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The Limited Impact of Free College Policies

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Abstract

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Keywords: higher education, free college, financial aid.
JEL codes: E24, I21.

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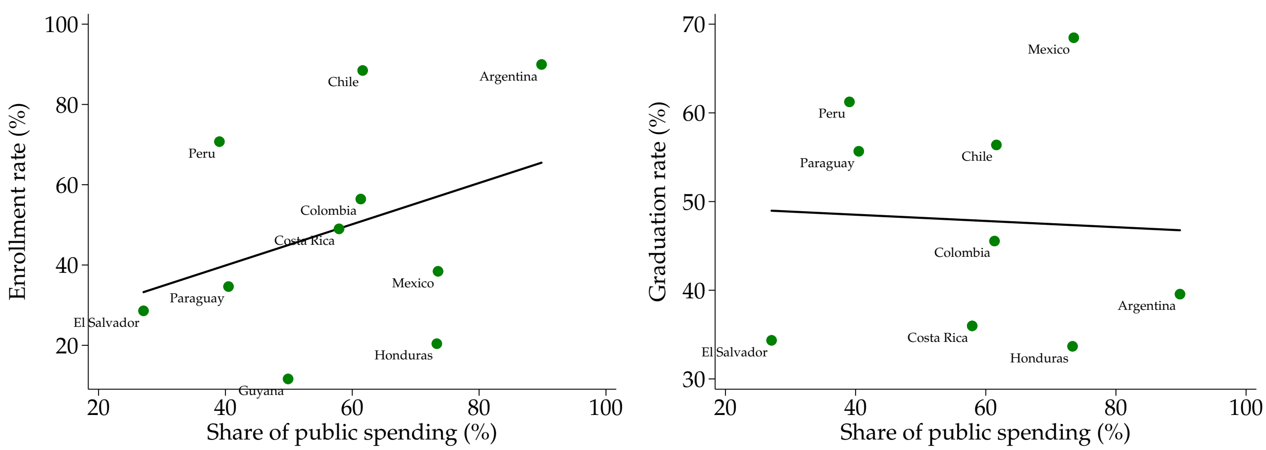
1 Introduction

In modern economies, higher education is crucial to the formation of skilled human capital. Not only can higher education raise a country's productivity; it can also lower income inequality. By subsidizing access to higher education, policymakers can contribute to these two roles. The question, then, is how large a subsidy they should provide. Free college advocates argue that policymakers should provide a full subsidy, resulting in zero tuition for students. While free college has existed for years in a number of countries, new proposals have sprouted recently in other countries, including the United States, Chile, and Colombia.[1]

Free college advocates claim that only when college is free can it realize its promise, particularly that of lowering inequality. Since Latin America is the most unequal region in the world (World Bank, 2016), many in the region view free college as the ultimate solution to persistent inequality and lack of social mobility. The existing evidence on government spending in higher education in the region, however, does not bode well for free college. As Figure 1 shows, countries in the region that finance a greater share of higher education spending have higher enrollment rates (panel a) but not higher graduation rates (panel b).[2]

Figure 1: Higher Education Enrollment and Graduation by Public Spending Share in Latin America.



a. Enrollment b. Graduation

Source: UNESCO for 2017 enrollment rates and share of public spending in higher education; own calculations based on Socio-economic Database for Latin America and the Caribbean—SEDLAC (CEDLAS and The World Bank) for 2017 graduation rates.
Notes: Gross enrollment rate is the ratio between higher education enrollment and the number of individuals ages 18-24. Graduation rate is the ratio between the number of individuals ages 25-29 who have graduated from higher education and the number of individuals in that age group who have ever started higher education. Share of public spending is government spending in higher education relative to total higher education spending.

[1] Among the countries surveyed by OECD (2018), college is free at public institutions in Argentina, Brazil, Cuba, Czech Republic, Denmark, Ecuador, Estonia, Egypt, Finland, Germany, Greece, Iceland, Mexico, Norway, Panama, Poland, Slovenia, Sweden, Turkey, and Uruguay. Most recently, Chile introduced free college (*gratuidad*) in 2016 for students from the six lowest income deciles; in Colombia the newly elected government has proposed universal free college.

[2] This evidence, however, is not unique to Latin America. Evidence from a sample of eleven developed countries yields similar results (see Appendix A.) These countries are not included in Figure 1 because their graduation rates are not fully comparable to those of Latin American countries.

To capture this evidence and investigate the potential effects of free college policies, in this paper we focus on a specific determinant of their success—student effort. While free college can have the direct and straightforward effect of expanding college access and enrollment rates, any effect on graduation rate will be necessarily mediated by student effort. Whether free college succeeds or not at boosting graduation and attainment will largely depend on its impact on student effort.

Thus, in this paper we exploit the dynamic model of college enrollment, performance, and graduation developed and estimated in Ferreyra et al. (2022). In the model, a college student faces risks which may prevent her from completing a class or remaining in college, yet she can mitigate them by exerting effort. The model is estimated with unique administrative data on the universe of higher education students in Colombia, a country highly representative of Latin America. According to the estimates, effort has a much larger role than ability in class completion, and failure to model effort leads to overestimating ability's role by a factor of two or three. We use the parameter estimates to simulate various free college programs which differ in eligibility requirements. We study free college effects on enrollment and graduation and conduct a cost-benefit analysis of the policies. Our analysis is relevant for any country considering free college, as student effort is a universal determinant of student success.[3]

In Latin America, *Mincerian* returns to higher education are high—104 percent on average relative to a high school diploma (Ferreyra et al., 2017)—yet higher education access is often limited by severe liquidity and credit constraints.[4] Free college can help overcome these constraints yet might not be fiscally feasible, particularly in the aftermath of the COVID-19 pandemic. Further, the cross-country evidence presented above suggests that free college might not raise the percentage of college graduates.[5] One possible explanation is that free college might disproportionately attract poorly prepared students, yet another is that it might discourage student effort. By eliminating tuition payments, free college raises student consumption during college and therefore the attractiveness of being a college student (the "college experience"), with three potential effects on effort. First, the student may want to enjoy the enhanced college experience and delay graduation (*loss of urgency* effect), thereby lowering effort. Second, the student may become more willing to exert costly effort since the consumption increase would compensate for it (*substitution* effect). Third, to the extent that academic performance is persistent over time, effort changes affect not just current but also future performance and the student's capacity to withstand shocks (*risk* effect). While the net impact of the three effects might vary across students, a negative net effect on many students could, in principle, lead to lower graduation rates in the aggregate.

Because of its potential role in free college's success, student effort is a critical piece in our study. It represents inputs chosen by the student—such as hours and intensity of study time—that are costly (particularly for low-ability students) yet contribute to academic performance. In the structural model, a high school graduate decides whether to enroll in college. In college, she must complete a set number of classes to graduate. Each year she chooses her effort;

[3]The empirical literature on effort, cited below in the Introduction, uses data from a wide a variety of countries, including Spain, the US, Canada, and the almost thirty countries participating in the PISA test.

[4]In Colombia, for example, the the market for student loans is limited limited, covering only 7 percent of students in 2003 (ICETEX, 2010).

[5]Throughout, "percentage of college graduates" refers to the percentage of high school graduates that graduate from college. For a given set of high school graduates, it is the product of their college enrollment rate and the graduation rate for those who enroll in college.

together with her ability and a performance shock, effort determines how many classes she completes. At the end of the year she receives another shock which may force her to drop out. Since both shocks are dependent on past performance, she can insure against them by keeping a good cumulative performance. Effort, then, provides a direct benefit on class completion and an indirect one on risk mitigation.

We use the Simulated Method of Moments (SMM) parameter estimates from Ferreyra et al. (2022), which capture the main features of the data and yield a realistic baseline for our policy analysis. In the baseline, a staggering 70 percent of high school graduates come from low-income families and only 32 percent of students enroll in college within five years. Among those who attend college, only 46 percent graduate, mostly late. Student ability—measured by a proxy of college academic readiness—plays a large role in first-year survival but a lesser role in subsequent performance. In contrast with ability, which explains little of the variation in performance across students and over time, effort and performance shocks have greater explanatory power. Further, performance is persistent over time. As a result, early performance is a strong predictor of final outcomes.

We simulate multiple free college programs with different eligibility requirements: *universal* (all students), *need-based* (low-income students), *ability-based* (high-ability students), *performance-based* (all students eligible in the first year; eligibility conditional on past cumulative performance in subsequent years), and a need-based version of the ability- and performance-based programs. In each counterfactual we distinguish between *existing* students (who enroll in the baseline and the counterfactual) and *new* students (who do not enroll in the baseline but enroll in the counterfactual). This allows us to separate impacts on the intensive margin (due to the effort response of existing students) from those on the extensive margin (due to composition effects associated with new students).

Our findings can be summarized as follows. First, at the aggregate level, free college programs expand enrollment but not necessarily graduation. The greatest enrollment expansion corresponds to universal free college, followed by need- and performance-based free college (85, 72, and 66 percent relative to the baseline, respectively). On average, new students are of lower income and ability than existing students except under ability-based programs, which by design attract high-ability students. Graduation rate effects are modest—between -3 and 6 percent relative to the baseline—yet vary between new and existing students. New students pull down the overall graduation rate except under ability-based free college, in which case they pull it up. For existing students, graduation rates change little relative to the baseline except under performance-based programs, when they rise by 8-14 percent. Similar patterns hold for on-time graduation rates. Even though performance-based free college does not expand enrollment as much a universal free college, it compensates with a higher graduation rate and delivers a similar increase in the ultimate object of interest—the fraction of college graduates. Since most Latin American countries provide either universal or need-based college subsidies (Ferreyra et al., 2017), these predicted aggregate outcomes rationalize the pattern in Figure 1: greater tuition subsidies raise enrollment rates but have little or no effect on graduation rates.

Second, free college effects vary greatly across students, within and across programs. Consider, for instance, universal free college. Although enrollment rates rise for all students, effects are largest for low-income students. Graduation rates, in contrast, do not rise for all (existing) students. They rise by about 10 percent relative to the baseline for mid-ability students due to a strong substitution effect, but fall for high-ability and high-income students due to a strong loss-of-urgency effect. In contrast, graduation rates rise for *all* students under performance-based free college, with larger gains for lower-income, lower-ability students. By making the level of college consumption contingent on performance, this program eliminates the loss-of-urgency effect and induces greater effort on the part of all students.

Third, free college provides some insurance against college's inherent uncertainty, yet not to the same extent across programs or college years. Using the uncertainty metric developed in Ferreyra et al. (2022), we find that, after the first college year, on average both universal and performance-based free college lower uncertainty relative to the baseline by raising the expected consumption during college. In the initial years, this insurance role is weaker under performance-based than universal free college because the insurance is conditional on performance. Nonetheless, it is stronger afterwards because that very conditionality induces greater effort, which insures students against poor academic performance and dropout risks. Providing students with conditional—rather than unconditional—insurance therefore leads to more human capital accumulation.

Fourth, the main mechanism by which free college programs raise the fraction of college graduates is increasing enrollment rather than graduation rates. To increase the latter, free college must lead students to exert a sufficiently large effort so as to complete *all* the required classes, something which is too costly for some students. This is reminiscent of Oreopoulos and Petronijevic (2019), who find that even when students see the need of greater effort to improve outcomes, they respond by lowering expectations rather than increasing effort. Free college, then, is a limited tool to raise the fraction of college graduates. Helping students lower the cost of effort—for example, by teaching them to study more effectively or by providing advising, mentoring and academic remediation—might be a necessary complement for free college.

Fifth, universal free college is not the most equitable or efficient free college program. It is not equitable because it gives a full tuition subsidy to all students regardless of their need. It is not efficient because a similar fraction of college graduates could be attained at a lower fiscal cost with need- or performance-based free college. In our simulations, the fiscal cost per graduate is about 20 percent lower under need- or performance-based free college than under universal free college while the fraction of college graduates is approximately the same (25 percent) for all three programs.

Since our counterfactuals assume the most favorable conditions for free college, our results provide an upper bound for free college effects. We assume colleges have no capacity constraints, the marginal cost of educating new and existing students is the same, and free college does not crowd out parental transfers to children in college. We do not model taxation (which might be required to pay for free college programs), and assume that the college wage premium relative to a high school diploma does not fall as the fraction of college graduates rises.[6] Relaxing any of these assumptions would lead to less favorable free college outcomes.

We contribute to several literatures. First, we relate to the emerging literature on free college, including Bucarey (2018) on the implementation of free college in Chile and Murphy et al. (2019) on the elimination of free college in England, and to the extensive literature on college financial aid in the US, including the recent literature on free community college and the so-called "Promise" programs.[7] We contribute to this literature by focusing on the role of student

[6] In Section 5.8 we investigate potential general equilibrium effects from the greater supply of college graduates. Since we find them to be small even in the medium run, we abstract away from them in our analysis.

[7] Section 5.5 reviews this literature. For recent reviews, see Avery et al. (2019) and Dynarski and Scott-Clayton

effort in the success of free college programs. Our results provide a theoretical justification for the financial aid literature in the U.S., which finds positive and large enrollment effects for financial aid, small or null graduation effects, and larger graduation effects for performance-based than unconditional financial aid. Our results are also consistent with a tuition subsidy program implemented in Colombia between 2014 and 2018, *Ser Pilo Paga* ("Being diligent pays off"), which provided performance-based free college to low-income, high-ability students and had large enrollment rate effects but relatively small graduation rate effects (Londoño et al., 2020, 2022). Second, we relate to the literature using structural models for college choices.[8] In Colombia, as in other developing countries, parental resources matter greatly to college enrollment even controlling for ability. This provides strong evidence for credit constraints limiting college access.[9] Absent credit market frictions, college enrollment would depend on student ability rather than parental resources.[10] While focusing on ability, the literature may have overlooked the role of effort, as argued by Ferreyra et al. (2022). Empirically, a growing number of studies highlight the importance of effort to explain cross-country variation in test score performance, or the variation across students in their response to academic incentives.[11] Third, we join in the literature exploring college as a risky endeavor.[12] We contribute to this literature by modeling risk via performance and dropout shocks that are not exogenous—as in these papers—but depend endogenously on student past performance and effort, and quantify the risk-reduction role of free college.

The rest of this paper is organized as follows. Section 2 describes the data and institutional environment for Colombia. Section 3 presents the theoretical model, and Section 4 describes its empirical implementation and estimates. Section 5 presents free college simulation results, analyzes the insurance role of free college, conducts a simple cost-benefit analysis, and examines potential general equilibrium effects. Section 6 concludes.

2 Data

This section presents our data and describes key stylized facts for Colombia's higher education environment. We draw from two administrative datasets at the student level, Saber 11 and SPADIES, and one at the program level, SNIES.[13] We focus on five-year bachelor's programs,

(2013). On "Promise" programs, see Scott-Clayton (2011), Castleman and Long (2016), Dynarski et al. (2018), Bettinger et al. (2019), Page et al. (2019), Gurantz (2020) and Bartik et al. (2021).

[8]This large literature started with seminal contributions by Keane and Wolpin (2001), Eckstein and Wolpin (1998), and Keane (2002). Close to our focus on effort, Ahn et al. (2019) have recently modeled effort in response to grading incentives. For other recent contributions, see Athreya and Eberly (2021), and the references therein.

[9]Garriga and Keightley (2007), Lochner and Monge-Naranjo (2011), Hai and Heckman (2017), and Solis (2017).

[10]See, for instance, Cameron and Heckman (1998, 1999) and Carneiro and Heckman (2002).

[11]Zamarro et al. (2019), Stinebrickner and Stinebrickner (2004, 2014), Ariely et al. (2009), Beneito et al. (2018), and Ahn et al. (2019)

[12]See Levhari and Weiss (1974), Altonji (1993), Akyol and Athreya (2005), Garriga and Keightley (2007), Stange (2012), Hendricks and Leukhina (2017, 2018), Matsuda (2020) and Athreya and Eberly (2021).

[13]Saber 11 contains students' test scores at the national mandatory high school exit exam—also called Saber 11—and self-reported socio-economic information, including family income bracket, expressed in monthly minimum wages (MW). SPADIES tracks the academic progression of college students by semester, including number of classes taken and completed as well as graduation/dropout status. SNIES contains program-level information, including institution, field, and tuition.

which captured most of the country's total higher education enrollment during our sample period. To analyze college enrollment, we focus on the decisions made by high school graduates from the 2005 cohort. We use students' standardized test scores in Saber 11, the mandatory high school exit exam, as our measure of student ability, broadly understood as academic readiness for higher education. We calculate deciles and quintiles of the Saber 11 distribution for high school graduates (in what follows, deciles and quintiles always refer to this distribution). For consistency with the model, we classify students into "student types," defined by combinations of student ability quintiles and family income brackets (income is not reported in levels but in brackets.) Table B1 shows the distribution of student types in this cohort. While 70 percent of high school graduates come from the lowest two income brackets, less than 5 percent come from the top one. Not surprisingly, income and ability and strongly and positively correlated.

Due to data availability, for our analysis of final outcomes and academic progression we focus on students from the 2006 college entry cohort and follow them for eight years. Since different programs require different numbers of classes completed for graduation, we normalize this requirement to 100 classes to facilitate exposition, and assume that students are required to complete 20 classes per year to be on track for on-time graduation. "Classes completed" (or "performance") denotes the number of classes completed *in a given year*, and "cumulative classes completed" (or "cumulative performance") is the total number of classes completed *over all years* up to (and including) that one. A student is on track for on-time graduation when she has completed her on-track requirements, equal to accumulating 20, 40, 60, 80, and 100 classes by the end of years 1 through 5 respectively. To analyze cumulative performance, we classify students into *tiers* based on their cumulative performance relative to the corresponding year's on-track requirement (tier 1 is the highest.)[14] Importantly, a student can change tiers over time—catching up to a higher tier or falling to a lower one.

For the 2005 high school cohort, the college enrollment rate is 32 percent.[15] Nonetheless, enrollment rates vary widely among student types (Figure 2 panel a), as students of higher income and ability are more likely to enroll. On average, the enrollment gap between the highest and lowest income brackets is equal to 55 percentage points (pp). Free college may therefore have ample room to raise enrollment.

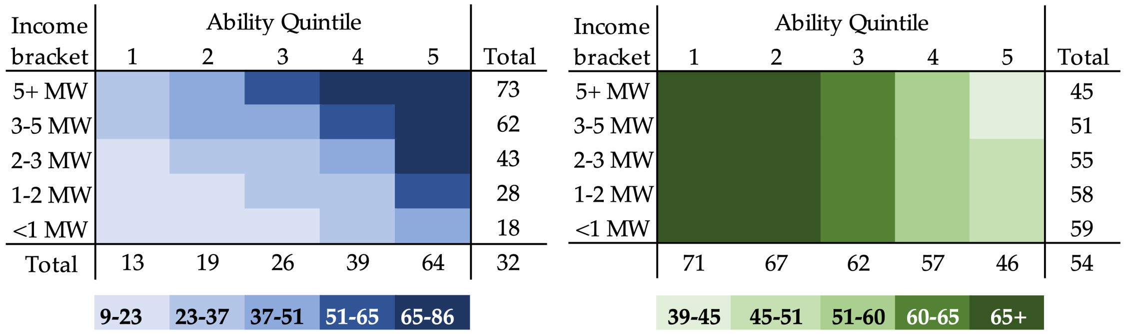
The riskiness of college is illustrated by the fact that only 45.7 percent of students from the 2006 entry cohort graduates—15.1 percent on time (in five years) and 30.6 percent late (in 6-8 years).[16] Dropout rates are far from uniform over time (Figure 3 panel a). Over a quarter of college students leave in the first year, and the first two years account for about 70 percent of all dropouts. Similar to enrollment rates, dropout rates vary widely across student types (Figure 2 panel b). Conditional on income, higher ability students have lower dropout rates;

[14]Tiers 1 through 4 correspond to students who complete the following percentage of the on-track requirements for the year: 95 percent or more for tier 1, (85, 95] percent for tier 2, (65, 85] percent for tier 3, and 65 percent or less for tier 4. For example, consider a student who accumulates 16, 35, 42, 50, and 60 classes by the end of years 1 through 5 respectively. This amounts to 80 (=16/20), 88 (=35/40), 70, 62.5, and 60 percent of the corresponding on-track requirements. Thus, the student falls in tiers 3, 2, 3, 4, and 4 in years 1 through 5 respectively. See Table B2 for further details on tier classification.

[15]This is the fraction of high school graduates who enroll in college within five years. For comparison, in the US the enrollment rate of individuals ages 16-24 who finished high school in 2005 and started college right away (rather than within five years) is 44.6% (Source: Digest of Education Statistics).

[16]For comparison, in the U.S. 59.2 percent of students from the 2006 cohort graduated within six years—39 percent on time (in four years), and 20.2 percent late (Source: Digest of Education Statistics).

Figure 2: Enrollment and Dropout Rates by Income and Ability.



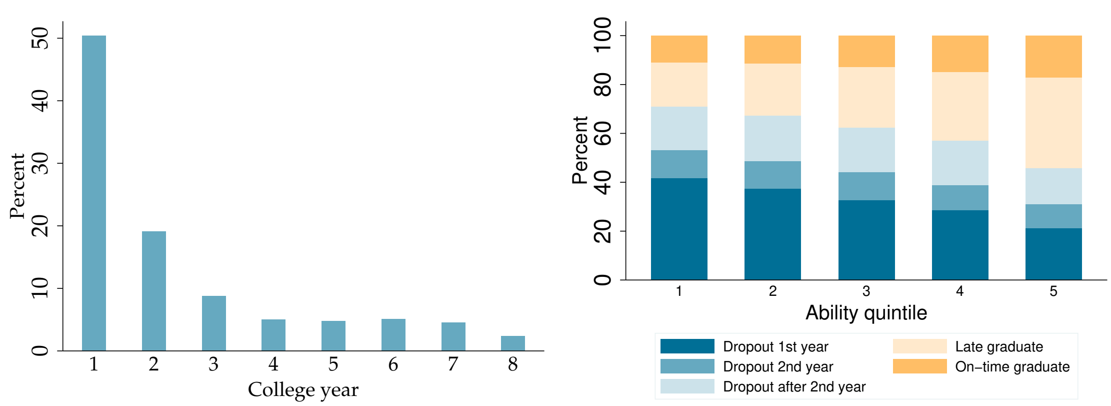
a. Enrollment Rate   b. Dropout Rate

Source: Calculations based on SPADIES and Saber 11 for 2005 high school graduates (Panel a) and students from the 2006 college entry cohort (Panel b).
Notes: Panel a depicts the percent of high school graduates from a given income bracket and ability quintile who enrolled in a bachelor's program between 2006 and 2010. Panel b depicts the percent of students from a given income bracket and ability quintile who drop out of their bachelor's program. A student is classified as a dropout if she does not graduate within eight years. Income is reported in brackets; MW = monthly minimum wage. Ability is reported in quintiles of standardized Saber 11 scores; quintile 1 is the lowest.

on average, the dropout rate gap between the highest and lowest ability quintiles is equal to 25 pp. In contrast, dropout rates vary less by income—suggesting that free college might affect enrollment more than graduation rates.

We now turn to the role of ability in college outcomes and academic performance. As Figure 3 panel b indicates, ability seems to play a large role in whether students drop out in the first year. While low-ability students are more likely than others to drop out in the first year, the likelihood of dropping out later is similar across abilities. Because they are more likely to survive the first-year dropout risk, higher-ability students are more likely to graduate (mostly late). The chances of on-time graduation, in contrast, vary little across abilities.

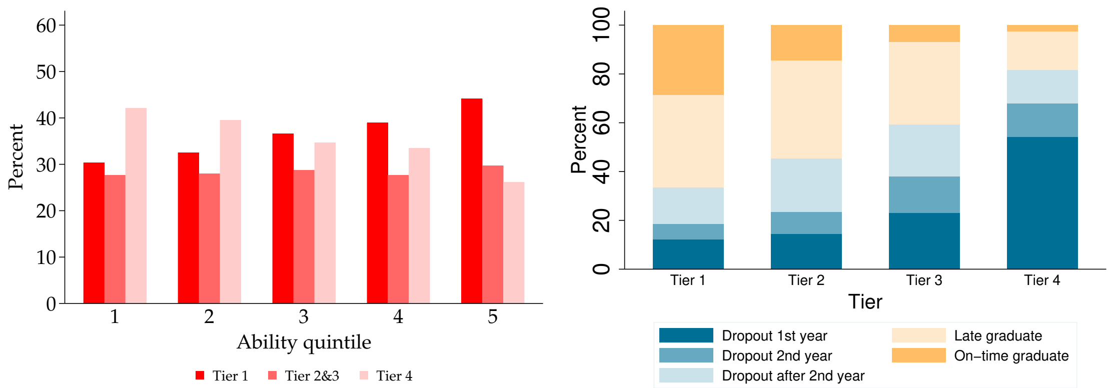
Figure 3: College Outcomes, Timing, and Ability.



a. Dropout Timing   b. College Outcomes by Ability

Source: Calculations based on SPADIES, for students from the 2006 college entry cohort.
Notes: In panel a, the figure shows the percent of students who drop out in each college year (relative to all students who drop out). In panel b, the figure shows the percent of students of a given ability quintile (quintile 1=lowest) who attain each outcome.

Figure 4: First-year Classes Completed and College Outcomes.



a. First-year Performance Tiers by Ability

b. College Outcomes by First-year Performance Tier

Source: Calculations based on SPADIES for students from the 2006 entry cohort.
Notes: For students of a given ability quintile, panel a shows their classification into year-1 performance tiers (tier 1 is the highest). Panel b shows the percent of students from each year-1 performance tier that attain every final college outcome. In year 1, tier 1 corresponds to 19+ classes completed; tier 2 to [17, 19); tier 3 to [13, 17); and tier 4 to [0, 13).

Students make progress through college by accumulating classes completed. Perhaps surprisingly, academic progress does not bear a strong relation with ability. Panel a of Figure 4 shows the distribution of students of every ability quintile by year 1's performance tiers. Performance shows some variation across abilities, as higher-ability students are more likely to perform at the top tiers than their lower-ability counterparts. But, more strikingly, performance varies widely *within* abilities, as some low-ability students perform in the top tiers, some high-ability students perform in the bottom ones, and a sizable fraction of students from every ability perform in the middle tiers. Given this large within-ability variation, cumulative performance varies little, on average, across abilities (a similar pattern holds for other years.)

Unlike ability, past performance is a strong predictor of future performance. For instance, the number of classes completed—as early as in year 1—is a powerful predictor of final outcomes (Figure 4 panel b). For example, about 70 percent of top-tier students in year 1 go on to graduate whereas less than 20 percent of the bottom-tier students graduate. Further, cumulative performance is highly persistent over time—students who start on track are more likely to remain on track, less likely to fall behind, and more likely to catch up should they fall behind (Ferreyra et al., 2022).

To summarize, family income seems related more related to enrollment than to dropout rates. Most dropouts leave college in year 1 and are low-ability students. Conditional on surviving the first year, ability plays a small role explaining student performance, but past performance plays a strong one. The model and parameter estimates capture these data features.

3 Model

The model developed in Ferreyra et al. (2022) is for a representative cohort of high school graduates who differ in ability, family income, and idiosyncratic preferences for college enrollment.

They choose whether to enroll in college or enter the labor force as high school graduates. College graduation requires the completion of a set number of classes. The combination of ability, effort, and performance and dropout shocks determines class completion and final college outcomes. Being on track with classes completed helps students mitigate the risk posed by these shocks. In the labor market, wages depend on educational attainment (high school graduate, college graduate, or college dropout) and work experience.

Before continuing, it is important to clarify the meaning of "ability" and "effort" in the model. Ability refers to academic readiness—not innate ability—and may therefore capture pre-college elements such as high school quality and home environment. Ability is predetermined at the time of college enrollment and remains fixed during college. Effort, in contrast, is chosen by the student every year during college. It represents all student inputs that can change over time and are costly to the student, such as hours and intensity of study time. Increasing effort, therefore, may not mean studying more hours but studying more effectively. The important point is that effort is costly, and more so for less-prepared students (who may not have been taught to study effectively, for instance).

Further, the model captures the notion that ability alone does not determine a student's performance; rather, low-ability students who exert high effort might perform at the same level as high-ability students who exert little effort. It also captures the notion that "success begets success" because the performance and dropout shocks depend on the student's cumulative performance. As a result, a student who performs well in the first year is more likely to perform well later on and graduate.

3.1 Endowments and preferences

High school graduates differ in ability, $\theta \in \{\theta_1, \theta_2, \ldots, \theta_{n_\theta}\}$, and annual parental transfers received while in college, $y \in \{y_1, y_2, \ldots, y_{n_y}\}$. The combination of ability and parental transfers defines the student's type $j = 1, 2, \ldots, J$, with $J = n_\theta \times n_y$. For simplicity we refer to y as "income." Students receive y only if enrolled in college; if not, they earn a labor market wage as explained below. In our computational version we allow y and θ to be correlated.

A period, t, represents a year (and an academic year during college). For college students, instant utility depends on consumption, c, and study effort, e. Effort cost is heterogeneous across students and depends on ability. The instant utility at t is $U(c_t, e_t, \theta) = u(c_t) - g(e_t, \theta)$. Function U satisfies $u' > 0$, $u'' < 0$, $g_1 > 0, g_{11} > 0$, $g_2 < 0$, and $g_{12} < 0$. The effort cost is therefore increasing and convex, with higher total and marginal costs for lower-ability students. For workers, instant utility depends only on consumption. Both for college students and workers, the discount factor is β.

3.2 College decisions

College is a multi-period, risky investment. To graduate, students must complete a required number of classes, h^{grad}. Students must spend a minimum of five and a maximum of eight years in college in order to graduate. Every year, students must complete $\bar{x}$ classes in order to graduate on time. The number of actual classes they complete, x_t, may be higher or lower than $\bar{x}$, and depends on student's ability, effort, and a performance shock. Students choose effort based on their *target* number of classes to complete, $q_t = E(x_t)$.[17]

3.2.1 College technology

Let h_t denote the cumulative number of classes completed by the end of t, or $h_t = \sum_{n=1}^{t} x_n$. Let $\bar{h}_t$ denote the average number of classes completed per year up to the end of t, or $\bar{h}_t = h_t/t$. Students start college with $h_0 = \bar{h}_0 = 0$, and by the end of year 1 attain $h_1 = \bar{h}_1 = x_1$. Students complete classes in year t according to the following production function:

$$x_t = H(z_t, \theta, e_t)\ \overline{x}. \tag{1}$$

The number of classes completed x_t, is a multiple of the annual requirement for on-time graduation, $\overline{x}$. The scalar $H(.)$ is a function of ability, effort, and a performance shock, $z_t > 0$. Since $H(.)$ is non-negative and can be greater or lower than one, the student can complete more or fewer classes than the annual requirement. The shock, drawn from a continuous distribution known to the student, includes a random *i.i.d.* component as well as a component that depends on her ability, number of cumulative classes completed up to the beginning of t, and year. The shock's dependence on past cumulative classes completed seeks to capture the observed persistence of classes completed, and allows students to affect their future performance by completing as many classes as possible in the current one. In addition, the shock's dependence on ability captures the fact that "good luck" may not be equally likely for students of different abilities, and that elements associated with ability but not systematically modeled may affect class completion.[18]

Since the student chooses e_t before z_t is realized (see below), choosing effort is equivalent to choosing a target, q_t. Both target and effort are functions of the expected shock, as students factor in their expected "luck" when making decisions. Assuming $H(\cdot)$ is linear on z_t,

$$q_t = E(z_t)\tilde{H}(\theta, e_t)\ \overline{x} \qquad \text{and} \qquad e_t = \tilde{H}_e^{-1}[\theta, q_t/(E(z_t)\ \overline{x})]. \tag{2}$$

The actual number of classes completed, x_t, is a function of the chosen effort and the realized z_t. Cumulative classes completed by the end of the year, h_t, is

$$h_t = h_{t-1} + x_t. \tag{3}$$

3.2.2 The student's optimization problem

The college student faces a sequential optimization problem. Figure C1 summarizes the timing of events and her decisions. At the beginning of year t, a student's state vector is (t, h_{t-1}, θ, y),

[17] In the data, we do not observe a student's target; rather, we observe the number of classes she takes, which is neither x nor q. Since tuition is often constant regardless of the number of classes taken in Colombia, students usually attempt the maximum allowed number of classes even if they do not expect to complete them all—i.e., their target may be lower than the number of classes taken. We model the target rather than the number of classes taken because effort is determined by the target. Data on the number of classes taken is used for estimation; it serves as an upper bound for q_t.

[18] For example, lower ability students may choose less selective or demanding programs than other students, or may have lower levels of the non-cognitive skills necessary to succeed in college. In the first case, $E(z)$ would be higher for low- than high-ability students; in the second case, it would be lower.

implying that she will make decisions based on her income, ability, cumulative past performance, and college year. To simplify exposition, we distinguish between the *pre-graduation years* (years 1 through 4, when she cannot yet graduate) and the *graduation years* (years 5 through 8, when she is eligible to graduate). We divide each year into two sub-periods. In the *first sub-period*, she chooses her target number of classes and hence effort; at the end of it, she receives the performance shock, which determines her actual number of classes completed. In the *second sub-period*, she graduates if she has accumulated the required number of classes and is eligible to graduate; otherwise she draws a shock that determines whether she will remain in college next year or drop out ("dropout shock"). This shock captures the fact that students may leave college not only due to poor performance but also due to other shocks (e.g., family job losses or health shocks). Since the student experiences these two shocks as long as she is enrolled, staying longer in college increases her risk exposure. Because they depend on cumulative performance, the two shocks are endogenous and can be affected through effort.

Pre-graduation Years (t = 1,...,4). In year 1, students start with zero cumulative classes completed and vary only in their type. By the end of the year, students of a given type may vary in how many classes they completed because of their different performance shocks. Therefore, from year 2 onward students are heterogeneous not only in type but also in cumulative performance by the beginning of the year, h_{t-1}.

At the beginning of the *first sub-period* the student chooses e_t. At the end of the first sup-period, the z_t shock is realized and helps determine the cumulative performance, h_t. In the *second sub-period* the student receives the dropout shock, $d_t^{drop} = \{0, 1\}$. The probability that this shock would lead her to drop out is

$$\Pr(d_t^{drop} = 1 \mid z_t) = \tilde{p}^d(t, h_t, \theta, y). \tag{4}$$

Since this probability depends negatively on cumulative performance, when she chooses effort the student internalizes its impact on future dropout shocks. The probability varies across student types because some of them may systematically face more non-academic shocks (e.g., family shocks) than others, and varies over time because shocks may be more prevalent in some college years (e.g., the initial ones) than others. If the student drops out, she joins the labor market as a college dropout and receives the corresponding wage. The value of dropping out is $V^{drop}(t + 1)$ and the value of remaining in college is $V^{coll}(t + 1, h_t, \theta, y)$.

Graduation Years (t = 5,...,7). The *first sub-period* is similar to that of the previous years. In the *second sub-period*, a student who has fulfilled the graduation requirements, $h_t \geq h^{grad}$, will graduate and enter the labor market, whose value is $V^{grad}(t + 1)$. A student who has not fulfilled them, in contrast, will draw the dropout shock to determine whether she stays in college the following year.

Terminal year (t = 8). This is the last year that the student can spend in college. By the end of it, the student will graduate if she has fulfilled the graduation requirements, or drop out otherwise. Continuation values for these outcomes are $V^{grad}(9)$ and $V^{drop}(9)$, respectively.

We can now present dynamic optimization problem facing the student in *first subperiod* of each college year:

$$V^{coll}(t, h_{t-1}, \theta, y) = \max_{e_t} \Bigg\{ U(c_t, e_t, \theta) + \beta E_z \Big[\mathbf{1}_{\{t \geq 5\}} \Pr\left(h_t \geq h^{grad}\right) V^{grad}(t+1) +$$
$$\Pr\left(h_t < h^{grad}\right) \left[\tilde{p}^d(t, h_t, \theta, y) V^{drop}(t+1) + \right. \tag{5}$$
$$\left.\left(1 - \tilde{p}^d(t, h_t, \theta, y)\right) V^{coll}(t+1, h_t, \theta, y)\right] \Big] \Bigg\},$$

$$\begin{aligned} s.t. \quad & c_t = y - T(t, h_{t-1}, \theta, y) \\ & h_t = h_{t-1} + x_t \\ & x_t = H(z_t, \theta, e_t)\overline{x} \\ & c_t > 0. \end{aligned}$$

Since the argument of $E_z[\cdot]$ is the continuation value function, this formulation shows that, in choosing current effort, the student weights the current effort cost against its impact on expected classes completed in the period as well as expected cumulative performance (and therefore dropout probability) in future periods. Variable $T(\cdot)$ is tuition; it can depend on student characteristics and captures the enrollment cost by academic year regardless of the target number of classes, q_t (in Colombia, tuition is often fixed regardless of the number of classes taken.) To accommodate our counterfactuals, we write $T(\cdot)$ in general form so that it can vary by year, cumulative performance, ability, or income. In our baseline it varies only by y (see Section 4.1 below). Note the severe credit constraint: students cannot save or borrow to pay for college.[19] The solution to the dynamic problem defined in (5) is the sequence of optimal effort levels (or policy function), $e^*(t, h_t, \theta, y)$.

3.3 Workers

Individuals can join the labor force at one of three points: after graduating from high school or college, and after dropping out from college. Once they join the labor force, they cannot enter or re-enter college. The worker's optimization problem, written in recursive form, is

$$V^m(t) = \max_{c_t} \{u(c_t) + \beta V^m(t+1)\}, \tag{6}$$

$$s.t. \qquad c_t = w_t^m,$$

[19]We do not model a student's decision to work during college because our administrative data does not record this information. Further, data from Colombia's National Survey of Time Use (*ENUT*) reveals that high-income college students are more likely to work during college than their lower-income counterparts, suggesting that the primary motivation to work is not necessarily paying for college (details available upon request). For a model of students working during college, see Garriga and Keightley (2007).

where $V^m(t)$ is the value function for a worker with educational attainment $m = \{hs, grad, drop\}$, denoting high school graduate, college graduate, and college dropout, respectively.[20] The worker's wage, w_t^m, varies by educational attainment and over time to allow for returns to experience.

3.4 Enrollment decision

To decide whether to enroll in college, a high school graduate compares the expected payoff of two choices—going to college, and joining the labor force as a high school graduate. The enrollment decision is a discrete choice problem where the payoff associated to each option is the sum of three components. For the option of *college enrollment*, the first component is the expected value of going to college, $V^{coll}(t = 1, h_0 = 0, \theta, y)$, which varies across student types. The second component is a type-specific preference for college enrollment, $\xi_j = \tilde{\xi}(\theta_j, y_j)$, which captures unobserved factors associated with student type (not included in the model) that might affect enrollment. For example, low income, low ability students may have low parental education and therefore exhibit a systematically lower propensity to enroll in higher education than predicted by their income and ability. This component helps match college enrollment rates by student type and varies across—but not within—student types.[21] The third component is an idiosyncratic preference for attending college, ϵ^{coll}, which varies across and within student types and helps capture within-type variation in choices, as not all students of a given type, in the data, make the same choice (e.g., some attend college while others do not.) For the option of *joining the labor force as a high school graduate*, the first component, V^{hs}, is common to all individuals; the second component (type specific-preference for the option) is normalized to zero; and the third component (idiosyncratic preference for the option), ϵ^{hs}, varies across and within student types.

As a result of this structure, the relative payoffs of going to college and joining the workforce as a high school graduate vary within and across student types. The individual chooses to attend college if the expected payoff from college surpasses that of joining the labor force as a high school graduate:

$$\underbrace{V^{coll}(1, 0, \theta_j, y_j) + \xi_j + \sigma_\epsilon \epsilon^{coll}}_{\text{Value of going to college}} \geq \underbrace{V^{hs} + \sigma_\epsilon \epsilon^{hs}}_{\text{Value of working as a high school graduate}} \tag{7}$$

We assume that ϵ^{hs} and ϵ^{coll} are *iid* and distributed Type I Extreme Value with a scaling factor of σ_ϵ. Thus, the probability that an individual of type j chooses to enroll in college is

$$P^{coll}(\theta_j, y_j) = \frac{\exp\{(V^{coll}(1, 0, \theta_j, y_j) + \xi_j)/\sigma_\epsilon\}}{\exp\{(V^{coll}(1, 0, \theta_j, y_j) + \xi_j)/\sigma_\epsilon\} + \exp\{V^{hs}/\sigma_\epsilon\}}, \tag{8}$$

and the probability that she will join the labor force as a high school graduate is $P^{hs}(\theta, y) = 1 - P^{coll}(\theta, y)$. Since P^{coll} varies by ability, θ, and parental transfer, y, predicted enrollment

[20] We assume that workers consume all their earnings and do not have access to credit markets, which is an accurate representation of developing economies. Modeling savings does not affect the payoff differential between college and high school graduates.

[21] This component is analogous to the product mean utility modeled by Berry et al. (1995), which allows them to match observed market share. See Appendix D for further details.

rates vary across student types.

4 Empirical implementation and estimation

This section describes the model's computational version, estimation strategy, and fit to the data along key dimensions. It also presents the parameter estimates, which are used to simulate the counterfactual policies.

4.1 Student types, tuition, and wages

Student types. To build student types, we start from the observed empirical distribution of ability and income for the high school class of 2005. The distribution, shown in Table B1, classifies high school graduates by ability quintile and family income bracket (recall that our administrative data reports income brackets rather than income levels). We refine this table to work with ability deciles rather than quintiles. To construct the θ values, which must range between 0 and 1, we standardize Saber 11 test scores and normalize them between 0 and 1.[22] The 5th, 15th, ...95th percentiles of the distribution of normalized scores are our θ values. To construct the parental transfer values, y, we must assign students in each income bracket a monetary transfer value. To do this, we turn to an external data source—2005 household survey data for Colombia (SEDLAC)—which reports household income and size. We classify households in the survey into the same income brackets as in our administrative data, and calculate average per-capita household income by bracket. This measure of disposable income by household member is our proxy of parental transfers for college students, y. The mapping between income brackets and the resulting parental transfer levels is shown in the first two columns of Table B3. The final distribution of ability and parental transfers, $\Phi(\theta, y)$, includes $J = 50$ student types and features a positive, strong correlation between θ and y.[23]

Tuition. Our administrative data does not record the tuition paid by individual students but allows us to compute the average annual tuition paid by students from a given income bracket at public institutions.[24] This is our proxy for the tuition paid by students with a given y, as shown in Table B3, third column. As the table shows, average per-capita household income (our proxy for parental transfer) varies greatly across income brackets (by a factor of about 20 between the top and bottom brackets) but tuition varies much less (by a factor of about 2.5). As a result, tuition amounts to about 10 percent of income for the highest income individuals but almost 80 percent for the lowest income ones.

Workers. In the model, a period represents a year, where $t = 1$ corresponds to age 18 and $t = 48$ corresponds to the retirement age of 65. Regardless of her educational attainment or when she joined the labor force, we assume the individual is "experienced" from age 35 ($t = 28$) onward. To compute the wages used in the simulations, we use household surveys (SEDLAC) and compute average wages by educational attainment (high school, college, one year of college,

[22] The normalized test score is equal to $(sts - \min(sts))/(\max(sts) - \min(sts))$, where sts is the standardized test score.

[23] All monetary values are in Colombian pesos (COP) of 2005; 1 USD=$2,300$ COP in 2005.

[24] We use tuition at public institutions because, in Colombia, there is always a public institution that the student can attend. Modelling the choice of college type (public or private) is beyond the scope of this paper.

2+ years of college)[25] and experience (experienced / not experienced) in 2005. Returns to college are substantive: for workers ages 18-60, the average wage of a college graduate, a college dropout with at least two years of complete college, and a college dropout with up to one year of complete college is 160, 58, and 28 percent higher than the average wage of a high school graduate, respectively (see Table B4). Returns to experience are also substantive: the average wage of experienced workers is 35 percent higher than that of inexperienced workers among college graduates, and 29 percent higher among high school graduates. Consistent with the data, we assume that the returns to experience of college dropouts are the same as those of high school graduates.

4.2 Functional forms

Preferences. The utility of college students depends on consumption and effort:

$$U(c, e, \theta) = \frac{c^{1-\rho} - 1}{1-\rho} - \mu \frac{e^{\gamma}}{(1+\theta)^k}. \tag{9}$$

where the curvatures with respect to consumption and effort are represented by ρ and γ, respectively. This formulation allows student ability, θ, to shape the marginal cost of effort as determined by k. The utility of workers is given by

$$u(c) = \frac{c^{1-\rho} - 1}{1-\rho}. \tag{10}$$

which is a special case of the utility function for college students when the coefficient on effort, μ, is set to zero. The time discount factor is set to $\beta = 0.96$ for all individuals, roughly consistent with an implicit interest rate of 4 percent. The scaling factor σ_ϵ of the Type I Extreme Value distribution of idiosyncratic preferences for enrolling or not in college is set equal to 1.

Production function of classes completed. The production function to complete college courses has constant returns to scale in ability and effort:

$$x_t = H(z_t, \theta, e_t)\overline{x} = z_t(\theta^{\alpha} e_t^{1-\alpha})\overline{x}, \tag{11}$$

where $\alpha \in (0, 1)$ is the elasticity of classes completed with respect to ability. We set the required number of classes per year, $\bar{x}$, to 20 classes, and the required number of classes for graduation, h^{grad}, to 98 (instead of 100, since some students in the data graduate with slightly fewer than 100 classes). Students who are fully on track graduate at the end of year 5.

Performance shock. The functional form that governs the performance shock, z_t, has an exponential representation:

$$z_t = \exp\{-\exp\{-(\kappa_0 + \kappa_1 d_1 + \kappa_h \tilde{h}_{t-1} + \kappa_\theta \theta + (\sigma + \sigma_1 d_1 + \sigma_\theta \theta)\nu_t)\}\}, \tag{12}$$

where $\tilde{h}_{t-1}$ is a measure of the cumulative number of classes completed until the previous period,

[25] Although the last two educational attainments are just one in the model—college dropouts—we keep them separate in our computations because they have fairly different average wages in the data (see Table B4), which can affect the timing of dropout decisions.

defined as $\tilde{h}_t = \ln(h_t)$ for every $t > 1$ and $\tilde{h}_0 = 0$ for $t = 1$. The terms associated with d_1 allow the shock distribution to be different in year 1, when $d_1 = 1$, than in other years. The shock depends on an *iid* component, ν_t, drawn from the uniform distribution $U(0, 1)$. The functional form in (12) ensures that $z_t \in (0, 1)$ for any combination of parameter values and for all $\tilde{h}, \theta \in \mathbb{R}$. Importantly, all the parameters in (12) affect the mean and variance of z_t. In Section 4.4 below we discuss the effect of $\tilde{h}_{t-1}$ and θ on the mean and variance of z_t at our specific parameter estimates.

Dropout shock. The functional form for the probability that the dropout shock forces the student to drop out is given by

$$\tilde{p}^d(t, h_t, \theta, y) = \frac{\exp\{\delta(t, \theta, y) + \pi \tilde{h}_t\}}{1 + \exp\{\delta(t, \theta, y) + \pi \tilde{h}_t\}}, \tag{13}$$

where $\delta(t, \theta, y)$ is a year-, ability- and income-specific fixed effect, and $\tilde{h}_t$ measures cumulative performance over all periods, including the current one. In this formulation, the dropout probability includes both an exogenous component which the student cannot affect (associated with $\delta(t, \theta, y)$) and an endogenous one, which the student can affect via effort (associated with $\tilde{h}_t$). This formulation is flexible and includes the fully exogenous dropout risk as a limiting case. More specifically, evaluating $\tilde{p}^d(t, h_t, \theta, y)$ at $\pi = 0$ yields the "exogenous dropout probability"—the probability that students of a given type drop out in a given year even if cumulative performance does not affect the chances of dropping out. We allow this exogenous component to vary across types and over time to capture, for instance, that low-income, low-ability students may be at higher risk dropping out in year 1 than other students (due, perhaps, to the lack of family guidance to navigate the transition into college) and that, even if this risk subsides afterwards, it may still be higher than the risk facing other students.

4.3 Estimation

Ferreyra et al. (2022) estimate the model parameters using Simulated Method of Moments (SMM). The model's full parameter vector is $\tilde{\Theta} = (\Theta, \boldsymbol{\xi}, \boldsymbol{\delta})$, where

$$\Theta = (\rho, \mu, \gamma, k, \alpha, \kappa_0, \kappa_1, \kappa_h, \kappa_\theta, \sigma, \sigma_1, \sigma_\theta, \pi) \tag{14}$$

is the vector of parameters common across individuals; vector $\boldsymbol{\xi}_{J\times 1}$ contains type-specific unobserved preferences for college, ξ_j (see equation (8)), and vector $\boldsymbol{\delta}_{(J*8)\times 1}$ contains the fixed effects of the exogenous dropout probability, $\delta(t, \theta_j, y_j)$, for the $J = 50$ types and 8 years (see equation (13)).

The estimation searches for the value of Θ whose predicted moments, $\hat{\mathbf{M}}(\Theta)$, best match the observed ones, $\mathbf{M}$. Ferreyra et al. (2022) provides further detail on the estimation strategy, also summarized in Appendix E. The estimation matches 585 moments related to dropout rates, college outcomes, academic progression by year, transitions across performance tiers over time, and target number of classes. These moments—which are matched overall as well as by student type and, where it corresponds, by year—provide a rich characterization of the data and allow for the identification of the parameters of interest.

Whereas a full discussion of parameter identification can be found in Ferreyra et al. (2022), we now provide intuition for the identification of the roles of ability, effort, and the performance shock. In the model (equation 1), the production of classes completed is a function of ability, effort, and the performance shock. For a given student type, we observe its ability by construction. As we saw in Figure 4 panel a, the average number of classes completed varies little by ability but greatly within abilities, suggesting that ability alone cannot explain the observed variation in classes completed. Similarly, college outcomes vary substantially within abilities as well. These data features create a role for the non-ability determinants of performance, namely effort and the performance shock. Model assumptions and functional forms help to separately identify the roles of these two elements. Ferreyra et al. (2022) present regressions of simulated classes completed by student type and year on ability, effort, and the performance shock, and show that ability explains only 20 percent of the variation in classes completed. An additional 30 percent is explained by adding effort, and the remaining 50 percent can be finally explained by adding the performance shock. Moreover, when effort is omitted from the model, the elasticity of classes completed with respect to ability is overestimated by a factor of two or three, and the model attains a much worse fit because it cannot replicate the observed variation in performance and college outcomes within abilities—the fact that many low-ability students perform better, and many high-ability students worse, than predicted by ability alone.[26]

Evaluating the model at the parameter estimates yields the baseline scenario that we use for our policy analysis. Since the estimated model fits the data well (see Appendix F), it provides a realistic baseline for our policy simulations.[27] The observed graduation rate is 45.64 percent and the predicted one is 45.02 percent. The model captures the distribution of dropouts over time (Table F1) and across student types (Table F2). As Figure F1 shows, it also captures the distribution of college outcomes by ability. The on-time graduation rate (15.1 percent) is predicted perfectly. The predicted and observed fraction of 2005 high school graduates that complete college are 14.5 and 14.7 percent, respectively.

As Tables F3-F4 show, the model captures average classes completed by year, ability, and final outcome. It replicates the wide variation in classes completed within abilities as well as the low variation across abilities (Figure F3). Further, it captures the qualitative patterns of cumulative performance in terms of persistence, drop out, catch-up and fall behind (Table F5) and the resulting concentration of students in the upper tiers over time (Figure F2) as low-performing students progressively drop out. Finally, Figure F4 shows average predicted target and average number of classes taken by the student; recall that the latter provides an upper bound for the former (section 3.2).

[26]It might be argued that the relatively good performance of some low-ability students is due to enrolling in less-demanding institutions or majors than their high-ability counterparts. Regressions using individual-level data on ability, a rich set of student characteristics, and program fixed effects explain no more than 30 percent of variation in classes completed, therefore leaving a large unexplained residual. In our model, this residual is captured by effort and the performance shock. Further, the performance shock's modeling is flexible enough to account for elements such as heterogeneous standards. For example, since the shock varies by ability, it captures elements such as the ability-based self-selection of students into programs with varying standards.

[27]Since the estimation weighs moments by their sample standard error, moments with a greater number of underlying observations (such as those from early college years or for higher-ability students) attain a better fit than others.

4.4 Parameter estimates

Table 1 shows the parameter estimates, which are used in our counterfactuals. Ferreyra et al. (2022) discusses all parameter estimates; here we focus on those most closely related to college performance and discuss their implications for our policy simulations.

A critical parameter is the elasticity of classes completed with respect to ability, α, which can range between 0 and 1. The parameter estimate (0.085) is low, which is consistent with the low observed variation of average number of classes completed across abilities and yields a high estimate (0.915) for the elasticity of classes completed with respect to effort. Since our ability measure (Saber 11 score) captures college academic readiness, these estimates indicate a relatively small role for college academic readiness relative to effort in the accumulation of classes completed. The policy implication is clear: to affect college performance and graduation, policies must affect effort.

Table 1: Parameter Estimates.

Parameter	Symbol	Estimate
Utility function		
Consumption curvature	ρ	0.882
Effort weight	μ	0.062
Effort curvature	γ	4.727
Effort cost w.r.t. ability	k	1.225
Number of classes completed		
Elasticity w.r.t. ability	α	0.085
Performance shock		
Constant	κ_0	-4.207
Year 1 shifter	κ_1	3.534
Persistence component	κ_h	1.304
Ability component	κ_θ	0.407
Std. dev. of *iid* shock	σ	1.789
Std. dev. of *iid* shock - Year 1 shifter	σ_1	0.317
Std. dev. of *iid* shock - Ability shifter	σ_θ	-1.282
Dropout shock		
Cumulative performance component	π	-2.951

Source: Ferreyra et al. (2022).

The estimated effort curvature, γ, is equal to 4.73 and indicates a very high marginal cost of effort—exceeding the typical quadratic cost of $\gamma = 2$. Large catch-up efforts—or overturning a poor initial performance—are therefore very costly. Given the estimate for k, which captures the relationship between effort cost and ability, effort is negatively and strongly related to ability. Note that $k = 0$ would imply the same effort cost for all abilities, whereas $k = 1$ would imply an effort cost that decreases with ability, at a decreasing rate. Our estimated value of 1.23 yields the same—albeit more pronounced—qualitative pattern as $k = 1$. These estimates imply that policies attempting to raise effort are more likely to succeed with higher-ability students than with others .

To interpret the parameters related to the performance shock, z, we consider their implications on the mean and variance of the shock, $E(z_t)$ and $Var(z_t)$. Based on our estimates, the shock has higher mean for students with higher past performance—in other words, "success begets success," and performance is persistent. At the same time, the shock has a (slightly) *higher* mean for lower ability students. This "better luck" for low-ability students is consistent with the the observed fact that they enroll in less selective (and presumably less demanding) programs than their abler counterparts.[28] Together with effort, this higher mean helps explain the good performance and college outcomes of some low-ability students. In addition, the shock also has a higher variance for lower ability students as well, capturing the fact that their performance exhibits greater variation than that of higher-ability students.

To examine their relative impact of ability and past performance on the performance shock, we consider two hypothetical students, Red and Blue. Red is more able than Blue; the ability difference is $\Delta_\theta = \theta_{Red} - \theta_{Blue} = 0.22$. This is a large difference, equal to the difference between abilities at the 55th and 5th percentiles, or between the 95th and 75th percentiles. Assume that, in addition to being higher-ability, Red has completed one more class than Blue by the beginning of academic year t. In principle, Red's performance shock could be lower than Blue's because of her higher ability, or higher because of her better past performance. Based on our estimates, having completed that one additional class gives Red the same performance shock mean as Blue even though her ability is much higher. In other words, the performance shock mean is much more sensitive to past performance than to ability. As a result, the performance shock is highly persistent and more dependent on something the student can affect—her performance—than on ability, which she cannot affect. Policies that induce a strong initial performance are therefore more likely to succeed than others.

The estimated parameter that relates the dropout shock to cumulative performance, π, indicates that, on average, an additional class completed by the end of the year decreases the probability of dropping out by about 5 pp. Our full set of parameter estimates includes the dropout probability fixed effects in (13), $\hat{\delta}(t, \theta, y)$, which give rise to the exogenous dropout probability facing students of different types regardless of their cumulative performance. Can a student overcome her exogenous dropout probability through her performance? To answer this question and illustrate the relative magnitude of $\hat{\pi}$ and $\hat{\delta}(t, \theta, y)$, consider the average number of additional classes that a student from the second ability quintile ("Q2 student") must complete to attain the same dropout probability as a student from the top ability quintile ("Q5 student"). In year 1, she must at least complete four additional classes to reach that goal. This amounts to at least 20 percent of the annual requirements, which reflects a high exogenous dropout probability. In year 5 she only needs to complete one additional class, since the cumulative performance of Q2 students reaching year 5 is approximately on par with Q5 students. In other words, the exogenous dropout probability falls drastically over time for this student. The important point is that, early on, low-ability students face a relatively high exogenous dropout probability but can counter it through high initial efforts or highly favorable performance shocks. This, too, suggests that policies that induce a strong initial effort are more likely to succeed than others.

[28] When we measure program selectivity as the average Saber 11 test score of the program's students, we find a negative correlation between student ability and program selectivity. Results are available upon request.

5 Free college simulations

In this section we present our simulation results for alternative free college programs. We begin by describing their eligibility requirements and then present free college impacts on overall enrollment and graduation. Next, we turn to the heterogeneity of free college effects by student type and relate our counterfactual results with findings from the literature. We examine free college effects on the uncertainty facing students in college. We conduct a simple cost-benefit analysis of free college and conclude with an examination of its potential long-run effects.

5.1 Simulations' setup

We simulate various free college programs, offering free tuition to the following sets of students:

- **Universal free college:** all college students.
- **Need-based free college:** low-income students, defined as those from the lowest two income brackets.
- **Ability-based free college:** high-ability students, defined as those from the highest ability quintile.
- **Ability- and need-based free college**: students from the lowest two income brackets and the highest ability quintile.
- **Performance-based free college:** all students are eligible in year 1 but only high-performing students are eligible afterwards. In a given year, a high-performing student is one who finished the previous year in tiers 1 or 2 based on her cumulative performance. Note that a student may be high-performing in one year but not in another.
- **Performance- and need-based free college:** all low-income students (from the lowest two income brackets) are eligible in year 1 but, among them, only those who are high-performing are eligible afterwards.

Note that, by design, performance-based programs create uncertainty for the student, as the zero tuition is conditional on performance. In contrast, the other free college programs guarantee zero tuition for eligible students regardless of performance.

As we analyze these simulations, it is convenient to distinguish between two groups of students—*existing* and *new.* For a given counterfactual, we define existing students as those who start college both in the baseline and counterfactual. In contrast, new students do not start college in the baseline but they do in the counterfactual. This distinction allows us to separate effects due to changes in student body composition—as new students enter college—and changes in the behavior of existing students.

Three important assumptions hold in our counterfactuals. First, we assume a perfectly elastic higher education supply, whereby institutions can adjust capacity to absorb additional students at a constant marginal cost, and tuition does not rise in response to greater demand. If there were capacity constraints, institutions would need to ration free college. Second, we assume that parents continue to transfer the same y to their children in college even when college becomes free. In other words, public college funding does not crowd out private funding at all. If, in contrast, parents reduced their transfers one-for-one (full crowd-out), free college would have no effects and would be similar to the baseline. More generally, crowding out of any degree would be analogous to a reduction in the tuition subsidy.[29] Third, we assume that the average cost of educating new and existing students is the same. This does not hold, for instance, when new students are more costly because they need additional services such as remedial education, in which case a government with fixed resources can only fund fewer students. Since these assumptions provide the most favorable setting for free college, the results presented below are best viewed as an upper bound for free college effects.

5.2 Margins of student choice

In principle, free college can affect students both on the extensive and intensive margins. On the extensive margin it can affect whether a student goes to college; on the intensive margin, it can affect her effort choice. Extensive margin effects can alter enrollment rates and the composition of the student body, while intensive margin effects can alter graduation rates and timing.

By lowering tuition to zero, free college raises a student's disposable income for consumption, which makes college more attractive than in the baseline. On the intensive margin, this can unleash the following effects on her effort:

1. **Loss-of-urgency effect**. Since free college enhances the "college experience" by raising the value of being a student relative to joining the labor force, the student becomes less eager to leave college. Other things equal, this effect lowers effort. It is particularly strong for middle- and high-income students, whose college consumption may be high relative to their expected consumption immediately after college.

2. **Substitution effect**. The increased consumption allows students to exert more effort without losing utility because it provides a compensation for the greater effort. Other things equal, this effect raises effort. It is particularly strong for low-ability students, for whom effort is costly, and low-income students, for whom the consumption increase may be large relative to a low baseline consumption.

3. **Risk effect.** The performance and dropout shocks, z_t and d_t^{drop} respectively, depend on the number of cumulative classes completed, which in turn depends on (past) effort. By raising a student's effort, free college can lower the risk of future negative shocks and speed up graduation, thereby lowering exposure to further risks. The reverse is also true—if free college lowers effort, the risk of negative shocks rises and graduation may be delayed, thereby prolonging the time that the student is exposed to risks. A student with a strong loss-of-urgency effect and a weak substitution effect, for example, is subject to a strong and negative risk effect.

Since a student could experience all three effects, the net impact of free college on graduation rates and time-to-degree depends on the relative strength of these effects by student and on

[29] A large literature endogenizes parental transfers as a function of education costs and labor market returns. See, for instance, Keane and Wolpin (2001), Restuccia and Urrutia (2004), and Abbot et al. (2013).

the size and characteristics of the student body eligible for free college. There is, however, one exception—performance-based programs. By making free tuition conditional on performance, these programs do not guarantee a higher consumption but make it contingent on performance, thereby muting the loss-of-urgency effect and incentivizing effort.

5.3 Aggregate outcomes

5.3.1 Enrollment and graduation

Table 2 shows the aggregate effects of free college programs on enrollment and college outcomes. As expected, the magnitude of enrollment effects is related to the percent of eligible students, which ranges from 100 percent under universal free college down to 9.8 for ability-and-need based free college. All programs raise enrollment relative to the baseline rate of 32.3 percent. Universal free college delivers the largest enrollment increase (28 pp), followed by need-based free college (23 pp) and performance-based free college (21.3 pp). In contrast, ability-based free college (whether need-based or not) has the smallest effect on enrollment rates (3 or 4 pp).

New students change the composition of the student body yet to different extents depending on the program. New students account for almost half of the student body under universal free college but just about 10 percent under ability-based free college. The fraction of low-income students rises in all programs, particularly the need-based ones. The fraction of high-ability students rises with ability-based programs, which induce a positive selection of new students, but falls under the other programs, which induce a negative selection of new students.

While four out of six programs raise enrollment rates by more than 15 pp, no program raises the graduation rate by more than 3 pp—and some programs actually lower it. Aggregate graduation effects are small yet mask considerable differences between existing and new students. The graduation rate of existing students remains almost constant in all programs except for performance-based programs, which raise it by 4 to 6 pp. As for new students, their graduation rate is higher than that of existing students only under ability-based programs, but lower otherwise. Similar patterns hold for the on-time graduation rate, which drops slightly under universal and need-based free college but rises under ability-based free college (due to the positively selected new students) and performance-based free college. Free college, then, can raise overall graduation and on-time graduation rates by inducing positive ability-based selection or by incentivizing effort—but will hardly raise them otherwise.

The ultimate goal of free college programs is raising the fraction of college graduates, equal to the product of enrollment and graduation rates. All programs raise this fraction relative to the baseline. Universal free college raises it the most (by about 12 pp, or 80 percent relative to the baseline), followed closely by performance-based free college. Relative to universal free college, performance-based free college raises enrollment to a lesser extent because of the uncertainty regarding free tuition, which deters many students from enrolling. However, since performance-based free college attains higher graduation rates than universal free college, it delivers almost the same increase in the fraction of college graduates. This trade-off between risk and outcomes is a theme in the analysis that follows.

Table 2: Free College Counterfactuals: Aggregate Outcomes.

Outcome	Data	Baseline	Universal	Need	Ability	Ability & need	Perf.	Perf. & need
Enrollment rate (%)	32.3	32.3	59.9	54.9	36.8	35.4	53.6	49.7
Eligible students (%)			100.0	71.0	20.0	9.8	100.0	71.0
Student body composition (%)								
New students			46.1	41.2	12.2	8.9	39.8	35.0
Low income	52.4	52.4	66.0	72.1	54.5	56.6	64.0	69.0
High ability	39.5	39.5	28.8	29.0	46.9	44.9	30.9	31.0
Graduation rate (%)	45.6	45.0	43.5	43.6	45.6	45.7	47.8	44.9
Existing students			45.8	45.6	44.4	44.8	51.3	48.7
New students			40.9	40.8	54.3	54.1	42.7	42.6
On-time graduation rate (%)	15.1	15.1	13.9	14.4	15.2	15.6	15.9	16.1
Existing students			14.0	14.5	14.3	14.8	16.0	15.9
New students			13.8	14.3	22.2	24.2	15.7	16.4
High school graduates that complete college (%)	14.7	14.5	26.1	24.0	16.8	16.2	25.6	22.3

Source: Model's predictions for baseline and counterfactuals.
Notes: Eligible students are those who could, in principle, make use of free college; for performance-based free college, eligibility refers only to year 1 since it is contingent on performance in years 2+. Existing students are those who enroll both in the baseline and counterfactual. New students are those who enroll in the counterfactual but not the baseline. Low income=two lowest income brackets; high ability=top ability quintile.

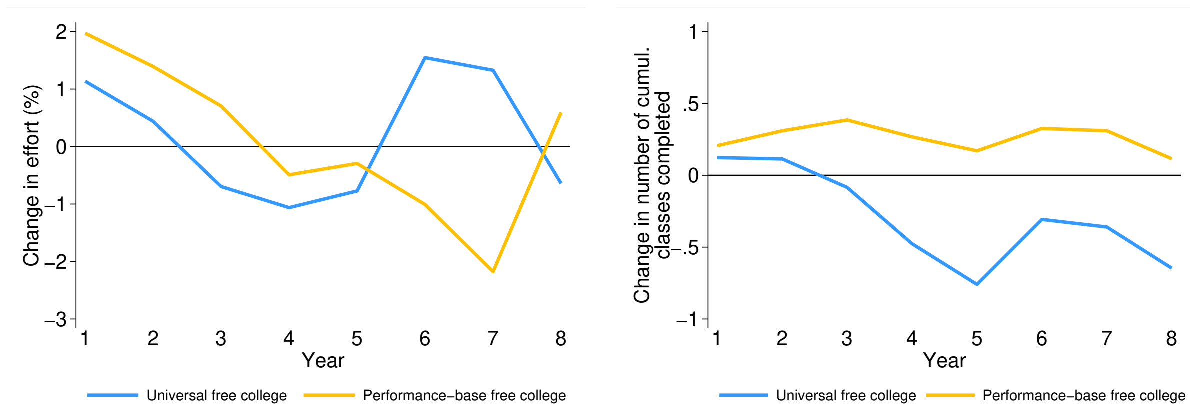
5.3.2 Graduation and student effort

To further understand the graduation rate difference between universal and performance-based free college, we focus on existing students and examine how their average effort and accumulation of classes completed differs between the baseline and those two scenarios.

Under universal free college, on average students increase effort relative to the baseline in the first two years but lower it in years 3-5. In year 6, they ramp it up in order to graduate. Of the three effort effects, the substitution and risk effects prevail in years 1 and 2, leading students to work harder than in the baseline (Figure 5 panel a) and accumulate more classes (Figure 5 panel b). Nonetheless, the greater number of classes accumulated early on, together with the loss-of-urgency effect, leads students in years 3-5 to work less and accumulate fewer classes than in the baseline. To compensate for this slower pace and graduate, students raise effort in years 6-8. Thus, students conduct an intertemporal re-allocation of effort that leads them to graduate almost at the same rate as in the baseline (about 45 percent) yet at a slower pace (on-time graduation rate falls from 15.1 to 14.0; see Table 2) .

In contrast, under performance-based free college students frontload effort. Absent the loss-of-urgency effect, the substitution and risk effect produce greater effort than in the baseline in years 1-3. Since students accumulate more classes than in the baseline during those years, they are able work less later on while still accumulating more classes. These effort changes imply not

Figure 5: Free college: Changes in Effort and Cumulative Classes Completed



a. Change in effort w.r.t. to baseline (%) b. Change in number of cumulative classes

Source: Model's simulations.
Notes: For existing students in the counterfactuals, panel a shows average effort in the corresponding counterfactual minus average effort in the baseline, expressed as a percent of baseline effort. Panel b shows average cumulative classes in the corresponding counterfactual minus average cumulative classes in the baseline.

just an intertemporal reallocation of effort relative to the baseline but also a net effort increase that raises both graduation rates (from 45 to 51.3 percent) and on-time graduation rates (from 15.1 to 16 percent).

Although the average effects shown in Figure 5 are small, their size varies across students. More generally, the aggregate outcomes examined so far mask great heterogeneity among student types. For a policymaker interested in promoting the enrollment or graduation of specific students, this heterogeneity is critical. We turn to this issue now.

5.4 Outcomes by student type

To facilitate the analysis, we aggregate our fifty student types into nine student groups defined by combinations of income and ability. Income groups include high, middle and low-income—corresponding to the top, two middle, and two bottom income brackets, respectively. Ability groups include high, middle, and low-ability—corresponding to the top, two middle, and two bottom ability quintiles, respectively.

5.4.1 Enrollment

Table 3 shows enrollment rate by student group in the baseline (panel a) and enrollment rate increase relative to the baseline under universal and performance-based free college (panels b and c, respectively). We focus on these two counterfactuals because the others are special cases of these. For example, the "low income" row of panel b displays the effects of need-based free college, while the "high ability" column displays the effects of ability-based free college.

Both programs raise enrollment rates for every student group. Under universal free college, the greatest effects are for low-income students, who are most budget-constrained in the baseline. Their greater responsiveness justifies need-based free college as opposed to universal free

Table 3: Free College Counterfactuals: Enrollment Effects.

	a. Baseline Enrollment Rate			b. Universal Free College: Change			c. Performance-Based Free College: Change		
				Ability					
Income	High	Mid	Low	High	Mid	Low	High	Mid	Low
High	83.8	65.5	39.3	7.1	11.4	12.0	5.8	9.0	9.2
Mid	73.1	47.4	27.3	15.0	21.1	18.3	12.5	16.8	13.9
Low	51.4	26.0	13.6	32.2	36.5	27.8	27.1	28.5	20.1

Source: Model's predictions for baseline and counterfactuals.
Notes: For each student group, panel a shows predicted enrollment rate (%) in the baseline; panel b shows the enrollment rate difference (pp) between universal free college and baseline; and panel c shows the enrollment rate difference (pp) between performance-based free college and baseline.

college, which provides a subsidy to many students who would attend college anyway. Relative to universal free college, the enrollment effects of performance-based free college are similar (because performance-based free college provides unconditional free tuition to *all* students in year 1) yet smaller (because some students do not enroll in order to avoid the effort necessary to fulfill the performance requirements in subsequent years.)

5.4.2 Graduation

To compare graduation rates in the baseline and counterfactuals we focus on existing students, whose graduation rate changes are entirely driven by the effort effects triggered by free college.[30] Following the same logic as with enrollment, Table 4 shows baseline graduation rates (panel a), as well as the graduation rate changes relative to baseline under universal and performance-based free college (panels b and c, respectively.)

Table 4: Free College Counterfactuals: Graduation Rate Effects for Existing Students.

	a. Baseline Graduation Rate			b. Universal Free College: Change			c. Performance-Based Free College: Change		
				Ability					
Income	High	Mid	Low	High	Mid	Low	High	Mid	Low
High	59.3	44.4	26.3	-1.8	-1.9	3.9	4.4	3.2	5.5
Mid	55.6	39.9	29.9	-1.9	3.5	1.7	4.9	6.6	6.5
Low	53.3	42.5	32.1	-1.3	4.4	-1.5	8.1	8.8	2.6

Source: Model's predictions for baseline and counterfactuals.
Notes: For existing students of each group, panel a shows predicted graduation rate (%) in the baseline; panel b shows graduation rate difference (pp) between universal free college and baseline; and panel c shows graduation rate difference (pp) between performance-based free college and baseline.

Universal free college raises the graduation rate of some student groups but lowers it for others. The reason is that the prevailing effort effect—loss of urgency, substitution, or risk—varies among student groups. Loss of urgency is stronger among higher-income students, whose

[30] Free college generates incentives both for existing and new students. We focus on existing students because they allow us to compare behavioral changes between the baseline and counterfactuals. New students do not allow for this comparison because they do not enroll in the baseline.

high baseline consumption becomes even higher with free college. The substitution effect is stronger among lower-ability students, for whom effort is relatively more costly and who have greater need of compensation for additional effort. The risk effect is stronger for students with fewer cumulative classes completed, particularly those who slow down due to the loss-of-urgency effect and are exposed to risk for a longer time.

As panel b shows, graduation rates fall for students of high ability or high income. Since their baseline effort is high due to their low effort cost and/or high consumption, little room is left for additional effort and the substitution effect is therefore weak. A strong loss-of-urgency effect prevails, leading to lower effort, greater risk, and lower graduation rates. In contrast, graduation rates rise for middle- and low-ability students. Their baseline effort is low due to their high effort cost and low consumption, which creates room for a strong substitution effect. Since their consumption remains low even with free college, they experience a weak loss-of-urgency effect and the substitution effect prevails, leading to higher effort, lower risk, and higher graduation rates.

In contrast to universal free college, performance-based free college raises graduation rates for *all* student groups because it eliminates the loss-of-urgency effect. As a result, the substitution effect leads to greater effort and lower risk. In the aggregate, performance-based free college raises the average graduation rate of existing students by 14 percent—the largest effect among all the programs considered here. Effects are heterogeneous across students and range from 7 percent for high-income, high-ability students to 21 percent for lower income or lower ability students. Moreover, even new students attain a higher graduation rate under performance-based than universal free college (42.7 v. 40.9 percent).

We now return to the policymaker's goal of raising the fraction of college graduates. Table 5 shows this fraction in the baseline (panel a) as well as the changes under universal and performance-based free college (panels b and c, respectively.) Relative to the baseline, both programs raise this fraction for every student group. Which one is more successful depends on the student type. Universal free college is more effective for low-income students of middle or low ability, for whom the difficulty of meeting performance requirements acts as an enrollment deterrent. For all other student types, however, performance-based free college is at least as effective as universal free college.

To summarize, the enrollment and graduation effects of free college are heterogeneous among student types and across programs. In general, though, these programs raise the fraction of college graduates mostly by raising enrollment rather than graduation rates. We discuss their limited impact on graduation rates below.

5.5 Discussion: Evidence on financial aid and free college

The motivating cross-country evidence depicted in Figure 1 shows that, in Latin America, government funding for college has a large, positive relationship with enrollment rates but a weak (actually negative) relationship with graduation rates. Since the most common public financial aid regimes in the region are universal and need-based aid (Ferreyra et al., 2017), the evidence is consistent with our simulation results, which predict a large enrollment increase for universal and need-based free college but a (slight) decline in graduation rate (Table 2).

Our findings are also consistent with the literature on U.S. college financial aid. This litera-

Table 5: Free College Counterfactuals: Percent of High School Graduates That Complete College.

	a. Baseline Percent of High School Graduates			b. Universal Free College: Change			c. Performance-Based Free College: Change		
	Ability								
Income	High	Mid	Low	High	Mid	Low	High	Mid	Low
High	49.7	29.1	10.3	2.9	3.1	5.1	7.1	5.9	5.3
Mid	40.7	18.9	8.2	6.7	10.1	6.4	10.7	10.1	6.4
Low	27.4	11.0	4.4	16.7	17.5	8.5	19.1	15.5	7.0

Source: Model's predictions for baseline and counterfactuals.
Notes: For students of each group, panel a shows the percent of high school graduates that graduate from college; panel b shows difference (pp) in this variable between universal free college and baseline; and panel c shows difference (pp) in this variable between performance-based free college and baseline.

ture has generally found positive enrollment and graduation effects for financial aid.[31] Moreover, it has found greater effects on enrollment than graduation rates (the latter being in the modest range of 0 to 6-7 pp)[32] and greater effects for performance-based than unconditional aid (Dynarski & Scott-Clayton, 2013). In recent years, several U.S. states have implemented a variety of financial aid programs based on ability and/or need,[33] as well as place-based "Promise" programs, which provide free tuition to eligible students for local community colleges or state four-year institutions.[34] Consistent with our findings, these programs have had positive effects on enrollment and degree attainment.

Moreover, our findings are consistent with those from Colombia's *Ser Pilo Paga* ("being diligent pays off"), the program that offered free tuition to high-ability, low-income students for the theoretical duration of their program between 2014 and 2018. The program contained a performance-based component, since students who dropped out were required to pay tuition back. Among the eligible population, *Ser Pilo Paga* raised enrollment rates by 15-21 pp and the fraction of college graduates by about 15 pp, yet only raised graduation rates in those programs by 7-8 pp (Londoño et al., 2022).[35]

Our findings, as well as those from the literature, indicate that even the programs that

[31] See, for instance, Bettinger (2004), Dynarski (2003), Hoxby and Turner (2013) and the references therein, as well as the surveys by Avery et al. (2019), Deming and Dynarski (2009), Dynarski and Scott-Clayton (2013), Long (2008), Page and Scott-Clayton (2016).

[32] For recent, well identified studies, see Bettinger et al. (2019), Denning (2017), Mayer et al. (2015), and Scott-Clayton (2011).

[33] See Bettinger et al. (2019), Castleman and Long (2016), Cornwell et al. (2006), Dynarski (2000, 2004, 2008), Scott-Clayton (2011), Scott-Clayton and Zafar (2016), and the references therein. Angrist et al. (2022) provide evidence from a randomized control trial.

[34] These programs vary across states in terms of eligible institutions and students. See, for instance, Scott-Clayton (2011), Castleman and Long (2016), Dynarski et al. (2018), Bettinger et al. (2019), Page et al (2019), Gurantz (2020) and Bartik et al. (2021).

[35] These comparisons focus on bachelor's degrees and are only approximate, since Londoño et al. (2022) do not compute the enrollment or graduation rates for specific cohorts, but rather measure enrollment, degree attainment (akin to our fraction of college graduates, which is unconditional on college enrollment) and graduation (conditional on college enrollment) within seven years of high school completion (see Tables 1, 2, and 6 of their paper, respectively.)

raise graduation rate the most only have a modest impact, which begs the question of why free college (or financial aid, in general) fails to raise graduation rates more substantially. The answer emerging from our model is that free college fails to induce in many students the large, non-marginal effort increase necessary to complete *all* the required classes and graduate. This suggests that additional supports for class completion—particularly in year 1—might be needed, including early interventions, remedial education, advising, and tutoring.[36] Indeed, when reviewing possible policies to raise graduation rates in the U.S., Avery et al. (2019) conclude that need-based free college combined with institutional funding for these supports—and perhaps student stipends for living expenses—might be the most cost-effective policy. A cautionary tale, however, comes from Oreopoulos and Petronijevic (2019), who find that these supports help students realize the need for greater effort but have little effect on college persistence or graduation. The reason is that students respond not by raising effort but by expecting less of themselves.[37]

Moreover, our counterfactuals have assumed some highly favorable—perhaps unrealistic—conditions. One of them is no capacity constraints in higher education. Free college, however, would likely run into capacity constraints and force institutions to ration access. Bucarey (2018) explores the potential effects of Chile's free college program (*gratuidad*), introduced in 2016 for the bottom 60 percent of the income distribution. Data prior to 2016 shows that when low-income students were given financial aid, institutions responded by becoming more selective, thereby leading to a *lower* share of low-income students. Using his structural model, Bucarey (2018) predicts that capacity-constrained institutions would follow a similar strategy under free college. We have also implicitly assumed that college quality is unchanged after college becomes free. This may not happen if the policymaker reimburses colleges for less than the per-student average cost. Indeed, Murphy et al. (2019) provide evidence that higher education quality in England was lower when college was free because institutions were not receiving full funding. College quality may also fall if the policymaker reimburses colleges at the same rate for new and existing students even though the former may be costlier to educate. According to our simulations, new students are relatively more disadvantaged than existing ones and might need additional services and support, whose provision would indeed costly.[38]

5.6 Free college and student uncertainty

The typical rationale for free college is that students face financial constraints that may prevent them from undertaking an investment with positive returns. Our work highlights another important rationale: the investment is risky and students are uncertain about their final outcome. They are uncertain about their performance and chances to remain enrolled due to

[36] Clotfelter et al. (2018), Evans et al. (2017), Scrivener et al. (2015) and Sommo et al. (2018) document positive effects of these supports on graduation rates.

[37] Similarly, Harris and Mills (2021) study ninth-graders in Milwaukee, Wisconsin who were randomly offered a scholarship for college conditional on their high-school performance. They find a null college enrollment response and a negligible two-degree completion increase, and find no effect on high school performance metrics that require student effort (test scores, attendance, graduation) even though these determined access to the scholarship.

[38] Free college might have other effects as well. For example, if it does not apply to all programs at the same time, it might affect students' choice of program and major. See Castro-Zarzur et al. (2022) for an analysis of these effects in Chile.

shocks that might be particularly important in developing economies (e.g., family job losses or health shocks). By providing insurance against the uncertainty, free college might induce greater enrollment and graduation.

To study how free college affects uncertainty, we use the uncertainty measure developed in Ferreyra et al. (2022), which quantifies the variability in the distribution of college payoffs. It measures uncertainty for student i at the beginning of t under scenario p (baseline or counterfactual), as the coefficient of variation of her college payoffs:

$$CV_{it}^{p} = \left(\text{Var}_z\left[\tilde{V}^{coll}(t, h_{it-1}, \theta, y; z_{it}, e_{it}^{*})\,|\,p\right]\right)^{1/2}\left(E_z\left[\tilde{V}^{coll}(t, h_{it-1}, \theta, y; z_{it}, e_{it}^{*})\,|\,p\right]\right)^{-1}, \quad (15)$$

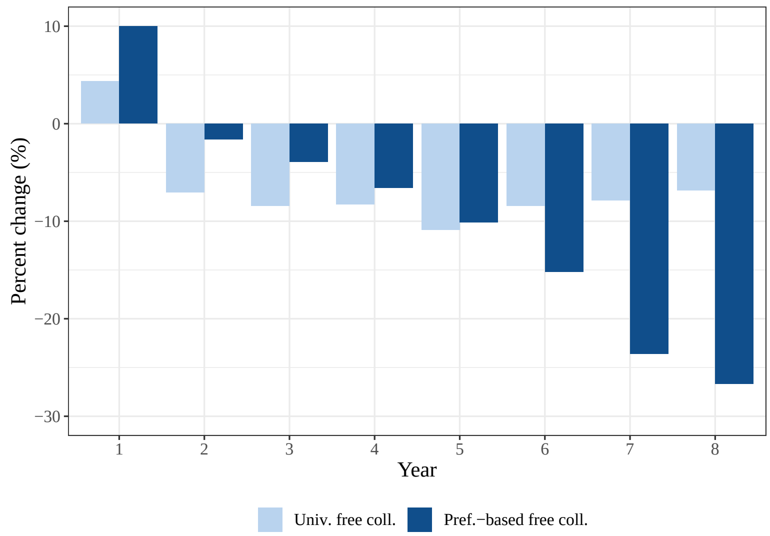
where the right-hand side is the ratio between the standard deviation and expected value of college payoffs given the student's optimal effort, e_{it}^{*}, under scenario p. Conditional on e_{it}^{*}, the randomness in $\tilde{V}^{coll}(\cdot)$ comes from the performance and dropout shocks, z and d^{drop} respectively, which are a function of cumulative classes completed and therefore optimal effort. Thus, uncertainty varies across students and over time. It is particularly high in year 1, when the student faces the highest risk of dropping out and has not yet established a performance path. Moreover, uncertainty varies across scenarios because it is a function of expected consumption and effort, both of which are affected by free college.

Free college changes the distribution of college payoffs in two ways. By raising consumption during college, free college raises the value of remaining in college relative to dropping out. In addition, free college affects effort through the loss-of-urgency, substitution, and risk effects; effort changes, in turn, affect the current number of current classes as well as future performance shocks, dropout shocks, and overall performance. Figure 6 shows the average percent change in the uncertainty measure under universal and performance-based free college with respect to the baseline. To facilitate the comparison, we take this average over the set of students who start college in the baseline and both free-college programs.

Changes in the distribution of payoffs lead to an increase in $E_z[\tilde{V}^{coll}(\cdot)]$ every year relative to the baseline and to an initial increase in $\text{Var}_z[\tilde{V}^{coll}(\cdot)]$, although the latter subsequently falls as completion of the first few years removes some of the uncertainty. The net result is that, on average, uncertainty rises relative to the baseline under both free college regimes in year 1 but falls afterwards. Free college, therefore, can provide students with some insurance against the inherent college uncertainty by raising expected consumption and triggering effort changes.

In principle, which free college program is more effective at providing insurance depends on the college year. During years 2-5, universal free college is more effective than performance-based free college at lowering uncertainty, but the reverse happens later on. In years 2-5, the insurance role of performance-based free college is rather limited because free tuition is conditional on performance. Nonetheless, this very conditionality induces students to exert greater effort and provides them with more insurance in subsequent years—when they are eligible to graduate—against poor academic performance and dropout shocks. Free college, then, provides students with insurance against uncertainty and, from this perspective, may facilitate student enrollment and academic progression. At the same time, giving less insurance seems more efficient than giving more, as making insurance conditional on performance motivates greater student effort and leads to better college outcomes.

Figure 6: Change in Uncertainty.



Source: Own calculations based on model's predictions for baseline and counterfactuals.
Notes: The figure shows the average percent change in uncertainty under universal and performance-based free college relative to the baseline by year, calculated for students who begin college in year 1 in the baseline and the two counterfactuals. Upper 5% values have been trimmed off.

5.7 A simple cost-benefit analysis of free college programs

Just as free college programs vary in their final contribution to the fraction of college graduates, they also vary in the public spending required to produce those graduates. To the policymaker, the average net cost per graduate under policy p is as follows:

$$anc_p = \frac{\sum_{t=1}^{8} \sum_{i=1}^{N_t^p} (C - T^p(t, h_{it}, \theta_i, y_i))}{G^p}, \tag{16}$$

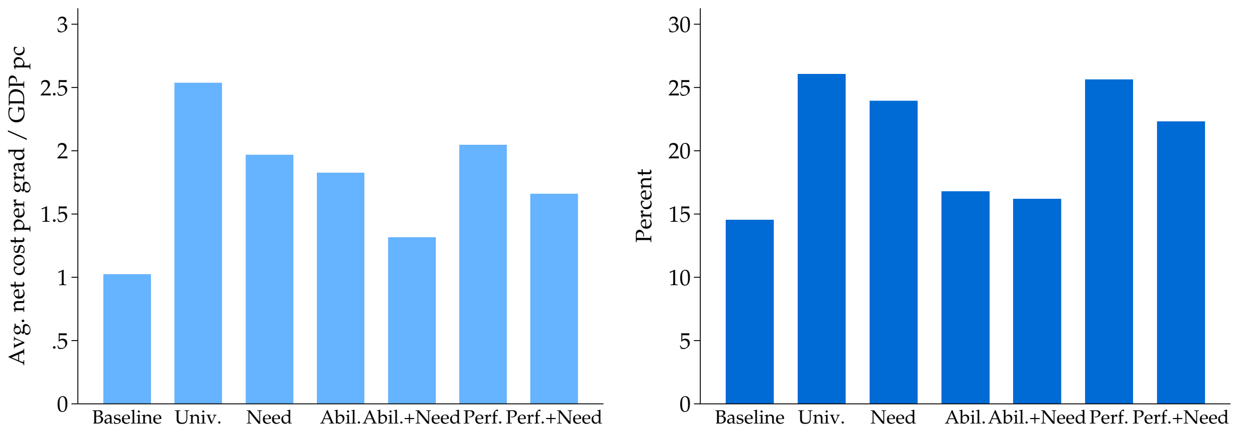
where N_t^p is the number of students enrolled under policy p in year t, C is the annual cost of educating a college student, $T^p(\cdot)$ is the tuition paid by student i under policy p, and G^p is the number of graduates under policy p. By adding in the numerator over *all* individuals enrolled rather than just the graduates, the per-graduate net cost accounts for the cost of graduates as well as dropouts.[39]

For each free college program, Figure 7 shows the average net cost per graduate in terms of per-capita GDP (panel a). For convenience, it also shows the fraction of high school graduates who finish college (panel b), which provides a measure of G^p. Net cost per graduate is already high in the baseline—about the same as per-capita GDP. Even if enrollment did not rise, free college would raise the net cost per graduate just because fewer students would pay

[39]Lacking data on the annual cost of educating a college student, C, we assume it is equal to the tuition paid by students from the highest income bracket at public universities (equal to 2.2 million COP on average; see Table B3). This is a lower bound of the true cost, as public colleges subsidize tuition even for the highest income students, and private universities—whose tuition might be closer to actual costs—charge more than 6 million COP on average. For an estimate of expected free college costs in Chile, see Urzua and Espinoza (2014.)

tuition. The combination of lower tuition revenues and higher enrollment raises the net cost per graduate relative to the baseline under all free college regimes. Unsurprisingly, the cost rises the least under ability-and-need based free college (which expands enrollment the least among all programs considered here) and the most under universal free college (which expands it the most).

Figure 7: Free College Cost



a. Average net cost per college graduate (relative to GDP per capita)

b. Percent of high school graduates that complete college

Source: Model simulations for enrollment and graduates. See the text for (gross) cost assumptions. GDP per capita is from Colombia's National Administrative Department of Statistics (DANE).
Notes: Average net cost per college graduate is computed as described in the text.

If the policymaker's goal were to minimize the per-graduate cost, offering free college only to high-ability, low-income students would be the best option due to its low eligibility and dropout rates. If, in contrast, the goal were to maximize the number of graduates, universal free college would in principle be the best option—except that another policy, performance-based free college, reaches almost the same number of graduates yet costs about 20 percent less per graduate given its lower dropout rate and higher on-time graduation rate.

Policymakers might be reluctant to adopt performance-based free college, perhaps for political considerations. Indeed, students throughout Latin America have been clamoring for unconditional, universal free college (*gratuidad*). As Figure 7 shows, universal free college raises the number of graduates only slightly more than need-based free college yet costs about 25 percent more per graduate. The reason is that universal free college provides a transfer to medium- and high-income students who would attend college anyway. In other words, universal free college is neither efficient nor equitable. Need-based programs—whether combined with other eligibility requirements or not—avoid these pitfalls.

To summarize, for a policymaker interested in maximizing the number of college graduates, performance-based and need-based free college are more efficient than universal free college. One caveat is in order, as college dropouts seem to acquire some human capital during college given their wage premium relative to high school graduates (Table B4). While this might justify attempts to maximize the enrollment rate rather than the fraction of college graduates, it is not clear that an incomplete bachelor's program is the most efficient vehicle to acquire post-secondary skills. A short-cycle program, lasting two or three years (e.g., associate's degrees in the U.S.), might be more cost-effective.[40] Subsidizing these programs—in the spirit of subsidies to community college students in the U.S.—might be a better option than providing free college to all students in bachelor's programs.

5.8 Short vs. long-run effects

So far we have assumed that free college does not alter the college premium despite raising the supply of college graduates. Nonetheless, free college might unleash general equilibrium effects undermining some of the impacts described so far (Heckman et al., 1998). For instance, the inflow of additional graduates might depress the college premium, and the taxes necessary to finance free college might further depress after-tax wages, thereby lowering the incentives for a college education.

To analyze the equilibrium relationship between the college premium and the number of college graduates, we postulate an aggregate production function following Katz and Murphy (1992), Heckman et al. (1998), and Card and Lemieux (2001). Ignoring for the moment the connection between capital and technology, consider a CES production function, $F(N_t^h, N_t^g) = \left(A_t^h (N_t^h)^\lambda + A_t^g (N_t^g)^\lambda\right)^{\frac{1}{\lambda}}$, that combines high school and college graduates, whose stocks are N_t^h and N_t^g respectively, to produce aggregate output. In this function, A_t^h and A_t^g are efficiency parameters, and $\omega = 1/(1-\lambda)$ is the elasticity of substitution between college and high school graduates. In a competitive labor market, the college premium is equal to

$$\frac{w_t^g}{w_t^h} = \frac{A_t^g}{A_t^h} \left(\frac{N_t^g}{N_t^h}\right)^{\lambda-1}, \tag{17}$$

where w_t^g and w_t^h are the wages of college and high school graduates, respectively. Taking logs on both sides and defining a time difference ($\triangle$) yields the following expression:

$$\triangle \ln\left(\frac{w_t^g}{w_t^h}\right) = \triangle \ln\left(\frac{A_t^g}{A_t^h}\right) - \frac{1}{\omega} \triangle \ln\left(\frac{N_t^g}{N_t^h}\right). \tag{18}$$

In this equation, changes in relative wages depend on two components. The first is technical changes in the relative productivity of the two labor inputs. Skill-biased technical change, or $\triangle \ln(\frac{A_t^g}{A_t^h}) > 0$, increases the college premium. The second is changes in relative supply, adjusted by the elasticity of substitution. An increase in the supply of college graduates lowers the college premium by an amount inversely related to ω. Over time, the evolution of the college premium depends on the relative strength of these two opposite forces.

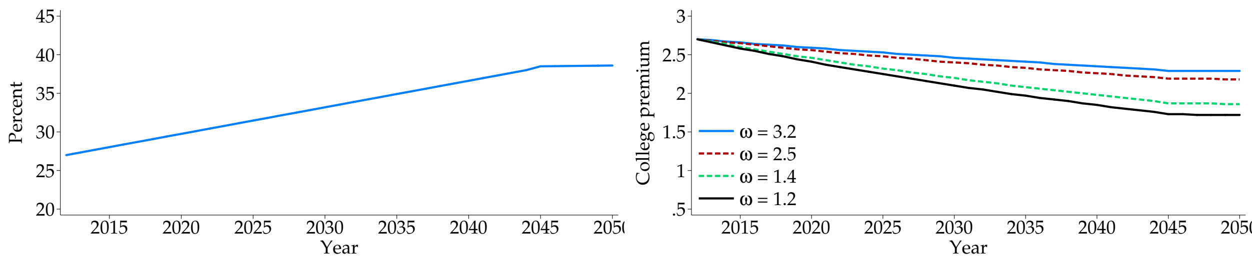
To investigate the extent to which the increased supply of college graduates might depress the college premium, we focus on universal free college, which increases supply the most and provides an upper bound to the potential college premium decline. We assume that universal free college becomes a permanent policy beginning with our 2006 entry cohort and simulate the evolution in the share of college graduates (relative to all workers in the economy) and the college premium. We assume no skill-biased technical change, and therefore estimate an upper

[40] Ferreyra et al. (2021) shows that, in Latin America, students in short-cycle programs graduate at higher rates than those in bachelor's programs, and their graduates obtain better labor market outcomes than dropouts from bachelor's programs.

bound for the college premium decline.

The critical parameter for this exercise is ω, which we estimate as 3.2 for Colombia.[41] Using this estimate, the left and right panel of Figure 8 show the evolution of the share of college educated workers and the college premium, respectively. The former rises over time as young, more educated cohorts replace older, less educated ones. The replacement is complete around the year 2045, when the economy reaches steady state.

Figure 8: Free College and and the College Premium



a. Labor Force Share of College Graduates

b.College Premium

Source: Own calculations based on model estimates.
Notes: Panel a shows the predicted share of college graduates in the labor force, calculated as the share of workers with a college degree relative to all workers in the economy. Panel b shows predicted college premium, calculated as the ratio between average wage for college graduates and for high school graduates.

As in our model, the 2006 entry cohort starts to graduate in 2010. In 2006, the share of college graduates in the workforce equals 27 percent.[42] Universal free college raises this share by about 12 pp (see Table 2) per cohort, to a long-run value of 39 percent (panel a). In the short-run the college premium falls relatively little (panel b) because the increase in college graduates from the first few cohorts is small relative to the full stock of college-educated workers. The negative impact on the college premium grows over time yet is always small, unlikely to dissuade many high school graduates from college enrollment. As a robustness check, panel b depicts the implied college premium path for several ω estimates for developed economies.[43] The college premium declines more for these values, yet even the greatest decline—down to 1.70—still leaves a substantial college premium, comparable to that in the U.S. Of course, skill-biased technical change would lead to an even smaller decline for a given ω value.

To summarize, the college premium decline induced by free college would be small in Colombia, both in the short and long run. Since biases from a partial equilibrium analysis appear

[41] There is a large number of estimates for this parameter in the literature. For example, Katz and Murphy (1992)'s estimate is 1.4 for the U.S. for 1963-1987; the low range of estimates also include 0.5. Card and Lemieux's (2001) estimate for the US and the UK at about 2-2.5. We estimate the production function parameters using Colombia's household surveys (SEDLAC) for 2001-12 following Card and Lemieux (2001).

[42] The initial share of 27 percent is higher than the initial fraction of high school graduates that finish college, equal to 14.5 in the baseline. The reason is that 27 percent includes graduates from all bachelor's programs (rather than only five-year programs) as well as graduates from two-year programs. This is for consistency with the fact that the college premium shown used in these simulations was calculated for all higher education graduates, since the data does not distinguish between graduates from bachelor's and two-year programs.

[43] We use the point estimates of 1.4 from Katz and Murphy (1992) and Heckman et al. (1998), and 2.5 from Card and Lemieux (2001); we also include a lower value of 1.2. For each ω value, the intercept has been adjusted to generate the same college premium for the year 2012.

small, we conclude that higher education in Colombia would remain a worthy investment in the medium and short run even if free college produced substantially more graduates.[44]

6 Conclusions

Although free college could arguably expand enrollment rates, particularly among financially constrained individuals, its success in expanding the percent of college graduates depends crucially on its impact on student effort. In this paper we apply the dynamic model of college enrollment, performance, and graduation developed in Ferreyra et al. (2022), where student effort is a central piece, and use it to evaluate the impact of free college programs. According to our analyses, universal free college expands enrollment the most among all programs considered here but has the highest per-graduate cost and does not raise graduation rates. Performance-based free college, in contrast, delivers a slightly lower enrollment expansion but has a higher graduation rate and a lower per-graduate cost. While both universal and performance-based free college provide some insurance against student uncertainty, the conditional insurance provided under performance-based free college elicits greater student effort and yields better outcomes.

The effects of free college on student effort and graduation vary across students and programs yet are generally small as effort, for many students, is very costly. In other words, free college alone is not likely to raise the fraction of college graduates, and complementary policies might be needed. Lowering the cost of effort through tutoring, remedial education, mentoring, and advising might be helpful, particularly for the most disadvantaged students. Additional reforms may be required given the structure of college programs in Latin America, most of which start with major-specific classes and rarely include general education classes that transfer easily across majors. The high transaction costs of switching majors lead many students to abandon higher education and further contribute to the dropout rate. Moreover, programs are long—at least five years theoretically, often stretching to eight or ten in practice—and rarely connect the student with the labor market, which discourages completion even more.

Finally, one additional reason might explain free college's failure to elicit large effort changes—zero tuition might not be enough. Low-income students, in particular, might need a supplementary, generous stipend for living expenses (such as that provided by *Ser Pilo Paga*) in addition to plentiful supports. By lowering college subsidies for affluent students, countries with limited fiscal resources could, in principle, provide such additional resources to their most disadvantaged students. All in all, helping individuals in the developing world reap the high returns to college takes more than free tuition and requires a serious consideration of the broad set of barriers preventing students from exerting effort and succeeding.

[44] These results are consistent with Garriga and Keightley (2007), who conduct a similar analysis for the U.S. in a model that endogenizes the college premium, government budget constraint, after-tax earnings, and labor supply decisions. They show that tuition subsidies have small effects on the college premium even when accounting for taxes. Their results are partly due to the limited effects of the policy on graduation rates, and to the high elasticity of substitution between college and high school graduates.

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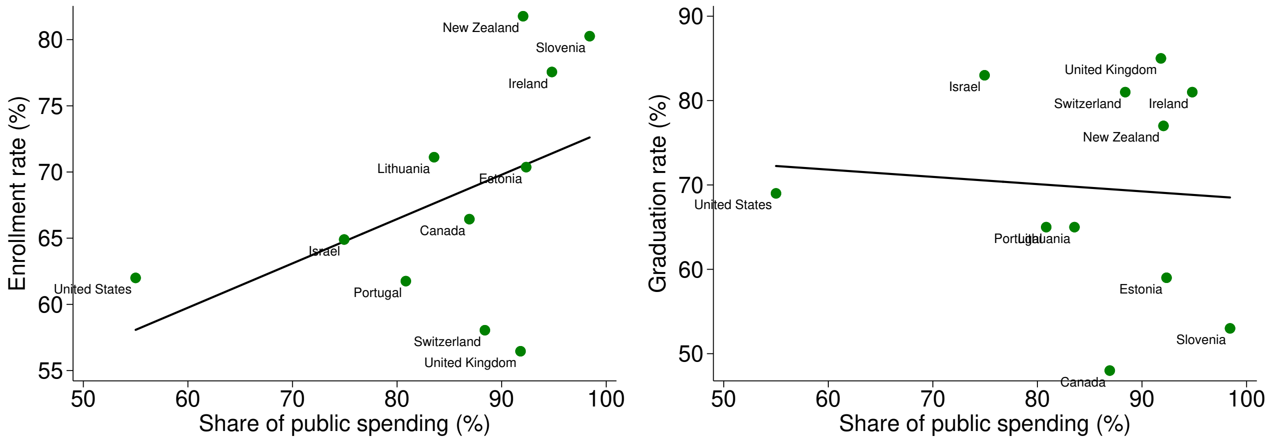
For Online Publication: Appendices

A Higher education enrollment and graduation by public spending share in OECD countries.



a. Enrollment

b. Graduation

Source: UNESCO for 2017 enrollment rates for all countries but the US, for which the source is OECD Education Statistics; OECD's Education at a Glance Report for graduation rates circa 2017; and UNESCO for the 2017 share of public spending in higher education.
Notes: Gross enrollment rate is the ratio between higher education enrollment and the number of individuals ages 18-24. Graduation rate is the percentage of students who started a bachelor's program and graduated within the theoretical duration of the program plus 3 years (relative to all the student who started a bachelor's program). Share of public spending is government spending in higher education relative to total higher education spending.

B Data

Table B1: Family Income and Ability Distribution of High School Graduates.

Income	Ability quintile					
Bracket	1	2	3	4	5	Total
5+ MW	0.21	0.31	0.48	0.90	3.15	5.05
3-5 MW	0.88	1.08	1.37	1.94	3.43	8.69
2-3 MW	2.72	2.94	3.30	3.69	3.95	16.60
1-2 MW	8.47	8.99	9.16	8.69	6.64	41.95
<1 MW	7.95	6.89	5.80	4.58	2.49	27.71
Total	20.23	20.21	20.11	19.80	19.65	100.00

Source: Calculations based on the Saber 11 dataset. The distribution refers to 415,269 high school graduates from 2005.
Notes: Family income is reported in brackets; MW = monthly minimum wage. Ability is reported in quintiles of standardized Saber 11 scores. Quintile 1 is the lowest.

Table B2: Performance Tiers: Lower Bound by Year.

Tier	Year 1	Year 2	Year 3	Year 4	Year 5
Tier 1	19	38	57	76	95
Tier 2	17	34	51	68	85
Tier 3	13	26	39	52	65
Tier 4	0	0	0	0	0
Required cumulative classes	20	40	60	80	100

Source: Own classification.
Notes: This table shows the lower bound of number of cumulative classes completed for each tier, by year. For a given year, tiers are defined relative to the required number of cumulative classes completed (equal to 20, 40, 60, 80, and 100 in years 1 through 5, respectively). Tier 1: 95 percent of the requirement or more; Tier 2: (85, 95] percent; Tier 3: (65, 85] percent; Tier 4: 65 percent or less. For example, in year 2 (when 40 cumulative classes are required), the tier lower bounds (expressed in cumulative classes completed) are as follows: 38 classes = 0.95×40 for Tier 1; 34 classes = 0.85×40 for Tier 2; and 26 classes = 0.65×40 for Tier 3.

Table B3: Family Income and Tuition.

Income Bracket	Avg. Per-Capita Household Income (y)	Avg. Per-Capita Tuition (T)
5+ MW	21,027,690	2,195,972
3-5 MW	9,191,642	1,826,386
2-3 MW	5,337,010	1,177,543
1-2 MW	2,952,288	978,690
<1 MW	1,119,633	855,493

Source: Calculations based on Saber 11 and SEDLAC (household surveys) for per-capita annual income; Ministry of Education of Colombia and SPADIES for annual tuition. Income and tuition are expressed in Colombian pesos (COP) of 2005.
Notes: Since Saber 11 provides income brackets rather than actual income, we use SEDLAC (household surveys) data on household income and size to calculate average per-capita income for households in a given bracket; this is our proxy for parental transfer or *income* (y). To calculate average tuition by bracket, we average over the tuitions paid by student from the corresponding income bracket at public institutions. MW = monthly minimum wage.

Table B4: Average Hourly Wage by Age Bracket and Educational Attainment.

	Age bracket			
	18-60	18-22	23-35	36-60
College graduates	6,308	3,636	5,305	7,171
HS graduates	2,424	1,845	2,213	2,864
College dropouts; completed 1 year or less	3,091	2,349	2,897	3,619
College dropouts, completed 2 years or more	3,824	2,459	3,340	4,451

Source: Household surveys for Colombia (SEDLAC); year 2005.
Notes: Wages are expressed in Colombian pesos (COP) of 2005. Calculations include males and females who work. Attainment reflects an individual's highest completed level of schooling.

C Model timeline

The figure below summarizes the timing of events and student decisions:

Figure C1: Summary of Timing of Events and Individuals' Decisions

Enrollment Decision ($t = 0$) $\begin{cases} \text{College} \\ \text{Labor force} \end{cases}$

	State	i. Choice	ii. Classes completed shock	iii. Accumulated classes completed	iv. Dropout shock	v. Payoffs
College ($t = 1{:}4$)	(t, h_{t-1}, θ, y)	e_t	shock z_t	completed h_t	shock d_t^{drop}	$V^{drop}(t+1)$ $V^{coll}(t+1, h_t, \theta, y)$

	State	i. Choice	ii. Classes completed shock	iii. Accumulated classes completed	iv. Dropout shock	v. Payoffs
College ($t = 5{:}7$)	(t, h_{t-1}, θ, y)	e_t	shock z_t	completed h_t	shock d_t^{drop}	$V^{drop}(t+1)$ $V^{coll}(t+1, h_t, \theta, y)$ $V^{grad}(t+1)$

	State	i. Choice	ii. Classes completed shock	iii. Accumulated classes completed	iv. Dropout shock	v. Payoffs
College ($t = 8$)	$(8, h_7, \theta, y)$	e_8	shock z_8	completed h_8	shock d_8^{drop}	$V^{drop}(9)$ $V^{grad}(9)$

D Computation

D.1 Solving the model: A Summary

Recall that the state vector is (t, h_{t-1}, θ, y). We discretize the state space for a total of 40,400 points. We simulate $N = 100{,}000$ high school graduates from the empirical distribution of ability and income (or parental transfer), $\Phi(\theta, y)$. For each simulated high school graduate, we draw one *i.i.d.* shock per year, $\{\nu_{it}\}_{t=1}^{8}$. These shocks enter the performance shock, z (see equation (12) in the main text). For a given simulated high school graduate, these shocks are the same across parameter vectors during estimation, and at baseline and counterfactuals.

Among the simulated high school graduates of a given type, a fraction of them receives a college enrollment shock equal to 1 and enrolls in college (thus becoming the "simulated college students"); the fraction is equal to the type's observed college enrollment rate.[45]

To compute the model's predictions for a given value of Θ, the algorithm proceeds as follows:

1. For each point in the state space, use backward induction to solve for the sequence of optimal efforts (the policy function) and the value function, $e^*(t, h_{t-1}, \theta, y)$ and $V^{coll}(t, h_{t-1}, \theta, y)$ respectively.

2. For each simulated college student, and for every year she is enrolled, combine her optimal effort with the corresponding ν_t shock to determine the performance shock and the probability of dropping out, $\tilde{p}^d(t, h_t, \theta, y)$. Draw the binary dropout shock; the shock is equal to 1 with probability $\tilde{p}^d(t, h_t, \theta, y)$.

3. Based on step 2, aggregate the simulated dropout decisions to obtain a predicted dropout rate for each of the 400 (t, θ, y)-combinations.

4. Find the vector $\boldsymbol{\delta}$ that minimizes the distance between the predicted and observed dropout rate for each (t, θ, y)combination, using the contraction mapping algorithm described in Appendix E.1.

5. By comparing the value of going and not going to college for each type, $V^{coll}(1, 0, \theta, y)$ and V^{hs}, respectively, find the type-specific college enrollment shock, ξ_j, that renders the type indifferent between going and not going to college. Further details are provided in Appendix E.2.

Solving steps 1-5 of the dynamic optimization problem for $100,000$ simulated high school graduates and $40,400$ states takes approximately 8 minutes in a 1.4 GHz Intel Core i5 processor. Since the model does not have a closed-form solution, in estimation the problem must be solved anew for each value of Θ. The estimation of $\boldsymbol{\delta}$ and $\boldsymbol{\xi}$ is nested within the model solution for a given of value of Θ, in the spirit of Berry et al (1995), as described in Appendix E.

D.2 Simulating college students

Recall that a student type j is given by a (θ_j, y_j) combination. We have $J = 50$ types.

[45] In the free-college counterfactuals, the fraction of enrolled students is given by equation (8) in the main text, where the value of college changes in response to free college.

For each type, let $P^{coll}(\theta_j, y_j)$ be equal to the actual, observed share of individuals *of that type* that enrolls in college. Note that $P^{coll}(\theta_j, y_j)$ varies across types, as illustrated by Figure panel a. Consider individual i who belongs to type j. For each simulated individual, we draw a binary variable, d_i^{enr}, to determine whether the student goes to college or not. More specifically,

$$d_i^{enr} = \begin{cases} 1, & i \text{ goes to college, with probability } P^{coll}(\theta_j, y_j) \\ 0, & i \text{ does not goes to college, with probability } 1 - P^{coll}(\theta_j, y_j) \end{cases} \tag{19}$$

Simulated students who receive $d_i^{enr} = 1$ are those who enroll in college. In other words, the proportion of simulated students of a given type who receive $d_i^{enr} = 1$ is the same as the proportion of actual students of that type who enroll in college.[46] For students who do not enroll in college, the value function is V^{hs}. For those who enroll in college, we simulate classes completed and dropout shocks as described below.

For $t = 1$, we use the policy function $e^*(1, 0, \theta_j, y_j)$ corresponding to every student type j. Since all students start at $t = 1$ with zero accumulated classes, $h_0 = 0$, the policy function assigns the same effort to all students of a given type, j. Then, we draw the *iid* shock ν_{i1} for each student; this, in turn, yields a value for the z_{i1} shock. The combination of the student's ability, effort, and z_{i1} shock yields the number of completed classes, h_{i1}. Because of the z shock, individuals of a given type attain different values of h by the end of the first period.

For student i, we use the realized h_{it} to establish whether the student drops out before the second period. The student receives a draw of the binary variable d_{it}^{drop}; if the draw is equal to 1, she drops out. The probability of $d_{it}^{drop} = 1$ is a function of student type, year, and average performance up to (and including) the corresponding year:

$$d_{it}^{drop} = \begin{cases} 1, & i \text{ drops out of college, with probability } \tilde{p}^d(t, h_{it}, \theta_j, y_j) \\ 0, & i \text{ continues in college, with probability } 1 - \tilde{p}^d(t, h_{it}, \theta_j, y_j) \end{cases} \tag{20}$$

where $\tilde{p}^d$ is defined as in equation (13) in the main text.

Another binary variable, d_{it}^{grad}, indicates whether a student graduates. The graduation requirement is $h^{grad} = 98$ rather than 100 because some students in the data graduate with fewer than 100 classes. Whenever $t \geq 5$ and $h_{it} \geq h^{grad}$, we set $d_{it}^{grad} = 1$ and $d_{it}^{drop} = 0$. In other words, a student in year 5 or beyond who has completed at least 98 classes is no longer subject to the risk of dropping out and automatically graduates. In addition, a student who reaches $t = 8$ without having completed at least 98 classes cannot graduate ($d_{it}^{grad} = 0$) and must drop out ($d_{it}^{drop} = 1$).

The final outcome of the simulation is a "dataset" with $N = 100{,}000$ simulated high school graduates, some of whom enroll in college. For those who enroll, we obtain their number of classes completed by year, final outcome (graduation or drop out), along with the period in which they either drop out or graduate. This dataset mimics our observed student-level administrative data.

[46] For a large number of simulations such as ours, this is asymptotically equivalent to simply assigning $d_i^{enr} = 1$ to a fraction of simulated students of a given type equal to the type's observed enrollment rate.

E Estimation

The Simulated Method of Moments (SMM) parameter estimates solve the following problem:

$$\arg\min_{\Theta} \quad (\hat{\mathbf{M}}(\Theta) - \mathbf{M})' W^{-1} (\hat{\mathbf{M}}(\Theta) - \mathbf{M}), \tag{21}$$

where Θ is a 13×1 vector of parameters, $\mathbf{M}$ and $\hat{\mathbf{M}}$ are 585×1 vectors of sample and predicted moments, respectively, and W is a diagonal weighting matrix whose diagonal contains the standard error of the sample moments. We compute numerically the predicted values, $\hat{\mathbf{M}}$, for every value of Θ. Since the model does not have a closed-form solution, we use a numerical algorithm to solve students' dynamic optimization problem for a given value of Θ. In the spirit of Berry, Levinsohn and Pakes (1995), the estimation of $\boldsymbol{\delta}$ and $\boldsymbol{\xi}$ is nested within the model solution for every value of Θ. Section D provides a full description of the algorithm.

The moments we match are listed in Table E1. Note that we do not match enrollment rates because our solution algorithm replicates enrollment rates perfectly by construction. In contrast, we match dropout rates because our solution algorithm does not perfectly replicate observed dropout rates at the (year, ability quintile, income) level. See Section E.1 for further details). Matching these 585 moments enables us to estimate our 13 model parameters.

E.1 Estimation of fixed effects in the dropout probability

We now describe the estimation of the time- and type-specific fixed effects that enter in the dropout probability, $\delta(t, \theta, y)$. This estimation is nested within the estimation of Θ, as it must take place for every possible value of Θ.

Based on the simulation of college students described in Appendix D, we compute the predicted fraction of students of type j who drop out in every t, or $\hat{p}_{jt}^{drop} = f^d(\delta(t, \theta, y); \Theta)$. We compare these predicted rates with the observed ones, denoted by p_{jt}^{drop}, and compute a measure of the distance between them.

For each pair of predicted and observed dropout rates, we calculate the fixed effects $\delta(t, \theta, y)$ that minimize this distance. We do so through an iterative contraction mapping, in the spirit of Berry et al (1995). While Berry et al (1995) uses a contraction mapping to find the unobserved product characteristics that make predicted market shares by product equal to their observed counterparts, we search for the time- and type-fixed effects that bring the observed dropout rates as close as possible to their observed counterparts for every period and student type.

Formally, we use a contraction mapping algorithm to find the vector $\boldsymbol{\delta} = [\delta(t, \theta, y)]_{J(8) \times 1}$ that fulfills the following condition:

$$\| \mathbf{f}^d(\boldsymbol{\delta}; \Theta) - \mathbf{p}^{drop} \| \leq \epsilon^d, \tag{22}$$

where ϵ^d is our chosen tolerance level. Below are the algorithm steps; recall that they are conditional on a given parameter point, Θ:

1. Establish an initial guess for the fixed effects vector, $\boldsymbol{\delta}^{(0)}$.

2. Solve the dynamic optimization problem (see Appendix D.)

Table E1: Moments Matched in Estimation.

Data aspect	Moments	Number of Moments
Dropout rates	Dropout rate by year.	8
	Dropout rate by ability quintile and income.	25
	Dropout rate by ability decile.	10
College outcomes	College outcomes by ability quintile.	25
	Fraction of students that graduate by year (years 5-8).	4
Cumulative classes completed	Average number of cumulative classes completed by year, ability quintile, and college outcome.	140
	Average number of cumulative classes completed by year and ability decile (years 1-5).	50
	Distribution of students into tiers of cumulative classes completed, by year.	24
	Distribution of students into tiers of cumulative classes completed, by ability quintile and year (years 1-5).	75
Transition probabilities	Pr(tier Y in $t+1$|tier X in t) for years 1-7.	112
	Pr($d_t^{drop} = 1$|tier X in t) for years 1-8.	32
Target number of classes	Average target number of classes by ability decile and year.	80
Total		585

Source: Own estimation.
Notes: Moments per year are computed for years 1-8 unless otherwise specified. Tiers are 1-4, based on cumulative classes completed. Under the second data aspect, "College outcomes," outcomes include on-time graduate, late graduate, drop out first year, drop out second year, drop out after second year. Under the third data aspect, "Cumulative classes completed," outcomes include on-time graduate (until year 5), late graduate, drop out this year, drop out later (until year 7); "this year" and "later" refer to the year under consideration. Under the fourth data aspect, "Transition probabilities", t refers to year; tiers X and Y are 1,...,4. For target number of classes, data consists of the average number of classes taken by the corresponding students.

3. Compute the predicted vector of dropout rates $\mathbf{f}^d(\boldsymbol{\delta}^{(0)};\Theta) = \hat{\mathbf{p}}^{drop}$.

4. Using the observed dropout rates, compute the updated fixed effects vector, $\boldsymbol{\delta}^{(1)}$, as follows:

$$\delta^{(1)}(t,\theta_j,y_j) = \ln\left(\frac{p_{jt}^{drop}}{f^d(\delta^{(0)}(t,\theta_j,y_j);\Theta)}\right). \tag{23}$$

5. Using $\boldsymbol{\delta}^{(1)}$ as the new initial guess, repeat steps 1 through 4 until either condition (22) is satisfied or a predetermined maximum number iterations is reached.

Depending on the parameter values, the algorithm is at times unable to meet (22) due to model non-convexities. For instance, in $t = 8$, graduating in the model is a deterministic function of the number of classes completed, whereas in the data we observe some individuals graduate without having completed all classes, likely due to measurement errors in number of classes completed. Since we do not match drop out rates perfectly, we use them as a moment in our Simulated Method of Moments (SMM) estimator.

E.2 Recovering type-specific preferences for college enrollment

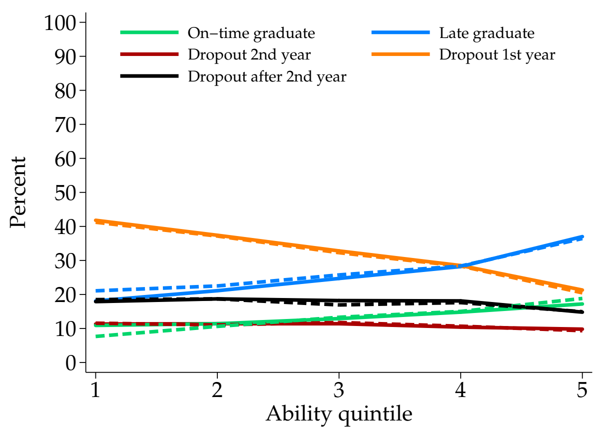
Recall that $\xi_j = \tilde{\xi}(\theta_j, y_j)$ is the type-specific unobserved preference shock for enrolling in college. For a given value of Θ, we recover it as follows. As described above, we compute the value function, $V^{coll}(\cdot)$, for every state (t, h_t, θ, y), which allows us to compare the value of going to college, $V^{coll}(1, 0, \theta_j, y_j)$, with the value of working as a high school graduate, V^{hs}. Thus, ξ_j takes on the value that makes the predicted probability of enrolling to college be equal to the observed one. Under the assumption that $\sigma_\epsilon = 1$, we solve for ξ_j in equation (8):

$$\xi_j = \ln\left(\frac{P^{coll}(\theta_j, y_j)}{1 - P^{coll}(\theta_j, y_j)}\right) - (V^{coll}(1, 0, \theta_j, y_j) - V^{hs}). \tag{24}$$

At the counterfactuals, we hold these shocks at their baseline values, since they are preference parameters.

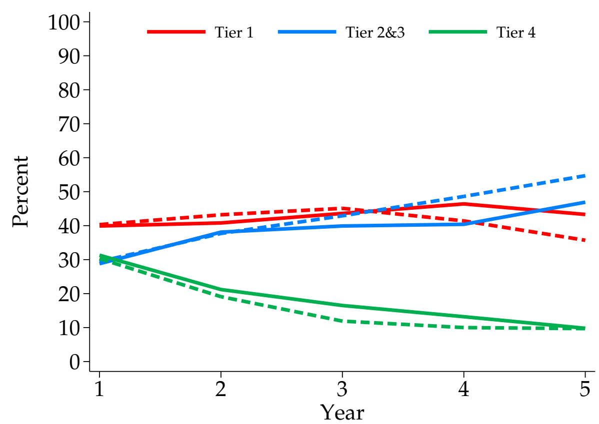
F Goodness of fit

Figure F1: College Outcomes.



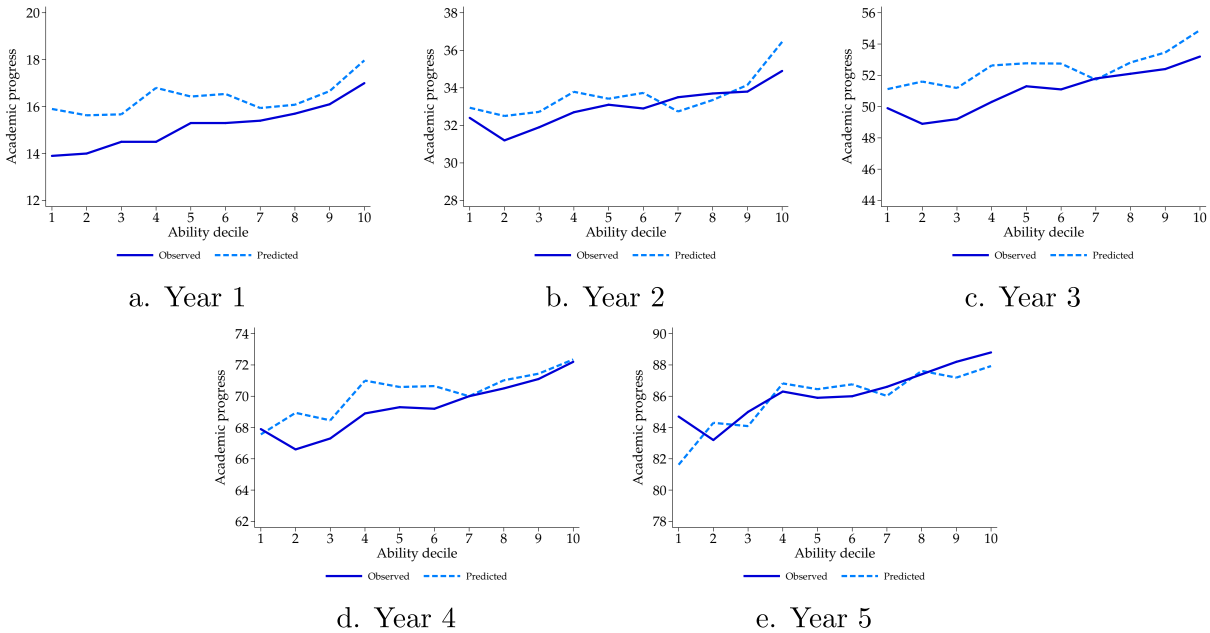
Source: SPADIES for observed data; fitted values for predicted data.
Notes: Whole lines show observed values; dashed lines show fitted values. For ability, quintile 1 is the lowest.

Figure F2: Tiers of Cumulative Classes Completed, by Year.



Source: SPADIES for observed data; fitted values for predicted data.
Notes: For each year, the figure shows the percent of students by tier of cumulative classes completed. Whole and dashed lines show observed and predicted percentages, respectively. Tier 1 is the top tier.

Figure F3: Cumulative Classes Completed by Ability Decile and Year.

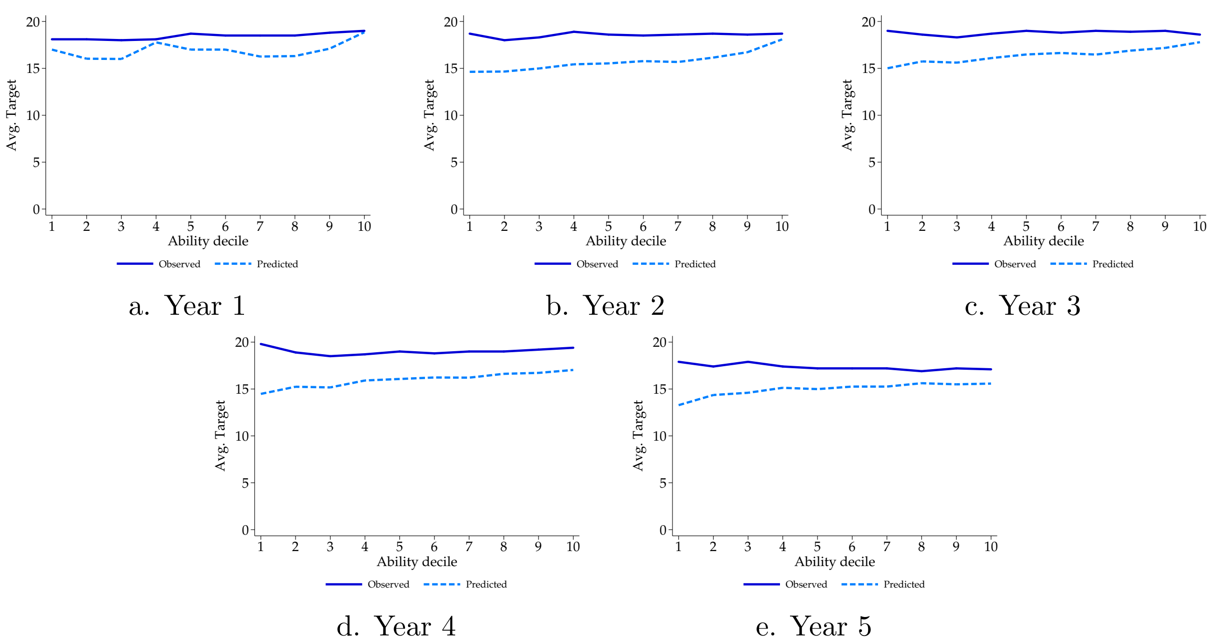


a. Year 1 b. Year 2 c. Year 3

d. Year 4 e. Year 5

Source: SPADIES for observed data; model simulations for predicted data.
Note: For each year, the panels depict observed and predicted cumulative number of classes completed by ability decile (decile 1=lowest). Figures correspond to students who begin each year.

Figure F4: Target Number of Classes by Ability Decile and Year



a. Year 1 b. Year 2 c. Year 3

d. Year 4 e. Year 5

Source: SPADIES for observed values; model's simulations for predicted values.
Note: Observed values correspond to the average number of classes attempted; predicted values correspond to average target number of classes as defined in the model.

Table F1: Distribution of Dropouts by Year.

Year	Observed	Predicted
1st	27.41	27.92
2nd	10.38	10.43
3rd	4.77	4.94
4th	2.7	2.83
5th	2.61	2.81
6th	2.74	2.92
7th	2.48	1.94
8th	1.28	1.19
Total	54.36	54.98

Source: SPADIES for observed data; fitted values for predicted data.
Notes: Table shows the observed and predicted percent of students who drop out each year, relative to the entry cohort.

Table F2: Dropout Rates by Income and Ability.

	Ability quintiles											
Income	Observed values						Predicted values					
Bracket	1	2	3	4	5	Total	1	2	3	4	5	Total
5+ MW	81.4	65.8	61.5	52.1	39.1	44.7	84.4	67.8	63.4	51.9	40.7	46.7
3-5 MW	74.2	69.4	62.2	57.9	43.8	51.3	81.6	68.3	62.2	57.3	44.4	52.5
2-3 MW	68.5	67.6	63.7	57.7	46.5	55.1	70.8	67.5	61.9	60.1	44.4	55.6
1-2 MW	71.6	66.6	62.2	57.7	50.6	57.8	69.9	66.5	60.9	56.2	46.9	56.7
<1 MW	69.0	67.9	61.3	55.9	50.3	58.7	69.6	66.3	58.6	53.7	46.2	57.5
Total	71.0	67.4	62.4	60.0	45.8	54.4	71.3	66.9	61.0	56.6	44.8	55.0

Source: Source: SPADIES for observed data; fitted values for predicted data.
Notes: Values are expressed in percentages (%). Dropout rates are relative to students who start college in year 1. Income is reported in brackets; MW = monthly minimum wage. Ability is reported in quintiles of standardized Saber 11 scores. Quintile 1 is the lowest.

Table F3: Cumulative Classes Completed; Years 1-4.

	Observed values				Predicted values			
	Year 1	Year 2	Year 3	Year 4	Year 1	Year 2	Year 3	Year 4
Ability quintile								
1	13.9	31.7	49.3	67.2	15.7	32.7	51.4	68.3
2	14.5	32.3	49.8	68.2	16.3	33.3	52.0	69.9
3	15.3	33.0	51.2	69.2	16.5	36.6	52.8	70.6
4	15.6	33.6	52.0	70.3	16.0	33.1	52.3	70.6
5	16.6	34.5	52.9	71.8	17.4	35.5	54.3	72.0
On-time graduate	20.5	41.2	62.0	82.8	20.7	41.5	62.2	82.1
Late graduate	18.0	35.4	52.5	70.1	19.4	37.8	55.4	72.0
Dropout later	15.8	30.4	44.5	59.3	14.9	29.0	42.9	53.9
Dropout this year	10.9	23.8	36.4	46.4	13.2	21.7	37.5	55.6
Total	15.8	33.8	52.1	70.6	16.7	34.2	53.2	71.0

Source: SPADIES for observed data; model simulations for predicted data.
Notes: For each group of students (row) and year (column), the table shows the cumulative number of classes completed by students from that group in the corresponding year. Rows classify students by ability quintile (quintiles 1 through 5; quintile 1 is the lowest) or by their final college outcome (on time graduate, late graduate, dropout later, dropout this year.) For instance, students who go on to graduate on time complete 20.5 classes by the end of year 1 and 41.2 by the end of year 2, and so forth.

Table F4: Cumulative Classes Completed; Years 5-8.

	Observed values				Predicted values			
	Year 5	Year 6	Year 7	Year 8	Year 5	Year 6	Year 7	Year 8
Ability quintile								
1	83.9	88.8	93.6	96.0	83.1	90.4	91.3	92.2
2	85.7	91.3	95.3	97.2	85.7	92.0	92.3	91.6
3	85.9	91.5	95.8	98.0	86.8	92.9	93.1	94.3
4	87.1	92.7	96.6	98.4	86.9	92.6	92.3	90.5
5	88.6	94.0	97.6	99.0	87.6	93.3	93.5	91.4
On-time graduate	99.0				99.5			
Late graduate	86.6	95.6	98.3	98.9	87.1	96.8	98.4	99.3
Dropout later	72.4	78.5	82.7		64.4	68.8	75.7	
Dropout this year	69.7	84.5	86.2	88.2	64.5	77.3	76.6	81.5
Total	87.5	93.0	96.8	98.5	86.9	92.8	92.9	91.6

Source: SPADIES for observed data; model simulations for predicted data.
Notes: See Table F3.

Table F5: Transitions Among Tiers of Cumulative Classes Completed.

	Observed values				Predicted values			
	Year 2	Year 3	Year 4	Year 5	Year 2	Year 3	Year 4	Year 5
Persistence								
Tier 1	64.33	79.78	86.98	79.89	63.70	75.80	75.10	74.30
Tier 2	28.67	39.23	51.47	57.76	22.80	38.40	53.70	60.10
Tier 3	34.94	49.44	60.94	69.04	35.10	59.20	71.20	78.80
Tier 4	29.67	45.75	57.87	58.59	37.10	42.50	60.70	76.00
Dropout rate								
Tier 1	12.16	4.03	1.75	0.71	11.60	4.20	3.00	2.20
Tier 2	14.43	6.50	3.25	1.52	16.20	6.40	4.60	3.00
Tier 3	23.02	12.30	7.29	4.02	25.10	9.20	7.00	5.20
Tier 4	54.23	41.95	28.24	24.24	55.20	50.70	35.20	21.40
Prob. of Catch up								
Tier 3 to Tiers 1 & 2	18.10	20.42	20.61	19.63	26.60	20.30	13.10	9.40
Tier 4 to Tiers 1 & 2	4.26	0.55	0.22	0.14	0.82	0.00	0.00	0.00
Prob. of Fall behind								
Tier 1 to Tiers 3 & 4	11.01	5.41	2.54	1.66	4.30	1.20	0.30	0.00
Tier 2 to Tiers 3 & 4	36.8	28.77	17.70	18.40	26.00	25.60	22.80	24.40

Source: SPADIES for observed data; model simulations for predicted data.
Notes: This table shows, for students who begin the school year (column) in a given tier (row), the percentage that persists in the same tier in that year ("persistence" panel), drops out ("dropout rate" panel), catches up to a higher tier ("prob. of catch up" panel) or falls behind ("prob. of fall behind"). Tier 1 is the highest. A student can change tiers over time.