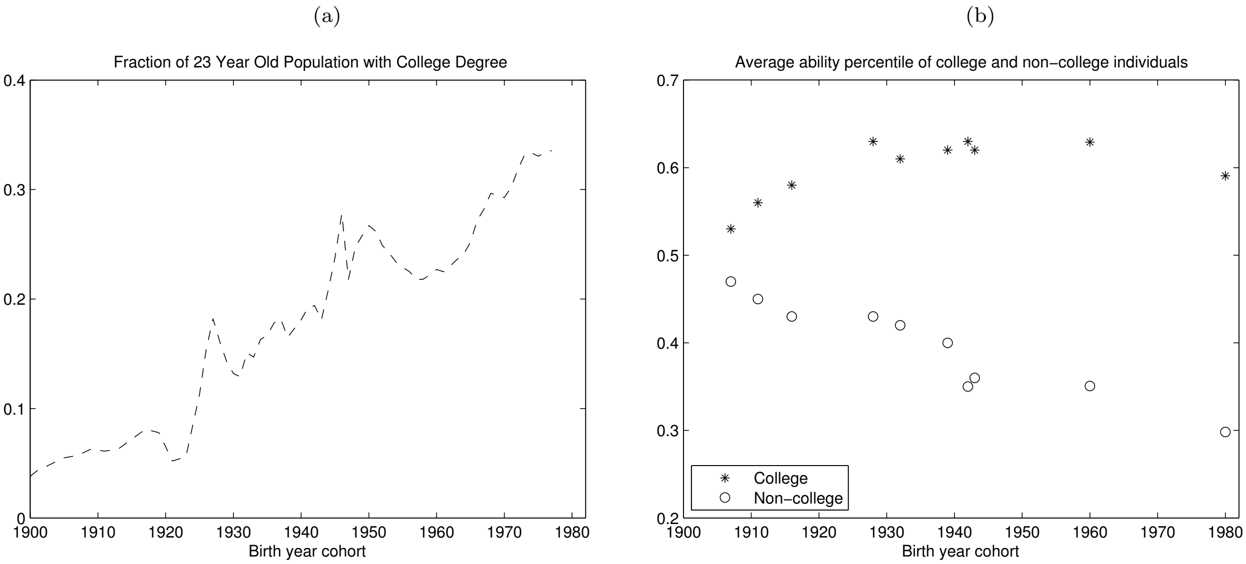
The twentieth century saw a dramatic expansion of higher education in the United States. Among those in the 1900 birth cohort, less than 4% held a bachelor's or first professional degree at age 23, but by the 1970 birth cohort this share had risen to more than 30%. Panel (a) of Figure 1 plots this series for all cohorts from 1900 through 1977.[1] Concurrent with the increase in college attendance, the ability gap widened substantially between college students and those individuals with a high school degree and no college experience, i.e., "non-college" individuals. This pattern is seen in Panel (b) of Figure 1, which plots the average IQ percentile (our proxy for "ability") of college and non-college individuals.[2] For example the average college student born in 1907 had an IQ in the 53$^{\text{rd}}$ percentile, very close to the average non-college individual whose IQ was in the 47$^{\text{th}}$ percentile. Yet over the next several decades, the average IQ percentile increased among college enrollees and decreased among those with only a high school degree. Most intriguing is that this trend of increased ability sorting occurred even as the share of students attempting college grew steadily larger.

The goal of this paper is to understand the causes of these two empirical trends. However, this task is complicated by the vast number of changes in both the aggregate economy and education sector over this time period. We combat this by developing an overlapping generations lifecycle model populated by high school graduates who are heterogeneous in both ability and financial assets. An important feature of the model is that individuals only see a noisy signal of their true ability when making risky decisions about college enrollment. We incorporate newly constructed data on college costs obtained from historical printed government sources. Additionally, we estimate life-cycle wage profiles for men and women in each birth-year cohort in order to accurately model the opportunity costs of wages foregone by college attendees and the education earnings premia realized by those who either complete some college or successfully graduate from college.

[1] The 1977 cohort was 23 years old in 2000 when this data series ends. Data for cohorts born up to 1967 are taken from Snyder (1993), and from 1968 through 1977 are the authors' calculation.

[2] These two data trends have also been documented by other authors, including Hendricks and Schoellman (2012). In panel (b), data points for cohorts prior to 1950 are from Taubman and Wales (1972). The 1960 data point is from the NLSY79, as calculated by Hendricks and Schoellman (2012). The 1980 data point is our calculation based on data from the NLSY97.

Figure 1: College Completion and Average Student Ability in the U.S. since 1900



We calibrate parameters of the model to match the U.S. data and then conduct a series of experiments in order to understand changes in college completion and ability sorting over time. First, we find that the secular increase in high school completion is responsible for less than half of the increase in college completion over the entire time period. The remainder is due to changes in college enrollment and completion rates *conditional on high school graduation*. Interestingly, however, the key features of the model allowing us to match the data depend critically on the time period considered. For cohorts born from 1930 to 1950, we find that changes in college costs are key for generating the increase in college completion, as they generate a large endogenous increase in college enrollment. Endogenous changes in the average ability of college students also affects college completion rates, but the impact is quantitatively much smaller.

For cohorts born after 1950, the benchmark model significantly overpredicts college completion rates in the data. We show that this is likely due to a sharp increase in the growth rate of the college earnings premium. While the college earnings premium was roughly flat for cohorts born between 1900 and 1950, the growth rate increased sharply for cohorts born after 1950. We find that modifying the model to allow for imperfect forecasting of the college wage premium improves substantially the predictions for college completion for cohorts born after 1950, while leaving the results for cohorts born before 1950 largely unaffected.

In terms of capturing increased ability sorting over time, we consistently find that changes in economic factors (i.e., earnings premia, college costs, opportunity costs, and asset endowments) have little impact. Instead, the key feature in the model that accounts for this is uncertainty about ability. We show that a decrease in the variance of ability signals can generate an increase in ability sorting similar to that in the data. We attribute this change to the increases in standardized testing which improved students knowledge of their own ability relative to other students in their cohort, as discussed in Hoxby (2009).

This paper is related to a large literature on the joint determination of enrollment changes and ability sorting, but previous work focuses almost exclusively on the post-World War II period. Lochner and Monge-Naranjo (2011) look at the role of student loan policies with limited commitment, and shows that this can generate ability sorting. Our focus on an earlier time period excludes the student loan innovations they consider, so we instead investigate other factors that may be relevant in understanding ability sorting. Garriga and Keightley (2007) consider the impact of different education subsidies for enrollment and time-to-degree decisions, in a model with borrowing constraints and risky education investment. Hendricks and Leukhina (2011) consider the role of borrowing constraints and learning in understanding the evolution of educational earnings premia. Like this paper, Altonji (1993) and Manski (1989) assume that high school students do not perfectly know their own ability, and they use this feature to investigate the role of preferences, ability, and earnings premia for enrollment and dropout. Cunha, Heckman, and Navarro (2005) extend the model developed in Willis and Rosen (1979) to include uncertain ability, and find that roughly sixty percent of the variability in returns to schooling is forecastable.

Hendricks and Schoellman (2012) study the same time period as we do, but they take data on college completion and student ability as given in order to understand changes in the college earnings premium in a complete markets model. By contrast, we seek to understand the economic factors that affected college completion and average student ability for cohorts since 1900. Perhaps most related to this paper is Castro and Coen-Pirani (2012), who ask whether educational attainment over time can be explained by earnings premia in a complete markets model. They find that it cannot. Our model, with limited borrowing and uncertainty about ability, matches college attainment well for early cohorts, but shares the problem that the model overpredicts attainment after 1950 due to the increase in the earnings premia for these cohorts. In both, disgarding individuals' ability to perfectly forecast future earnings premia helps the model fit, but not entirely.

Our work also relates to a number of empirical papers on the impact of different economic forces on historical post-secondary completion, including college costs and income (Campbell and Siegel, 1967), student ability (Taubman and Wales, 1972), academic quality (Kohn, Manski, and Mundel, 1976) and borrowing constraints (Hansen and Weisbrod, 1969).

2 Model

In this section, we develop an overlapping generations model to investigate the causes of increased college completion and increased ability sorting.[3] The relevant features include borrowing limits, uncertain ability, and risky completion of college education. The notation introduced in this section is summarized in Table 2 of the Appendix.

Demographics and Preferences Time in the model is discrete, and a model period is one year. Each period, N_{mt} males and N_{ft} females are born, each of whom lives for a total of T periods. Let $a = 1, 2, \ldots, T$ denote age. Each individual maximizes expected lifetime consumption

$$\mathbb{E}_0 \sum_{a=1}^{T} \beta^{a-1} \left(\frac{c_a^{1-\sigma} - 1}{1 - \sigma} \right)$$

Endowments and Signals Individuals are ex-ante heterogeneous along three dimensions: their sex, m or f, initial asset endowment k_0, and ability to complete college, denoted α. The probability that any individual completes his or her current year of college is given

[3] The counterpart to ability in the data is IQ.

by $\pi(\alpha)$, where $\pi' > 0$. Log initial assets, $\log(k_0)$, and ability α are drawn from a joint normal distribution with correlation ρ_t, means $\mu_{\alpha,t}$ and $\mu_{k,t}$, and standard deviations $\sigma_{\alpha,t}$ and $\sigma_{k,t}$. Note that the parameters on the joint distribution for $\{\alpha, k_0\}$ are potentially time-varying.

While sex and asset endowments are perfectly observable, ability α is not. Instead, each individual receives a signal $\theta = \alpha + \varepsilon$ at the beginning of life. The error term is $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. Note that because assets and ability are jointly distributed, individuals actually receive two pieces of information about ability – the signal θ and asset endowment k_0. Let $\nu = (k_0, \theta)$ be the information an individual has about his true ability. After the initial college enrollment decision, ability α becomes publicly observable.

Education Decisions The population we are considering consists of high school graduates, so that birth in this model translates to a high school graduation in the real world. At birth, every individual decides whether or not to enroll in college, given sex, asset endowment k_0, and signal θ. This is the only time this decision can be made. Once enrolled in college, individuals can only exit college by graduating or failing out with annual probability $\pi(\alpha)$. After failure, individuals enter the labor force and may not re-enroll, consistent with the finality of dropout decisions discussed in Card and Lemieux (2001). Graduating college requires C years of full-time education at a cost of λ_t per year. If an individual decides to not enter college, he or she immediately enters the labor market and begins to work.

Labor Market We adopt the common assumption that individuals of different ages, a, sex s, and education, e, are different inputs into a constant returns to scale production function that requires only labor. Therefore, wages depend on age, sex, education level, and the year. We write wages as $w_{a,t}(e, s)$ for $s \in \{f, m\}$ and $e \in \{0, 1, \ldots, C\}$. While ability α has no direct effect on realized wages, it does affect expected wages because higher ability students are more likely to graduate college and earn higher wages.

Savings Market Each individual can borrow and save at an exogenous interest rate r_t. We assume individuals must die with zeros assets, so $k_{T+1} = 0$. Borrowing is constrained to be a fraction $\gamma \in [0,1]$ of expected discounted future earnings. Therefore, individuals must keep assets k_t each period above some threshold $\bar{k}$, where

$$\bar{k} = -\gamma \cdot \mathbb{E} \sum_{n=a}^{n=T} \frac{w_{n,t}}{1+r_t}$$

Note that both the expectations operator and wage can depend on a number of factors, including ability α, age a, year t, education e, and sex s. Therefore, the borrowing constraint will be written as the function $\bar{k}(\alpha, a, t, e, s)$. In a slight abuse of notation, we will write $\bar{k}(a, t, e, s)$ when the borrowing constraint does not depend on ability α, as is the case once an individual finishes college.

2.1 Timing and Recursive Problem

At the beginning of year t, N_{mt} men and N_{ft} women are born at age $a = 1$. Again, each individual is initially endowed with assets k_0, sex s, ability α, and a signal θ of true ability. Immediately, each individual decides whether or not to enroll in college. If he or she enrolls in college, true ability is immediately realized, and the individual proceeds through college. In the case of failure (due to $\pi(\alpha)$) or graduation, he or she proceeds to the labor market and works for the remainder of his or her life. Individuals who do not enroll in college proceed directly to the labor market, where they receive the wage associated with age a, education $e = 0$, and sex s.

Recursive Problem for Worker For individuals currently not enrolled in college, their ability is irrelevant for their decision problem. Therefore, the value of entering year t at age a with assets k, years of college education e, and sex $s \in \{f, m\}$ is:

$$\begin{aligned} V^w_{a,t}(k,e,s) &= u(c) + \beta V^w_{a+1,t+1}(k',e,s) \\ s.t. \qquad c + k' &= (1+r)k + w_{a,t}(e,s) \\ k' &\geq \bar{k}(a,t,e,s) \\ k_{T+1} &= 0 \end{aligned}$$

Recursive Problem for College Student If instead an individual is currently enrolled in college, he has already completed e years of his education and must pay λ_t in college costs for the current year. The probability that he passes and remains enrolled the next year, however, depends on his ability α. Recall that α is known with certainty as soon as the education decision is made, so there is no uncertainty about ability.

The value of being enrolled in college at year t at age a, with assets k, ability α, e years of education completed, and sex $s \in \{f, m\}$ is:

$$\begin{aligned} V^c_{a,t}(k,\alpha,e,s) &= u(c) + \beta\Big[\pi(\alpha)V^c_{a+1,t+1}(k',\alpha,e+1,s) + (1-\pi(\alpha))V^w_{a+1,t+1}(k',\alpha,e,s)\Big] \\ s.t. \quad c + k' - \lambda_t &= (1+r)k \\ k' &\geq \bar{k}(\alpha,a,t,e,s) \\ \pi(\alpha) &= 0 \quad if \ a = C \ \forall\alpha \end{aligned}$$

The last restriction simply states that if $a = C$, that individual is graduating college and cannot acquire any more years of college education.

The College Enrollment Decision Given the value of being enrolled in college and working, it is possible then to define the educational decision rule at the beginning of life. Recall that at this point, α is unknown, but each individual receives a signal $\nu = (k_0, \theta)$. Each individual then constructs beliefs over possible ability levels by using Bayes' Rule.

Let $F(\alpha; k_0, \theta)$ be the cumulative distribution function of beliefs (as defined by Bayes' Rule) over ability levels. Given all this, an individual born in year t of sex s with assets k_0 and signal θ enters college if and only if the expected value of entering college is higher than the (certain) value of entering the workforce. This is given by the inequality

$$\int_\alpha V^c_{1,t}(k_0,\alpha,1,s)F(d\alpha;k_0,\theta) \geq V^w_{1,t}(k_0,0,s) \tag{2.1}$$

3 Calibration

The goal of this paper is to assess the role played by a number of features of the economy in understanding ability sorting and college enrollment over time. We therefore take a multi-faceted approach to parameterizing the model. First, we construct historical data series for N_{mt}, N_{ft}, and λ_t, which are incorporated directly into the model. Second, we estimate life-cycle wage profiles $w_{a,t}(e, s)$, which are taken as given by model individuals solving their dynamic problem. Third, we exogenously choose values for T, C, r_t, β, ρ_t, $\mu_{\alpha,t}$, $\mu_{k,t}$, $\sigma_{\alpha,t}$, $\sigma_{k,t}$, and $\pi(\alpha)$. Finally, we calibrate $\sigma_{\epsilon,t}$, and γ in order to match important features of the time series data. Each of these are discussed in more detail below.

3.1 Historical Time Series Data

As previously mentioned, N_{mt} males and N_{ft} females are "born" into the model each year, meaning they graduate high school and enter the model eligible to make college enrollment decisions. We take high school completion, and thus the population of potential college enrollees, as exogenous. The series for N_{mt} and N_{ft} are taken directly from the U.S. Statistical Abstract Historical Statistics, and we use linear interpolation to supply missing values.

Annual college costs per student, λ_t, are calculated as the average tuition and fee expenses paid out-of-pocket by students each year.[4] Note that because we measure average *out-of-pocket* costs in the data, λ_t accounts for changes over time in the average amount of financial aid received by students in the form of public and private scholarships and grants. Full details of the data construction are relegated to Appendix A. Briefly, however, we compute λ_t each period as the total revenues from student tuition and fees received by all institutions of higher education divided by the total number of students enrolled in those institutions. The complete time series is constructed by splicing together data from historical print sources including the *Biennial Surveys of Education* (1900 to 1958) and the *Digests of Education Statistics* (since 1962).

[4] Additional student expenses, such as room and board, could also be included, and in fact we do consider these costs as a robustness exercise in Section 5. We choose to leave these out of the benchmark specification because such costs are usually more accurately classified as consumption rather than education expenses, and must be paid regardless of college enrollment status.

3.2 Life-Cycle Wage Profiles

Life-cycle wage profiles $w_{a,t}(e, s)$ are estimated using decennial U.S. Census data from 1940 through 2000, along with American Community Survey (ACS) data from 2006-2010. Each ACS data set is a 1% sample of the U.S. population, so that when combined they constitute a 5% of the U.S. population, similar to a decennial census. The data are collected from the Integrated Public-Use Microdata Series (IPUMS) (Ruggles et al., 2010), and include wage and salary income, educational attainment, age, and sex. From age and education data we compute potential labor market experience, x, as age minus years of education minus six. We assume that wages can be drawn from one of three education categories - high school, some college, or college. These correspond to $e = 0$, $e \in [1, C - 1]$ and $e = C$ in the model. For each education category, we estimate wage profiles for the non-institutionalized population between ages 17 and 65 who report being in the labor force using the following regression:

$$\log(w_{i,t}) = \delta^b_{i,t} + \sum_{j=1}^{4} \beta^s_j x^j_{i,t} \tag{3.1}$$

where i denotes individuals, b is birth-year cohort, s is sex, and x is potential labor market experience. In words, we regress log wages on a full set of birth year dummies plus sex specific quartics in experience.

3.3 Exogenous Parameters

Parameters set exogenously prior to solving the model are: T, C, r_t, β, ρ_t, $\mu_{\alpha,t}$, $\mu_{k,t}$, $\sigma_{\alpha,t}$, $\sigma_{k,t}$, and $\pi(\alpha)$. We set the length of working life at $T = 48$, implying that individuals born into the model at age 18 would retire at age 65. The number of periods required to complete college is $C = 4$, so that all individuals in the model have post-secondary education $e \in \{0, 1, 2, 3, 4\}$.[5] The real interest rate is set to $r_t = 0.04$ in all periods, and the discount rate is $\beta = 0.96$, a standard value in models with annual periods.

We now turn to the parameters for the joint normal distribution over $\{\alpha, k\}$. Recall from Section 2 that α only affects an individual's probability of passing college. Fur-

[5] We are not presently concerned with educational attainment beyond the bachelor's degree level, so we do not model post-graduate education in this paper.

thermore, our interest in "ability" is limited to understanding changes over time in the average ability of college versus non-college students *within cohorts*. In other words, we only care here about the relative ability of students within the same birth year, as in the data from Figure 1b, not across birth years. As this is our objective, we do not have to worry about trends in average student ability (such as the so-called "Flynn effect") and can normalize the ability distribution for each birth cohort. For this reason, we set $\mu_{\alpha,t} = 0$ and $\sigma_{\alpha,t} = 1$, for all t, so the distribution for α is a standard normal, conditional on k_0.

Unlike with ability, we are certainly concerned about changes over time in the mean and variance of the initial asset distribution. We interpret k_0 as a reduced-form way of capturing all of the personal financial resources available to a new high school graduate, including but not limited to parental gifts and bequests, and the individual's own income and savings. Additionally, since the model does not allow for individuals to work while in college, we interpret initial assets to also include the present value of income earned while enrolled. With this in mind, we require that the mean and standard deviation of initial assets in the model to track the mean and standard deviation of income in U.S. data. To this end, we start with $\mu_{k,t}$ equal to the annual mean real income per person, as in Piketty and Saez (2006) so that the average real asset endowment in the model equals the actual real mean income in the U.S. each year. Then, in order to account for the fact that $\mu_{k,t}$ includes the individuals' own earnings while in college, we adjust it upward for men and downward for women so that the difference between mean asset endowments for men and women matches the gender earnings gap in our estimated wage profiles during college years.

Piketty and Saez (2006) also provide historical data on the share of income received by the top ten percent of individuals, as well as the cut-off income level for the 90th percentile. Assuming that the U.S. income distribution is log-normal as predicted by Gibrat's law, we can use these data to back out the implied standard deviation of the U.S. income distribution each year. The procedure is as follows. Let real income in year t, denoted Y_t, be a random variable with realization y_t such that $Y_t \sim \ln \mathcal{N}(\mu_t, \sigma_t^2)$ and the associated cumulative distribution function is $F_Y(y_t; \mu_t, \sigma_t^2)$. Observed data are the real mean income in the U.S. in year t, denoted $\overline{y}_t$, and the 90th percentile of real income in year t, denoted $y_{90,t}$. A standard property of the log-normal distribution is that $\mathbb{E}[Y_t] = \exp(\mu_t + \frac{\sigma_t^2}{2})$. Since $\mathbb{E}[Y_t] = \overline{y}_t$ is observed, we can guess a value $\tilde{\sigma}_t^2$ and solve for the associated mean of the distribution:

$$\tilde{\mu} = \ln(\overline{y}_t) - \frac{\tilde{\sigma}_t^2}{2}$$

Next, we compute $1 - F_Y(y_{90,t}; \tilde{\mu}, \tilde{\sigma}_t^2)$, which would be the fraction of total income received by those with income above the threshold value $y_{90,t}$ if the mean and variance of the income distribution were actually $\tilde{\mu}$ and $\tilde{\sigma}_t^2$. This process continues iteratively until we find a value σ_t^2, and associated μ_t such that the fraction of income received by the top ten percent equals that observed in the data. We then set $\sigma_{k,t} = \sigma_t$.

The last parameter related to the stochastic endowment process that we need to determine is ρ_t, the correlation between ability and initial asset endowments. Lacking the rich historical data that would be required to properly identify this parameter, we will assume for the benchmark parameterization that $\rho_t = 0$ for all t, so that ability and assets are independent random variables. Intuitively, though, one would expect some positive correlation between a student's financial resources and his or her probability of completing college. It is well known, for example, that parental income is positively related with student test scores and performance (Black, Devereux, and Salvanes, 2005; Cameron and Heckman, 1998). Moreover, this correlation also implies a more precise signal of ability. Thus, we later examine in Section 5.1 how the results may change as we allow ρ to increase.

Finally, we need to set the annual probability of passing college, $\pi(\alpha)$. Note that $\pi(\alpha)$ is a reduced form way to capture college non-completion for any reason, including failure and voluntary drop-out. We employ the simple assumption that an individual's *cumulative* probability of completing college equals her percentile rank in the ability distribution. For example, an individual whose ability is higher than 75% of the peers in her birth-year cohort will complete college with probability 0.75, conditional on enrollment. With the length of college set to $C = 4$, there are 3 independent opportunities for failure - after the first, second, and third years of school. Thus, the *annual* probability $\pi(\alpha)$ is simply the cumulative probability raised to the power one-third.

3.4 Calibrated Parameters

Finally, we choose the borrowing constraint, γ, and the variance of the noise on the ability signal, $\sigma_{\epsilon,t}$, to replicate the two main data series of interest – college completion and the average ability of college relative to non-college individuals. The borrowing constraint is set to $\gamma = 0.025$ in order to match the time series of college completion. Intuitively, this means that in any given period an individual can borrow up to 2.5% of his expected lifetime income. Post-schooling, this amount is known with certainty because the wage profiles are given, but during college the expected lifetime income is conditional on the probability of passing college.

Unfortunately, we do not have direct evidence on the precision with which individuals in a given cohort know their own ability relative to their peers. At a qualitative level, it is likely that this precision has increased – i.e., $\sigma_{\epsilon,t}$ has likely decreased – over time. In the early part of the 20th century, no standardized exams existed to compare students within cohorts across schools. Those college admissions exams that did exist were generally school-specific, so there was little scope for comparison of students across schools. During World War I, the U.S. military began testing recruits using the Army Alpha and Army Beta aptitude tests. By World War II, these tests were replaced by the Army General Classification Test (AGCT), a precursor to the Armed Forces Qualification Test (AFQT). On the civilian side, the introduction of the Scholastic Aptitude Test (SAT) in 1926 started a trend toward more widespread use of standardized exams as a college admissions criteria. As standardized testing became more common, students obtained more and more precise signals of their own ability relative to peers. In the modern era, virtually every student contemplating college takes either (or both) of the SAT or the ACT (American College Testing) exams. Even those who do not take these college admissions exams still have quite precise information about their relative ability because other standardized exams are mandated at public schools.

With this historical background in mind, we make the following assumptions on the time series structure of $\sigma_{\epsilon,t}$. For cohorts making college decisions prior to World War II, i.e., those born 1900 through 1923 and graduating high school from 1918 through 1941, we assume that $\sigma_{\epsilon,t}$ decreases linearly from $\sigma_{\epsilon,1900} = 2$ to $\sigma_{\epsilon,1923} = 0.2$. For cohorts born after 1923, $\sigma_{\epsilon,t}$ remains constant at 0.2. This is an admittedly ad hoc construction, but in a simple way it captures the trend of each subsequent cohort getting slightly better information than the previous cohort as aptitude and ability tests became more common in the time between the world wars. By the completion of World War II, such tests were in widespread use and students likely had quite precise signals about their own ability relative to peers.

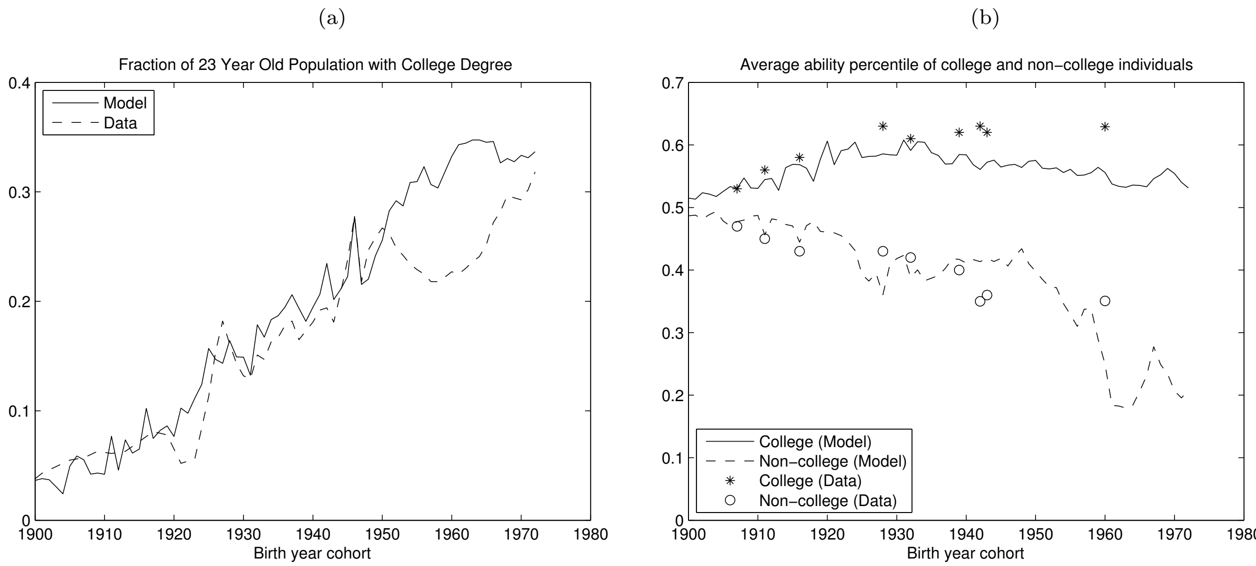
4 Results

Our main computational exercise consists of first simulating the model for U.S. birth cohorts from 1900 through 1972 (i.e., students who graduated high school from 1918 through 1990), verifying that the model replicates important features of the historical data, and then running counterfactual simulations to quantify the impact of changes in direct college costs, education earnings premia, and opportunity costs of college (foregone wages) on college completion and average student ability. Having discussed the benchmark model parameterization, we now examine how well the simulated model matches U.S. data.

4.1 Benchmark Model Fit

Figure 2 depicts the model predictions along with historical U.S. data for college completion and average student ability. The measure of college completion that we choose to match is the share of 23-year-olds with a college degree. While educational attainment is often measured later in life to capture those who complete college at older ages, we prefer this series for a couple of reasons. First, to our knowledge it is the only measure of college completion with consistent time series data for birth cohorts back to 1900. Second, our model is not constructed to evaluate college enrollment decisions of older students who: (i) are generally less financially-dependent upon parents when paying for education; (ii) face different opportunity costs of school after having been in the workforce for some time; and (iii) may anticipate different return on investment in education due to later-life completion.

Figure 2: Benchmark Model Results



Panel (a) of Figure 2 shows that, overall, the model replicates well the trends in U.S. college completion over much of the 20th century, with one notable exception. The model does not capture the initial decline and subsequent increase in college completion for cohorts born in the 1950s and 1960s. This deviation is due primarily to the modeling assumption that individuals know their lifetime wage profile with certainty, implying that they can perfectly forecast changes in the education earnings premium. Later we consider alternative assumptions, and find that the model can generate more accurate predictions over this time period.

Panel (b) of Figure 2 plots the average ability percentile of students who attempt college (even if they do not complete), and those who have only high school education. While we only have a few reliable data points to match, those we do have show a clear pattern of increased sorting by ability over time. For cohorts born at the beginning of the 20th century, college and non-college students had similar ability on average, but the ability gap widened throughout the century. This general pattern is also predicted by the model.

Table 1: Measures of Fit for Various Model Specifications

	Fraction of 23-year-olds with College Degree				Average Ability Difference
Model \ Cohorts	1900-1972	1900-1925	1926-1950	1951-1972	1900-1972
Benchmark	0.158	0.015	0.009	0.133	0.034
Imperfect foresight	0.055	0.020	0.013	0.022	0.028
Constant costs rel. to income	0.134	0.024	0.011	0.099	0.034
$\text{Corr}(\alpha, k_0) = 0.30$	0.183	0.023	0.017	0.143	0.038
Include room and board	0.159	0.019	0.017	0.123	0.035

In order to facilitate quantitative comparison with alternative specifications, we also provide measures of model fit over various time periods in Table 1. The measure of fit we report is the sum of squared deviations between model and data. The columns labeled "Fraction of 23-year-olds with college degree" refer to the series in Panel (a) of Figure 2. For this series, we compute the fit over all cohorts 1900-1972, and three subsamples: 1900-1925, 1926-1950, and 1951-1972. As seen in the "Benchmark" model specification in Panel (a) of Figure 2, the model matches the data very closely for cohorts born pre-1950, but does less well for cohorts born after 1950. The column labeled "average ability difference" measures how well the model matches the difference between the average ability percentile of college and non-college individuals. We only report the full sample for this statistic because there are so few data points to match within the sub-sample periods.

4.2 Discussion of Benchmark Results

Our measure of college completion – the fraction of twenty-three year olds with a college degree – can be decomposed as

$$\frac{P^{grad}}{P^{23}} = \left(\frac{P^{HS}}{P^{23}}\right)\left(\frac{P^{enroll}}{P^{HS}}\right)\left(\frac{P^{grad}}{P^{enroll}}\right) \tag{4.1}$$

where P^{HS}, P^{enroll}, and P^{grad} are the number of people that complete high school, enroll in college, and graduate college. The model's predictions for college completion can be decomposed into the three terms on the right hand side of equation (4.1). While the first is exogenous, the second and third terms are endogenous to the model. In this section, we use this decomposition to understand what drives the change in college completion predicted by the model.

Figure 3: College Enrollment Conditional on High School Graduation

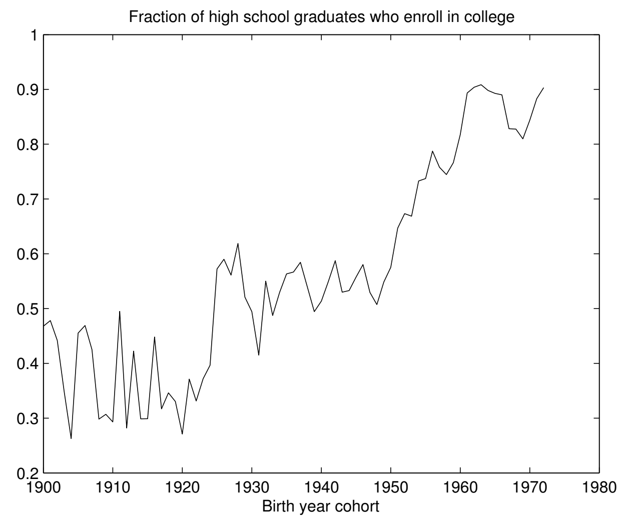
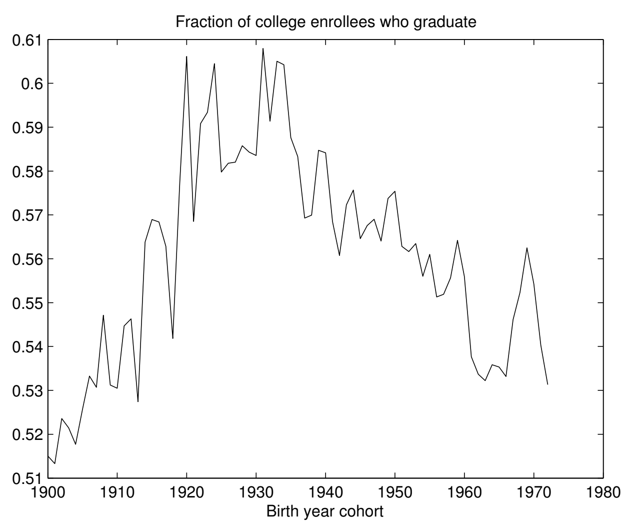


Figure 4: College Pass Rate



First, Figure 3 plots the share of high school graduates that enroll in college, as predicted by the model. In the language of equation (4.1), this is P^{enroll}/P^{HS}. Figure 3 shows that for cohorts born between 1900 and 1920, college enrollment rates conditional on high school graduation were between 30 and 50 percent, albeit with a lot of noise. This rate increased for cohorts born in the 1920s and generally remained between 50 and 60 percent for cohorts through 1950, after which the rate again increased substantially.

The third term in equation (4.1) is the share of college enrollees that graduate by age twenty-three. This is given by the ratio P^{grad}/P^{enroll} and is plotted in Figure 4. While Figure 4 shows that the college pass rate has a fair amount of year-to-year noise, the hump-shaped trend is still evident. From the 1900 through 1930 birth cohorts, the college pass rate increased from about 51% to nearly 61%. After the 1930 cohort, however, this trend reverses, and the pass rate steadily declines back down to around 53%. This result is consistent with evidence from Bound, Lovenheim, and Turner (2010), who compare the high school class of 1972 (roughly birth cohort 1954) to that of 1992 (birth cohort 1974) and find a significant decrease in college completion conditional on enrollment. In our model, this pattern is due entirely to the ability composition of college students. Recall from Panel (b) of Figure 2 that the average ability of college enrollees was generally increasing through the 1930 cohort, then decreasing in the following cohorts. Unfortunately, we have found no reliable historical data to compare with the model's predicted pass rates. However, the National Center for Education Statistics (NCES) does provide more recent data we can use for a rough comparison. For the cohort beginning college in 1996 (assuming they are around 18 years old on average, this would be approximately the 1976 birth cohort), the share completing college within five years was 50.2%.[6] Our last birth cohort in the model is 1972, so the comparison is not perfect, but the model pass rate of 53.1% for that cohort is quite close.

We now isolate the effects of the college enrollment and college pass rates through two counterfactual experiments. We ask two questions. First, how does college completion change relative to the benchmark if there were no endogenous increase in the college enrollment rate, as in Figure 3? Second, how does college completion change if there were no endogenous changes in the college pass rate, as in Figure 4? Results from these two experiments are plotted in Figure 5, along with the benchmark prediction for college completion.

[6] See Table 341 in the 2010 *Digest of Education Statistics*.

Figure 5: College Completion if Enrollment Rates and Pass Rates were Constant

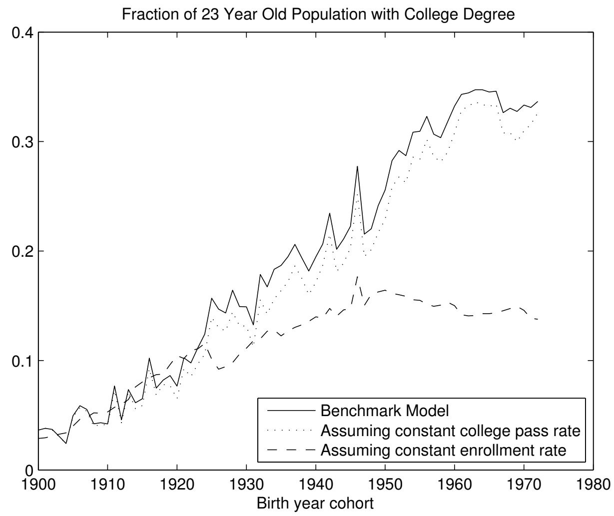


Figure 5 shows that if the college enrollment rate had remained constant instead of rising after the 1920 cohort, the model would have under-predicted college completion rates by more than half by the end of the time series.[7] Similarly, if the college pass rate had instead remained constant at the 1900 value of 51.5%, then college completion would have been several percentage points lower than in the benchmark model. It is clear, however, that the quantitative effects of changes in college enrollment are much larger than those due to changing college completion rates.

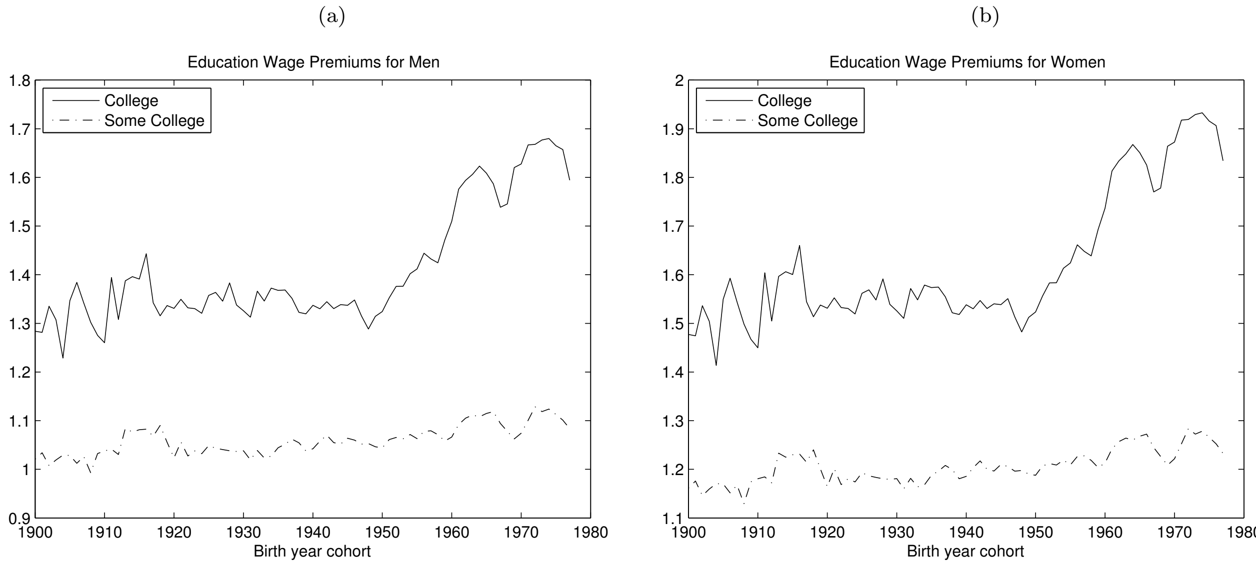
4.3 Counterfactual Experiments

4.3.1 What if individuals do not have perfect foresight of education earnings premia?

Figure 6 shows that for cohorts born in the U.S. prior to 1950, the education premia implied by our estimated life-cycle wage profiles exhibit some year to year variation, but essentially no trend. Beginning around the 1950 cohort, however, the college earnings premia began increasing steadily. We now examine how the model predictions for college completion and average student ability would differ if, instead of predicting changes in the education premium exactly, model individuals expected an historical average education earnings premia to prevail in the future as well.

[7] In Figure 5, we assume that the the college enrollment rate conditional on high school graduation is constant at 36.9%, which is the average enrollment rate for cohorts 1900 through 1920.

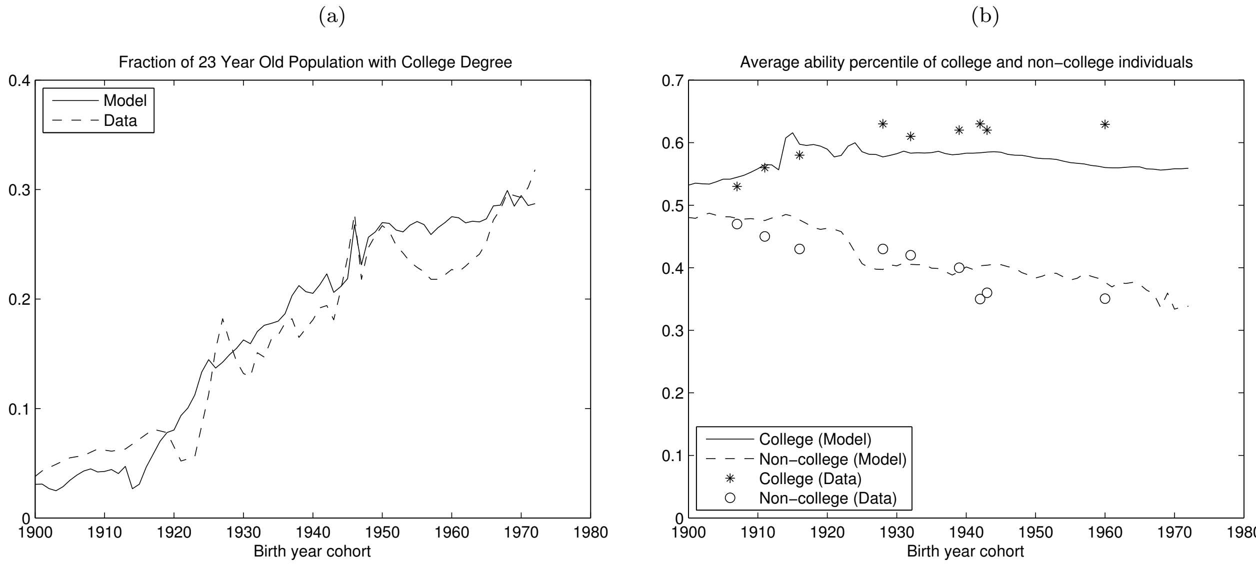
Figure 6: Education Premia Implied by Estimated Life-Cycle Wage Profiles



For this exercise, we assume that the high school wage for each cohort is observable, but the earnings premia for individuals who complete college or some college are not observable. Rather, individuals observe a moving average of the earnings premia earned by previous cohorts and assume their own cohort's earnings premia will be the same. Thus, as the true college earnings premium begins rising, newly born cohorts will predict the increase imperfectly and with several years lag.

Figure 7 shows the model predictions under this counterfactual experiment, assuming a 25-year moving average. Relative to the benchmark model results, notice that the model now comes much closer to the actual college completion rate in the data for cohorts born after 1950. The model still does not capture all of the decline for the cohorts in the 1950s, but as Table 1 clearly shows, this specification fits the data much better than the benchmark assumption that individuals perfectly forecast changes in the education premia. Over the entire time period, the sum of squared deviations declines by almost two-thirds from the benchmark value of 0.158 to 0.055. All of this gain is due to the 1951-1972 cohorts, where the sum of squared deviations changes from 0.133 to 0.022, a decrease of more than 83%. Additionally, the model's ability to match changes in average ability of college and non-college students also improves under this specification. According to the

Figure 7: Results with Imperfect Foresight of Education Earnings Premia



last column of Table 1, the sum of squared deviations declines from 0.034 to 0.028. These improvements strongly suggest that perfect foresight of education earnings premia is a problematic assumption. Accurately modeling students' expectations about the returns to education is crucial for understanding college enrollment decisions, particularly during periods of time when education premia are changing rapidly.

4.3.2 What if real college costs increased proportional to real disposable incomes?

We now ask how college completion rates and average student ability would have differed over the time period in question if real college costs were constant with respect to real average income. Figure 8 depicts the actual time series data for real college costs that we use in the benchmark model (solid line), along with a hypothetical series for college costs which are a constant fraction of annual real average income (dashed line). From 1920 to around 1940, the actual series exceeds the hypothetical series due the the fact that per student tuition and fees spiked relative to income during the Great Depression. Then from the early 1940s until about 1990, the hypothetical series is above the actual series. Holding all else constant, we would expect that individuals in the counterfactual model facing the hypothetical college costs should attend college in greater numbers for the cohorts born from about 1900 to 1920 (those in school from around 1920 to 1940), and fewer of those born after 1920 would attend college.

Figure 8: College Costs

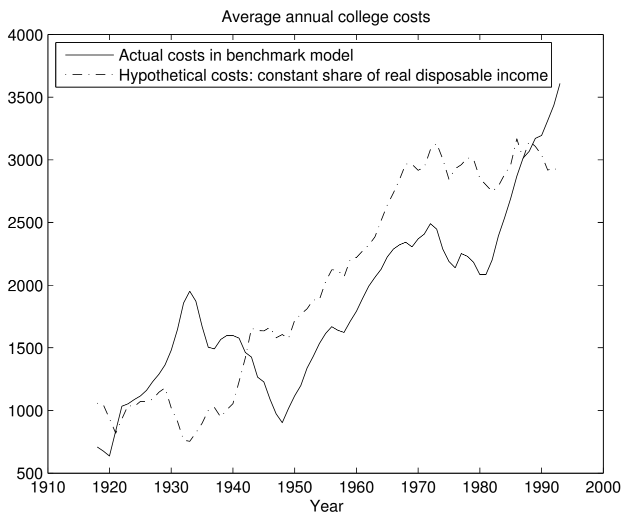
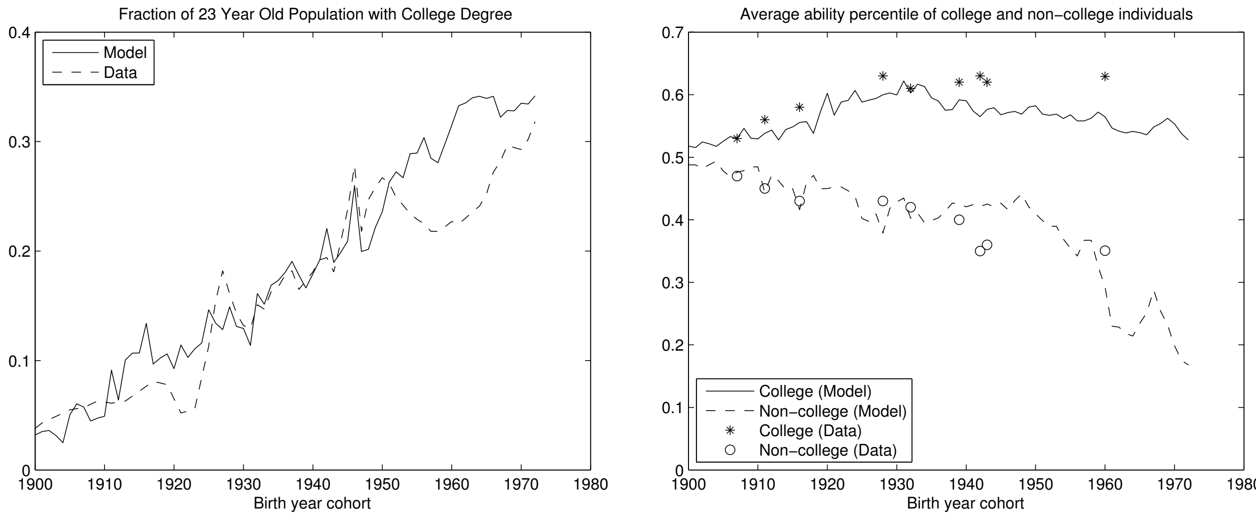


Figure 9 largely confirms these predictions. Relative to the data, the model predicts too many people attending college for those cohorts born between about 1910 and 1925. For the cohorts from 1925 through 1950, the model does predict slightly fewer college graduates, but still matches the data quite closely. And finally, for the cohorts born after 1950, the model still predicts more college graduates than in the data. However, as can be seen in Table 1, the model fit improves over this period since the sum of squared deviations fall from 0.133 to 0.099, a decrease of more than 25%. Turning to Panel (b) of Figure 9, there are hardly any discernible differences in average ability of college and non-college students relative to the benchmark model. This can also be confirmed by noting that sum of squared deviations for the average ability difference in Table 1 is unchanged from the benchmark value of 0.034. We conclude that the fluctuations in real college costs relative to real income are not a major factor in accounting for the increased ability sorting over time.

Figure 9: Results with Alternative College Costs

(a) (b)



5 Robustness

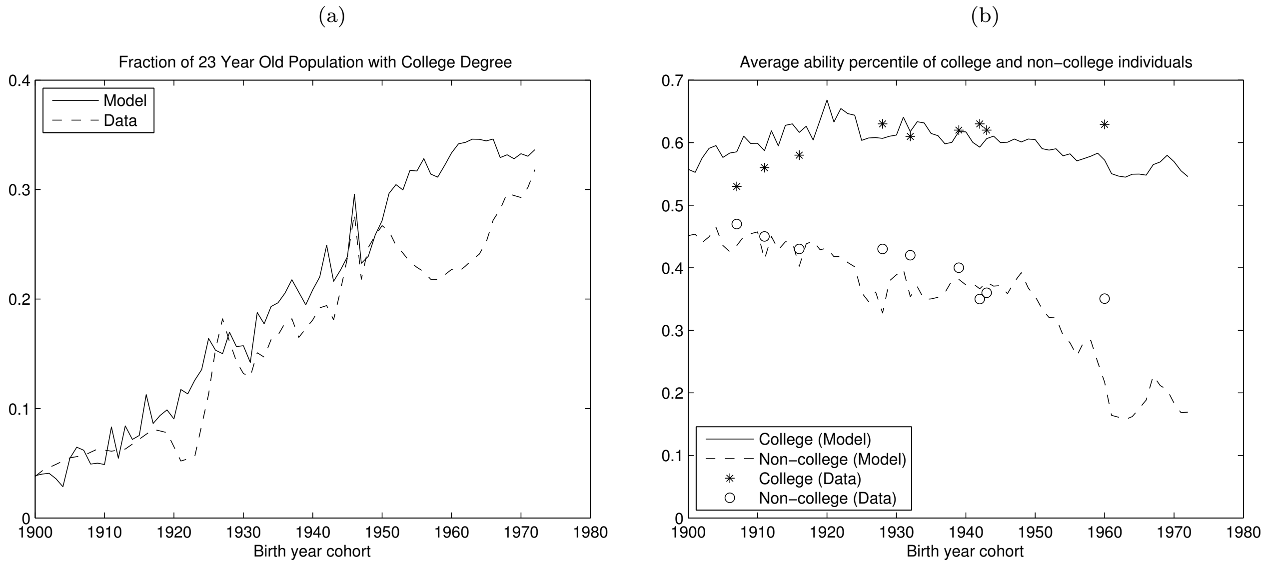
Having discussed the benchmark model results and counterfactual experiments, we now make a few remarks about the robustness of some modeling assumptions. In particular, we made the strong assumption that ability and initial assets were uncorrelated. We also assumed that room and board were excluded from college costs. We now relax these assumptions and see how they affect the results.

5.1 Correlation of Ability and Initial Assets

In the benchmark specification, we assumed that the random endowments for ability and assets were uncorrelated. However, there is evidence to suggest that these may be positively correlated, and we want to understand how this affects the results. We maintain the assumption that α and $\log(k_0)$ share a bivariate normal distribution, only now we set $\rho = 0.3$. All other parameters are maintained as in the benchmark specification. Figure 10 shows the model predictions for college completion and ability sorting between college and non-college individuals.

Relative to the benchmark model results, two things are notable. The positive correlation between ability and assets increases college completion minimally throughout

Figure 10: Results with Positive Correlation between Ability and Initial Assets



the time period, and it increases the difference in ability between college and non-college students during earliest birth cohorts. Both of these effects reduce the model fit slightly, as seen in Table 1. The increase in completion is simply due to the fact that higher ability students are now more likely to have greater financial resources as well, thus making them more likely to attend college. The effect on average ability is also quite intuitive. Recall that individuals receive information $\nu = (k_0, \theta)$, where $\theta = \alpha + \varepsilon$ is the noisy signal of true ability α. As ρ increases k_0 becomes more informative about α, so individuals with high initial assets will infer that they have higher ability, and thus be more likely to enroll in college. This increases the average ability of individuals who attempt college, while simultaneously decreasing the average ability of non-college individuals. The effect is largest for earlier birth cohorts because later birth cohorts received more accurate signals about their true ability.

5.2 College Costs Including Room and Board

College costs in the benchmark model were restricted only to tuition and fees. Now, we take a broader view of college costs and examine whether or not the results are sensitive to the inclusion of room and board expenses. Like the earlier time series data on college tuition and fees, we construct this data from printed historical government documents. The details are found in appendix A. For this experiment, all calibrated values are maintained just as in the benchmark economy, with the exception of the borrowing constraint, γ. We need to adjust γ because students now face additional college expenses, so college completion rates would be too low if we held γ constant at the benchmark value. The new borrowing constraint which allows us to match the time series of college completion is $\gamma = 0.04$.

Figure 11: Results for College Costs including Tuition, Fees, Room, and Board

(a) (b)

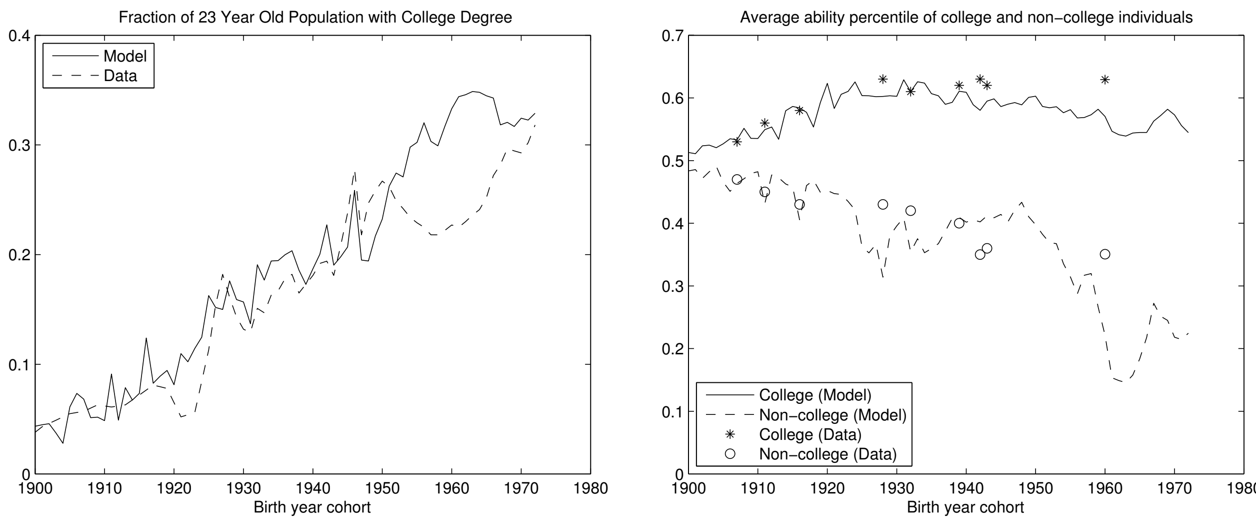


Figure 11 shows the model predictions for college completion and average student ability when room and board costs are included. Relative to the benchmark results in Figure 2, very little has changed. The model still predicts college completion rates in line with the data up until the 1950s and 1960s cohorts, when model and data diverge. Additionally, average ability of college and non-college students diverges over time just as in the benchmark model. Referring to Table 1, it is clear that while the model fits college completion slightly worse than the benchmark model pre-1950, it does slightly better post-1950. On the whole, this model fits almost exactly as well as the benchmark model for both college completion and average ability difference.

6 Conclusion

We develop an overlapping generations model with unobservable ability and borrowing constraints to investigate post-secondary completion and ability sorting in the birth cohorts of 1900–1972. To discipline our model, we digitize and utilize historical data series including statistics on college costs and high school graduation rates. We find that the share of high school graduates enrolling in college and the subsequent college pass rate are both key for understanding increased college graduation rates. However, we find no evidence that economic factors – including real college costs, opportunity costs, education wage premia, or asset endowments – have a major impact on increasing ability sorting over time. We do find, however, that a decrease in the variance of ability signals can properly match this fact, a trend which we attribute to increases over time in standardized testing.

An important deviation between the benchmark model and historical data is that the model does not properly match college completion after the 1950 birth cohort. We show that this could be due to individuals having imperfect foresight about the college earnings premium. If individuals observe a moving average of the earnings premia from previous cohorts and use this to estimate the future earnings premium, then changes in the earnings premium are taken into account only with a lag. We build this into the model and find that it significantly improves the model's fit. We therefore view this as evidence of backward looking wage estimation when making college enrollment decisions.

An interesting use of this framework would be an extension to multiple countries. Evidence suggests that ability is strongly related to growth (Hanushek and Kimko, 2000), but the causality from formal schooling to economic growth is somewhat tenuous (Bils and Klenow, 2000). If developing countries have very little ability sorting between education levels, as was the case in the early U.S., there may be a weak correlation between education level and labor efficiency. In a cross-country context, this could arise due to tighter borrowing constraints or less precise signals about true ability. We will explore this link in future research.

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Appendices

A Data

We take several historical data series as exogenous to the model, and this section details the construction of those series. Data are taken from several sources in order to construct a consistent series since 1900. From 1900 to 1958, most data were collected every two years and published in the Biennial Survey of Education (BSE). Since 1962, the Digest of Education Statistics (DES) has been published annually. Other publications including the annual U.S. Statistical Abstract, the Bicentennial Edition "Historical Statistics of the United States: Colonial Times to 1970", and "120 Years of American Education: A Statistical Portrait" help in bridging breaks between series, as well as verifying continuity of series that may have changed names from year to year. Also, many data were revised in later publications, so we take the most recent published estimates where available.

First, let c_t be the total annual cost of college per student. We assume that the total cost for educating *all* students in the U.S. in a given year equals the total revenues received in the current period by all institutions of higher education. Dividing this by the total enrollment each year yields the total annual cost per student. Alternatively, one could use the total current expenditures rather than revenues as the measure of total cost, but this makes little difference quantitatively because revenues and expenditures track each other quite closely. In addition, the revenue data is preferable because it allows us to determine how much of costs are paid out-of-pocket by students for tuition and fees, and how much comes from other sources such as state, local, and federal governments, private gifts, endowment earnings, auxiliary enterprises (athletics, dormitories, meal plans, etc.), and other sources. The numerator for c_t is constructed as follows:

- 1997-2000: total current revenue must be computed as the sum of current-fund revenue for public and private institutions, from the DES.
- 1976-1996: total current revenue equals "current-fund revenue of institutions of higher education" from the DES.
- 1932-1975: total current revenue equals "current-fund revenue of institutions of

higher education" in "120 Years of American Education: A Statistical Portrait".

- 1908-1930: total current revenue equals "total receipts exclusive of additions to endowment" for colleges, universities, and professional schools, from the BSE.
- 1900-1908: total current revenue equals "total receipts exclusive of additions to endowment" for colleges, universities, and professional schools, and is computed as (income per student)*(total students, excluding duplicates) from the BSE. Continuity with later years can be verified using the "income per student" series, which was published from 1890-1920.

The denominator for c_t is constructed as follows:

- 1946-2000: total fall enrollment for institutions of higher education, from the DES.
- 1938-1946: resident college enrollments, from the BSE. Continuity with the later series can be verified in that year 1946 data matches in both.
- 1900-1938: total students, excluding duplicates, in colleges, universities, and professional schools, from the BSE. Continuity with the later series can be verified in that year 1938 data matches in both.

Second, we construct two time series which estimate the share of annual college costs paid out-of-pocket by students. One measure, λ_t, includes only tuition and fees paid by students, and the other measure, ϕ_t includes tuition, fees, room, and board. In each year λ_t equals total tuition and fees paid by all students divided by total current revenue received by institutions of higher education. Similarly, ϕ_t equals total tuition, fees, room, and board aid by all students divided by total current revenue received by institutions of higher education. In each case, the measure of total current revenue is the same time series as was used above in constructing c_t. The time series for λ_t is constructed as follows:

- 1997-2000: current fund revenues from tuition and fees for all institutions of higher education is computed as the sum of the series for public and private institutions, from the DES.

- 1976-1996: current fund revenues from student tuition and fees, from the DES.
- 1930-1975: current fund revenues from student tuition and fees, from "120 Years of American Education: A Statistical Portrait".
- 1918-1930: receipts of universities, colleges, and professional schools for student tuition and fees, from BSE.
- 1900-1918: we are unable to obtain proper data for these years.

The time series for ϕ_t is constructed as follows:

- 1976-2000: Average tuition, fees, room, and board paid by full-time equivalent (FTE) students is obtained from the DES. We multiply this by enrollment of FTE students, also from the DES, and divide by the current fund revenues to compute ϕ_t.
- 1960-1976: we are unable to obtain proper data for these years.
- 1932-1958: Data available biennially on 1total revenues from student tuition and fees, as well as revenue from auxiliary enterprises and activities (room and board), in the BSE. ϕ_t computed as the sum of these, divided by total current revenue.
- 1900-1930: ϕ_t computed as total revenue from student fees (included tuition, fees, room, and board) divided by total current revenue.

Table 2: Summary of Notation

Symbol	Definition
N_{mt}	Number of males born into model (i.e., graduating high school) each year
N_{ft}	Number of females born into model (i.e., graduating high school) each year
a	Age of individual, where $a = 1, 2, ..., T$
s	Sex of individual, where $s \in \{f, m\}$
k_0	Initial asset endowment
α	Ability endowment
$\pi(\alpha)$	Annual probability of passing college, given ability α
ρ_t	Correlation between initial asset and ability endowments
$\mu_{\alpha,t}$	Mean of ability distribution
$\mu_{k,t}$	Mean of initial asset distribution
$\sigma_{\alpha,t}$	Standard deviation of ability distribution
$\sigma_{k,t}$	Standard deviation of initial asset distribution
θ	Signal of true ability, where $\theta = \alpha + \varepsilon$
ε	Error term on signal of true ability
σ_{ε}	Standard deviation on distribution for ε
ν	Vector of variables that are informative about true ability, where $\nu = (k_0, \theta)$
C	Number of years required to graduate from college
e	Years of education completed by individual, where $e \in \{0, 1, ..., C\}$
λ_t	Annual cost of college in year t
$w_{a,t}(e, s)$	Wage in year t for individual of age a, sex s, and education e
γ	Individuals may not borrow more than a fraction γ of expected discounted future earnings
$\bar{k}$	Minimum asset level for individual, given age, sex, education, and γ