The Macroeconomic Cost of College Dropouts*

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Abstract

Forty percent of full-time, four-year U.S. college students drop out before graduating. While academic and labor market risks are well studied, financial constraints remain underexplored despite growing evidence that family wealth plays a central role in college success. Using four longitudinal datasets, I show that many students face unpredictable grant reductions unrelated to academic performance. These shocks are not offset by alternative financial sources and strongly correlate with dropout decisions, particularly for high-ability, low-wealth students. To quantify the impact, I develop an overlapping generations model with endogenous college decisions. Grant reductions explain 34% of dropouts, while academic uncertainty accounts for only 10%. A reform that eliminates grant volatility raises social welfare by 2.4% and improves sorting by ability. Importantly, the policy is fiscally self-financing: aggregate productivity gains expand the tax base, offsetting costs. These findings underscore that stabilizing the grant system not only critically enhances equity and efficiency in higher education but also generates profound macroeconomic gains.

Keywords: Inequality, Financial Aid Uncertainty, College Dropouts, Skill Premium, Financial Constraints, General Equilibrium
JEL Codes: E24, H52, H53, I22, I26, I28

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1 Introduction

Forty percent of full-time, four-year college students in the United States drop out before earning a degree.[1] While a large literature has emphasized uncertainty over academic ability and labor market outcomes as key drivers of attrition (e.g., Hendricks and Leukhina 2017, 2018), the role of financial mechanisms has received comparatively less attention. Yet, recent evidence highlights that family wealth has become increasingly important in determining who succeeds in college (Lochner and Monge-Naranjo (2011)). Understanding how financial constraints shape dropout behavior is essential, given the individual and macroeconomic stakes of college completion.

This paper combines new empirical evidence with a General Equilibrium lifecycle model to show that grant volatility is a key, policy-relevant driver of college attrition. Using four nationally representative longitudinal datasets, I first document that a substantial fraction of students experience declines in grant aid during college. These downward adjustments are not explained by academic performance, are not offset by other financial resources, and are strongly predictive of dropout. To quantify its impact, I develop an overlapping generations model in which individuals make endogenous enrollment and dropout decisions. The model incorporates grant uncertainty as a dropout channel alongside academic ability and labor market risk. The findings show that downward grant revisions account for 34% of observed dropouts, highlighting the importance of financial risk for student persistence. In general equilibrium, stabilizing grant aid raises graduation rates, improves ability sorting, increases aggregate productivity, and delivers a 2.4% welfare gain. The reform is self-financing through higher tax revenue. Notably, a substantial share of the welfare gain arises from general equilibrium adjustments—particularly through a reduced skill premium—underscoring the importance of accounting for general equilibrium effects when studying large-scale policies.

Drawing on the National Longitudinal Surveys of Youth (NLSY79 and NLSY97), I begin by reassessing how family wealth shapes college trajectories. Consistent with earlier work (Bailey and Dynarski 2011; Belley and Lochner 2007; Lochner and Monge-Naranjo 2011) the wealth gradient in four-year enrollment has steepened across cohorts.[2] I show that the gradient is equally pronounced for dropout risk once students reach campus, even after conditioning on academic ability. To understand the mechanism, I examine how students finance college. Among low-wealth students, grants are the primary source of funding, and these awards are highly unstable: grant amounts frequently decline across academic years. This volatility is not offset by increases in parental transfers, loans, work-study, or other forms of support. To determine whether grant

[1] On average, 6% drop out after each year. See the detailed breakdown in Appendix J.5.

[2] To ensure a focused analysis on a representative segment of higher education, this study concentrates on four-year institutions. This approach allows for a clearer examination of dropout mechanisms without introducing the distinct dynamics of community colleges or the unique financial structures often found in highly selective, well-endowed Ivy League institutions.

volatility reflects student behavior or structural frictions, I turn to the administrative student-level data from the Beginning Postsecondary Students Longitudinal Study (BPS). I focus on first-time, full-time students at four-year institutions and show that even students who maintain academic eligibility (meeting GPA, course load), and their own earnings thresholds, frequently see their Pell grants reduced. My analysis specifically shows that this volatility represents residual variation in grant amounts—variation that persists even after accounting for student-level factors such as academic performance (GPA), earnings, and enrollment status, which are often cited as reasons for grant changes. This suggests that much of the observed aid volatility appears to be structural rather than behavioral. Moreover, losing Pell support is strongly associated with dropout within six years, even after conditioning on academic performance, institution type, and ex-ante ability. This finding is consistent with the causal estimates in Denning, Marx, and Turner (2019), which show that reductions in Pell grants increase the likelihood of dropping out. Together, the evidence points to uninsured grant shocks as a policy-relevant driver of college attrition.

The unpredictability of financial aid is well-documented. Eligibility is governed by the Free Application for Federal Student Aid (FAFSA), the outcome of which—the Expected Family Contribution (EFC)—determines not only federal awards but also most state and institutional grants. FAFSA's multi-step formula, frequent revisions, and limited transparency make it difficult for students to anticipate year-to-year aid, even when they remain academically eligible. This unpredictability has been highlighted in prior research (Dynarski and Scott-Clayton 2006, Bettinger et al. 2012, Dynarski et al. 2021a) and acknowledged in federal reform efforts. The FAFSA Simplification Act of 2019[3] explicitly addresses these issues, aiming "to make it easier to apply for Federal student aid [and] to make that aid predictable" through amendments to the Higher Education Act of 1965. Despite this recognition, successful implementation of these reforms remains pending.

Based on these empirical findings, I ask the following questions: What fraction of observed dropout rates can be attributed to volatility in the current grant system? How much arises from other mechanisms emphasized in the literature, such as learning about academic ability or changing labor market prospects? Is there policy space to increase college completion? What are the long-run fiscal costs or savings of such interventions, and how are the gains and losses distributed across the population?

To address these questions, I build a general equilibrium, lifecycle model with endogenous schooling. The economy has three stages—college, work, and retirement. Upon entering, individuals decide whether to enroll in college based on initial wealth, beliefs about ability, and idiosyncratic productivity shocks. Once enrolled, students may reassess the value of college and choose to drop out. Dropout decisions arise through three channels: (1) learning about ability through academic performance, (2) labor-market productivity shocks, and (3) revisions to expected

[3] https://www.congress.gov/bill/116th-congress/senate-bill/2667/text

grant amounts between academic years. A key modeling innovation is an explicit financial dropout channel in which grants vary through two mechanisms: (i) GPA-contingent rules, and (ii) an exogenous stochastic shock that captures unexplained variation in aid awards even after conditioning on eligibility criteria. Under mechanism (i), a low GPA can push students out not only because it lowers expected returns (the standard learning margin) but also because it directly reduces grants and tightens borrowing constraints. Mechanism (ii) delivers a pure liquidity shock that binds credit limits despite continued academic eligibility. By endogenizing both sources of volatility, the model uncovers financial forces absent from most macro-education frameworks; omitting them overstates the role of learning and understates the importance of credit constraints, resulting in misguided policy implications.

College participation is embedded in a general-equilibrium, overlapping-generations economy. The representative firm's production function treats college graduates as imperfect substitutes for both dropouts and high school graduates, so education choices influence the college wage premium through endogenous skill prices. Labor-market returns depend on ability, conditional on education status; hence, who sorts into and persists through college is critical for aggregate productivity. Because the wage premium is a key incentive for skill investment, a general-equilibrium framework is essential for assessing the long-run effects of education policy.

The model is calibrated to U.S. data on educational attainment—enrollment, completion, and skill premiums. Grant volatility is disciplined using academic-year variation in aid, conditional on students' academic performance and earnings. This approach provides a conservative calibration of grant uncertainty, as it focuses on volatility persisting even among students who maintain formal eligibility, thereby likely understating the full extent of uncertainty for the broader student population and making the quantified impact a robust, lower-bound estimate. GPA thresholds come from BPS micro data, and initial ability beliefs follow the empirical estimates of Stinebrickner and Stinebrickner (2014). The model also reproduces untargeted moments: subsidy-response elasticities aligned with empirical benchmarks (Deming and Dynarski 2009; Scott-Clayton 2011), college-participation patterns by family wealth, and the earnings distribution.

Using the calibrated model, I first examine how dropout risk varies across the joint distribution of wealth and ability. The analysis shows that high initial wealth or strong prior beliefs about ability attenuate the effect of negative shocks. In contrast, high-ability, low-wealth individuals and mid-ability, mid-wealth individuals are particularly exposed to reductions in grant aid: lacking self-insurance, they are less likely to enroll ex ante and more likely to exit if enrolled. This challenges the conventional view that marginal college students are primarily low-ability, and instead highlights that marginality is frequently driven by the interaction of high ability and limited parental wealth. This finding echoes the policy implications in Dynarski et al. (2021a), suggesting that guaranteeing need-based aid at the time of enrollment—thereby eliminating grant uncertainty—would

disproportionately raise enrollment, persistence, and completion among high-ability students from low-wealth families.

To quantify each dropout mechanism, I eliminate one channel at a time—holding taxes and skill prices fixed—and recompute completion rates. Removing grant uncertainty reduces dropout by 34 percent; eliminating GPA-contingent aid cuts it by a further 5 percent. In contrast, shutting down the learning channel lowers dropout by only 10 percent. The remaining dropout behavior is explained by labor market shocks and the dropout wage premium. This decomposition highlights the significant contribution of financial aid instability to college attrition, underscoring the policy relevance of addressing aid uncertainty.

I next examine grant-stabilization reforms in general equilibrium. In the main experiment I assume students keep the award they receive in the first year for the remainder of college, which is equivalent to eliminate reapplication requirements, with exceptional cases handled by institutional professional-judgment offices and GPA checks performed automatically on campus.[4] Stabilizing aid in this way raises completion among high-ability, low-wealth students who were previously liquidity-constrained, thereby strengthening ability sorting, lifting aggregate productivity, and increasing newborn welfare by 2.4 percent —about 70 percent of the gain obtained when GPA thresholds are also removed. The reform is fiscally self-financing: the extra grant outlays are more than offset by a broader tax base, so the budget-balancing labor tax rate falls. Over time, the composition of dropouts shifts: Attrition declines among low-wealth, high-ability students and rises among wealthier, lower-ability peers as the skill premium contracts, while the overall dropout rate remains roughly unchanged. These results underscore the importance of general-equilibrium feedbacks when evaluating large-scale financial-aid policies.

Related Literature. This paper contributes to several strands of the literature. First, it extends macroeconomic models of education that study the design of optimal subsidies in general equilibrium, including Abbott et al. (2019), Colas, Findeisen, and Sachs (2021), Heathcote, Storesletten, and Violante (2017), and Krueger and Ludwig (2013, 2016). I complement this work by introducing endogenous dropout decisions—a critical margin given high U.S. college attrition rates—and modeling time-varying grants as a novel dropout channel with macroeconomic consequences.

Second, this paper contributes to the literature on college dropout behavior. Prior studies, such as Arcidiacono et al. (2025), Hendricks and Leukhina (2017, 2018), Lee, Shin, and Lee (2015), Matsuda (2020), Ozdagli and Trachter (2015), and Trachter (2015), focus primarily on learning about academic ability and labor market productivity as the main dropout mechanisms. I extend this framework by identifying grant volatility as an additional, empirically salient driver of attrition. Unlike most of these studies, I embed the dropout decision within a general equilibrium

[4]This mirrors proposals to replace the yearly FAFSA renewal with a multi-year award, while preserving academic monitoring at the institutional level.

environment (with the exception of Matsuda 2020), which is essential for evaluating policy spillovers and equilibrium sorting effects.

Third, this paper contributes to empirical work documenting the growing role of family wealth in college success Bailey and Dynarski (2011), Belley and Lochner (2007), Cameron and Heckman (1998), Cameron and Taber (2004), Carneiro and Heckman (2002), and Lochner and Monge-Naranjo (2011). I extend this literature by using newer longitudinal data (NLSY97) to show that family wealth not only affects enrollment but also completion probabilities, and by comparing across cohorts to document the rising predictive power of wealth.

Finally, the paper builds on experimental and policy work emphasizing the complexity and instability of the financial aid system Bettinger et al. (2012), Dynarski et al. (2021a), and Dynarski and Scott-Clayton (2006). These studies show that reducing procedural barriers and increasing aid certainty improves enrollment and persistence. I extend this work by quantifying grant volatility using administrative data and assessing the macroeconomic implications of reforms that stabilize need-based aid.

The paper is organized as follows. Section 2 documents the increasing role of financial background in college completion and the volatility of grant aid using data from NLSY79, NLSY97, and BPS. Section 3 presents the general equilibrium model. Section 4 outlines the calibration strategy. Section 5 discusses model properties and validation. Section 6 quantifies the contribution of each dropout channel across wealth–ability groups. Section 7 evaluates grant-stabilization policies and their macroeconomic and distributional effects.

2 Empirical Analysis

Using recent data from the NLSY97 and the Beginning Postsecondary Students (BPS) survey, I document that low-wealth students today depend heavily on grant aid, face substantial year-to-year volatility in award amounts - even when formally eligible - and exhibit significantly higher dropout rates after grant reductions. This stands in contrast to earlier findings based on the NLSY79 cohort, which reported limited evidence of borrowing constraints or family wealth effects on college participation (e.g., Cameron and Heckman 1998; Cameron and Taber 2004; Carneiro and Heckman 2002). However, those results reflect a different institutional context, in which the average annual tuition at public four-year institutions was only $3,499 in today's dollars (NCES 2023), compared to $30,884 today—an increase of more than 780 percent.

2.1 The Role of Family Income on College Participation Margins

To examine the evolution of borrowing constraints, I draw on two nationally representative longitudinal datasets—the NLSY79 and NLSY97—which track U.S. cohorts born roughly two decades apart. The NLSY79 follows individuals born between 1957 and 1964; the NLSY97 covers those

born between 1980 and 1984. Both datasets contain detailed information on parental background, cognitive ability, and postsecondary outcomes, with follow-up data through ages 49 and 33, respectively, enabling the evaluation of long-run education outcomes.

Leveraging the rich longitudinal structure of these datasets, I estimate how family wealth shapes college outcomes across cohorts. I fit a linear probability model of college enrollment and dropout margins on wealth quartile indicators, as specified in Equation 1. Following Carneiro and Heckman (2002), I estimate separate regressions by ability tercile[5] to examine how the relationship between family wealth and college outcomes differs across the ability distribution:

$$Y_{it} = \alpha + \beta X_{it} + \gamma Z_{it} + \varepsilon_{it}, \tag{1}$$

where Y_{it} indicates enrollment or dropout status, X_{it} is a full set of family wealth quartile dummies (with the top quartile omitted as the reference category), and Z_{it} comprises controls for parental education, household structure, residential region, race, gender, number of siblings, and ability tercile. Details on sample construction and data cleaning are provided in Appendix A.1.

Table 1 summarizes the estimated gaps in four-year college enrollment (Panel A) and dropout rates (Panel B) by family wealth quartile for the NLSY97 cohort. Full regression results, including estimates for two-year institutions and the NLSY79 cohort, are delegated in Appendix A.2. Enrollment gaps are substantial: low-wealth students in the lowest ability tercile are 16 percentage points less likely to enroll in a four-year college than their highest-wealth peers. The gap widens to 26 percentage points in the middle ability tercile and 17 percentage points in the highest. Dropout disparities are even more pronounced. Among students in the middle ability tercile and lowest wealth quartile, the probability of dropping out is 40% higher than for their wealthiest counterparts. Lower-wealth students in the highest ability group remain 12% more likely to drop out.[6] By contrast, in the NLSY79 sample, family wealth has a negligible effect on college outcomes (Appendix Table A.4). A joint F-test confirms that wealth–related gaps in both enrollment and dropout are highly significant in the NLSY97 but statistically indistinguishable from zero in the NLSY79, consistent with earlier evidence that financial constraints were largely muted for the older cohort (Carneiro and Heckman 2002). The stark divergence across cohorts points to a structural break: by the late-1990s parental wealth had become a central determinant of college entry and persistence, highlighting the growing salience of borrowing constraints—a trend also documented at the enrollment margin by Bailey and Dynarski (2011), Belley and Lochner (2007), and Lochner and Monge-Naranjo (2011).

[5] Ability is measured by AFQT scores (see Appendix A.1); results are robust to using PIAT scores.

[6] While the dropout gap for low-income, low-ability students follows a similar pattern, estimates for this group should be interpreted with caution due to small sample sizes (Appendix Table A.2).

Table 1: Estimated Effects of Family Wealth on College Enrollment and Dropout (NLSY97 Cohort)

	AFQT Terciles			
Wealth Quartile	Tercile 1	Tercile 2	Tercile 3	All Abilities
Panel A: College Enrollment				
Q1 (Lowest)	-0.160***	-0.268***	-0.173***	-0.284***
	(0.046)	(0.049)	(0.041)	(0.027)
Q2	-0.167***	-0.224***	-0.036	-0.216***
	(0.045)	(0.044)	(0.033)	(0.024)
Q3	-0.152***	-0.115***	-0.047*	-0.123***
	(0.048)	(0.041)	(0.028)	(0.023)
All Gaps= 0	$F(3, 951) = 14.83^{***}$	$F(3, 1031) = 29.47^{***}$	$F(3, 1338) = 11.05^{***}$	$F(3, 3144) = 105.59^{***}$
Panel B: College Dropout				
Q1 (Lowest)	0.118	0.402***	0.125**	0.255***
	(0.118)	(0.072)	(0.054)	(0.040)
Q2	0.157	0.263***	0.085**	0.166***
	(0.114)	(0.062)	(0.041)	(0.033)
Q3	-0.069	0.188***	0.038	0.091***
	(0.119)	(0.053)	(0.033)	(0.028)
All Gaps= 0	$F(3, 175) = 0.4683$	$F(3, 521) = 32.4386^{***}$	$F(3, 916) = 6.6494^{***}$	$F(3, 1636) = 42.0546^{***}$

Notes: Linear probability model estimates of family wealth quartile effects on four-year college enrollment and dropout, relative to Q4 (highest wealth). Wealth quartiles use NLSY97 household net worth (1980–84 cohort). Ability terciles based on Armed Forces Qualification Test (AFQT) scores. Controls: parental education, household structure, region, race, gender, siblings. Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. F-tests assess if gaps equal zero. Methodology follows Carneiro and Heckman (2002). Source: NLSY97.

2.2 College Financing Sources and Grant Volatility

To understand why family wealth continues to predict college outcomes even conditional on enrollment, I examine how students finance college. In the NLSY97, college financing sources are grouped into seven categories: family transfers, family loans, institutional aid (grants and scholarships), government-subsidized or private loans, work-study, employer assistance, and out-of-pocket payments.[7] Table 2, panel A, shows that low-wealth students finance nearly half (49%) of their annual costs through grants, followed by loans (31%) and earnings (14%). In contrast, students from the highest wealth quartile finance 40% of their education through parental transfers, reducing their dependence on external sources.

Given poor students' heavy reliance on grants, I next examine the stability of financial aid during college. Using the panel structure of the NLSY97, I measure the frequency and size of grant reductions across academic years. Table 2 shows that nearly 60% of students experience a loss of grant aid at least once during college, with an average reduction of $\$3,368$—equivalent to 63% of initial aid. Notably, grant reductions do not vary significantly by family wealth,[8] suggesting that parental background, such as financial literacy, does not explain variation in grant loss.

One limitation of the NLSY97 is that it aggregates all grant sources, making it impossible to

[7] Minor sources are excluded for clarity. Details on data cleaning are provided in Appendix A.1.

[8] Nor by student ability; results omitted for brevity.

isolate eligibility-based changes. To address this, I turn to administrative data from the Beginning Postsecondary Students (BPS) survey, which allows for more precise conditioning on Pell Grant eligibility. Despite its limitations, the NLSY97 remains informative: (i) grant volatility is widespread across all aid types; (ii) lost aid is rarely offset by increased parental transfers or alternative sources such as loans, earnings, or work-study; and (iii) grant reductions are strongly associated with college attrition.

Table 2 (Panel B) examines whether students can smooth financial resources in response to grant reductions. Students lose a significant portion of their initial grants, with losses ranging from 67.5% to 77.9% across wealth quartiles. Among low-wealth students (Q1), the average grant loss is $3,399, with only $33.7 offset through family contributions. The replacement rate, which measures the percentage of lost grants offset by family or other sources (such as loans, out-of-pocket payments, work-study, employer assistance, and other aid), is 7.53% for Q1, indicating a modest ability to compensate. Across all wealth quartiles, students face grant volatility—57.5% to 68.3% lose grants, with average losses ranging from $3,130 to $4,242. Replacement rates vary from -4.54% to 7.53%.[9]

Table 2: College Financing, Grant Volatility, and Outcomes by Wealth Quartile

Panel A: Financing Composition (First Year)

Wealth Quartile	Family (%)	Loans (%)	Grants (%)	Out-of-Pocket (%)	Avg. Total ($)
Q1 (Low)	10.3	18.7	47.0	18.7	4322
Q2	13.0	22.4	49.2	12.7	5489
Q3	29.1	15.1	39.1	14.7	4882
Q4 (High)	46.5	8.4	32.7	11.3	6406

Panel B: Grant Volatility and Financial Response

Wealth Quartile	% Lost Grants	Avg. Grant Loss ($)	Offset by Family ($)	Offset by Other Sources ($)	Replacement Rate (%)
Q1 (Low)	58.2	3.399	33.7	222	7.53
Q2	68.3	4.242	−171	171	−0.01
Q3	60.3	3.130	−369	254	−3.66
Q4 (High)	57.5	3.375	−469	316	−4.54

Panel C: Educational Outcomes

Wealth Quartile	Enroll. (%)	Dropout (%)	Grad. (%)	Dropout & Lost (%)
Q1 (Low)	29.6	57.8	12.4	25.8
Q2	38.6	46.8	20.5	27.7
Q3	52.9	33.5	35.2	16.5
Q4 (High)	69.9	24.5	52.8	10.2
All	48.8	36.5	31.0	17.5

Notes: Panel A shows first-year financing sources. Panel B reports grant loss metrics and replacement behavior. "Replace Rate" is the percent of lost grants offset by family or other sources (loans, work-study, etc.). Panel C reports enrollment, graduation, dropout, and dropout conditional on grant loss. Source: NLSY97.

[9] A negative replacement rate indicates that students' total financial resources (including family contributions and other aid) actually decreased further when grants were lost, intensifying the financial strain and reflecting a limited and inconsistent capacity to self-insure against aid reductions.

Regression Analysis. This section examines how reductions in grant aid between the first and second years of college relate to students' likelihood of continuing into the third year. Because the NLSY97 aggregates all grant sources and lacks detailed eligibility information, the analysis is descriptive. It documents a broad association between grant volatility and persistence, which is examined more precisely using Pell-specific administrative data in Section 2.3.

I estimate a linear probability model where the dependent variable is enrollment in the third academic year. The key regressor is an indicator for whether the student experienced a grant reduction between Years 1 and 2. I interact this indicator with race and family wealth and include a rich set of baseline controls (see Appendix B for details). Table 3 presents four specifications that differ only in how parental wealth is parameterized. Columns (1)–(3) show that the *Grant Cut* coefficient is remarkably stable (about -0.031) and statistically significant, even after adding wealth-quartile dummies or a single *Low-Wealth (Q1–Q3)* indicator. That the estimate is unaffected by adding wealth controls implies that grant losses are not merely proxying for family resources; they constitute an independent shock.[10] Furthermore, the magnitude is comparable to the penalties associated with lower ability, lower wealth, or parents without a college degree, underscoring economic relevance. Column (4) interacts the grant-cut indicator with *Low-Wealth (Q1–Q3)*. The main effect (nearly zero) is now identified off the top wealth quartile, while the interaction coefficient is -0.054 (s.e. 0.027), indicating that the entire adverse impact is borne by the bottom 75 percent of the wealth distribution.

2.3 Pell Grant Volatility, and Its Association with Dropout Rates

To assess whether the observed grant volatility stems from exogenous variations or student behavior—such as enrollment decisions, academic performance, or work choices—I focus on Pell Grants, the largest need-based federal aid program. Pell Grants, with their standardized eligibility criteria, provide an ideal case for analyzing volatility among students who meet academic and financial requirements, thereby isolating variation that is not fully explained by student behavior or performance. This complements the NLSY97 findings, which demonstrate that total grant volatility (including non-Pell aid) is widespread, that these losses are rarely offset by family transfers or other alternative aid sources like loans or work-study, and that grant reductions are associated with college dropout decisions.

For this analysis, I use a nationally representative sample of students from the Beginning

[10] If Grant Loss were "mechanically correlated" with family wealth (e.g., if every time family wealth increased, grants mechanically decreased due to eligibility rules), then when adding wealth controls to the regression, the coefficient of Grant Loss should change significantly or even disappear. It would mean that Grant Loss was just capturing the effect of family wealth. The observed stability of the -0.031 coefficient (and its continued significance) across columns (1)-(3), despite adding progressively richer wealth controls, suggests that the impact of Grant Loss on persistence is not simply being driven by underlying changes in family wealth. It suggests that grant reductions have an independent, direct association with persistence, even after accounting for different levels of family resources.

Table 3: Grant Reductions and Two-Year Persistence (Linear Probability Models)

	Dependent variable: *Enrolled > 2 Years*			
	(1)	(2)	(3)	(4)
Grant Cut	−0.0308**	−0.0309**	−0.0308**	−0.0018
	(0.0147)	(0.0147)	(0.0147)	(0.0209)
Grant Cut × Low Wealth	–	–	–	−0.0535**
				(0.0274)
Low Wealth (Q1-Q3)	–	–	−0.0389**	−0.0221
			(0.0130)	(0.0156)
Wealth Q3	–	−0.0334**	–	–
		(0.0149)		
Wealth Q2	–	−0.0439**	–	–
		(0.0175)		
Wealth Q1	–	−0.0483**	–	–
		(0.0210)		
Observations	1,722	1,722	1,722	1,722

Notes: Robust s.e.'s clustered at the student level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Wealth quartile Q4, ability quartile Q4, and female are omitted categories. Further details on variable construction and additional regression results are provided in Appendix D.

Postsecondary Students (BPS) study, conducted by the National Center for Education Statistics. The BPS surveys first-time postsecondary students and tracks them over a six-year period. This survey is linked to individual-level data from official records, including college entrance exam scores (from the ACT and College Board), financial aid information (from the FAFSA), and aid disbursement details (from the National Student Loan Data System). Additionally, the BPS provides comprehensive data on enrollment patterns and degree attainment.

Institutional Setting. Understanding the institutional framework of federal financial aid is critical to identifying the sources of grant volatility and distinguishing between student-driven changes and those stemming from exogenous shocks. The Free Application for Federal Student Aid (FAFSA), administered by the U.S. Department of Education, serves as the central instrument for calculating the Expected Family Contribution (EFC) based on household income and demographics. EFC determines eligibility for Pell Grants, federal supplemental grants, state grants, institutional aid, federal loans, and work-study (Dynarski and Scott-Clayton 2006; U.S. DOE 2011).[11] The EFC is computed using a complex, opaque, nonlinear formula, making the final value difficult to predict. Because federal rules prohibit awarding aid beyond demonstrated need, nearly all aid is coordinated through FAFSA and capped at the cost of attendance (COA), which is set by each institution. Colleges award standardized Pell Grants first using $\min(\text{COA} - \text{EFC}, \text{Max Pell})$, followed by variable state and institutional grants, then federal loans (subsidized and unsubsidized, capped at $5,500-$12,500 annually depending on dependency status, or PLUS loans requiring a credit check), and finally work-study, limited by institutional allocations. Pell reductions are rarely offset due to constrained and inconsistent funding of other aid sources (Denning, Marx, and Turner

[11] See Table C.1 in Appendix C for a comprehensive summary of federal and institutional aid programs.

2019; U.S. DOE 2011). For four-year institutions, average COA was approximately $24,000 in 2011–2012 (NCES 2023).

To maintain eligibility, students must refile the FAFSA annually with updated income and household information, a process prone to errors and delays due to minor reporting inconsistencies (Bettinger et al. 2012). While students can influence Pell Grant amounts by maintaining Satisfactory Academic Progress (SAP, full-time enrollment, GPA $\geq$2.0) or managing earnings through undisclosed thresholds ($6,500, U.S. DOE 2011), variation can arise from factors beyond their control. Pell Grant volatility may stem from exogenous DOE policies, including annual adjustments to the zero-EFC income threshold and nonlinear formula revisions (Bettinger 2004; Denning, Marx, and Turner 2019; U.S. DOE 2011). Final disbursements, observed in BPS, occur approximately ten days before the term begins and often diverge from estimates (NCES 2012). All of these factors make the annual amounts of grants hard to predict. Recognizing this issue, the federal government enacted the FAFSA Simplification Act of 2019, aiming to reduce aid volatility through simplified EFC calculations, implemented for 2023–2024. Detailed institutional settings, including financial aid, EFC calculation, and FAFSA Simplification Act changes, are provided in Appendix C.

Thus, once students successfully apply for and receive initial grant aid, their capacity to influence the specific award amount is very limited. Furthermore, even if the change is a response to shifts in family wealth, actual parental contributions and other financing margins (as shown in Table 2, Panel B) do not consistently respond to changes in total grants. Given this, I now examine what fraction of Pell Grant volatility remains after controlling for student characteristics. I then run a regression, where reduced Pell amounts are regressed on dropout outcomes, which will strongly suggest a correlation, more precise than in the NLSY97 data, by accounting for eligibility criteria.

Pell Grants Volatility Controlling for Eligibility Criteria. To evaluate the nature of Pell Grant volatility, I analyze how persistent Pell Grants are across an academic career among first-time, full-time, dependent students at four-year colleges, using the BPS 2011–2012 dataset. Table 4 illustrates these grant transition patterns from Year 1 to Year 3, presenting them both without (Panel (a)) and with (Panel (b)) controls for eligibility criteria. These criteria include academic performance (such as GPA and accumulated credits) and student earnings. While the BPS data allow for conditioning on key eligibility factors—such as enrollment status, academic progress, and student earnings—they do not capture changes in EFC arising from shifts in parental income or DOE formula revisions. This limitation, however, is mitigated by complementary evidence from the NLSY97 (Table 2, Panel B), which shows that lost grant aid is rarely offset by increases in family transfers or other financial sources. As a result, even without directly observing EFC in the BPS, there is little reason to expect that students can self-insure against grant loss. Moreover, to the extent that volatility arises from formula revisions rather than income changes, the aid reductions function as plausibly exogenous, uninsured policy shocks.

In Table 4, the rows of both panels represent initial grant brackets in Year 1, with columns showing the probability distribution of grant brackets in Year 3 for enrolled students. For example, Panel (a) shows that 55% of students who started in the highest grant bracket (Bracket 1) in 2011-12 remained in the same bracket by 2013-14. The remaining 45% transitioned to lower brackets, with 26% falling to the lowest bracket (Bracket 5). Similarly, 94% of students initially in the lowest bracket stayed there, reflecting limited upward mobility in grants. Panel (b) in Table 4 contrasts this by controlling for eligibility criteria such as academic progress, enrollment status, and student earnings. Under these controls, 71% of students who initially received the highest level of Pell Grants (over $4,500) maintained their grant level by Year 3, while only 12% dropped to the lowest bracket. Conversely, 94% of those starting with the lowest grant level (less than $1,500) remained in that bracket.

Next, I discuss important considerations of endogeneity related to Pell Grant eligibility, arguing that its volatility is not primarily driven by student behavior, intrinsic ability, or parental wealth. First, all students in this sample successfully applied for and received nonzero Pell awards in Year 1, eliminating concerns about application-stage selection or administrative failure. FAFSA reapplication rates exceed 90% among Pell-eligible students who remain enrolled (Bird and Castleman 2016). Second, intrinsic ability—such as "grit" or administrative competence—cannot plausibly explain Pell Grant volatility. Conditional on applying and meeting eligibility requirements, students have virtually no scope to influence the award amount, as the Department of Education determines EFC using FAFSA inputs, and colleges rigorously verify this financial information. Third, Pell Grant volatility may stem from EFC increases due to exogenous DOE formula revisions or parental wealth changes—both beyond students' control. While formula revisions create an uninsurable policy shock, wealth-driven reductions should be insurable. Yet NLSY97 data show that parental contributions and other sources fail to offset volatility (Table 2, Panel B), a finding consistent with Denning, Marx, and Turner (2019). Other sources—including Direct Subsidized Loans (capped at $3,500–$5,500), Parent PLUS Loans (subject to credit checks), and work-study (which contributes just $1 billion annually versus $30 billion for Pell)—also fail to adjust (Panel B). Taken together, these patterns reinforce that, after conditioning on academic performance and earnings, Pell Grant volatility functions as an exogenous, uninsurable financial shock from the student's perspective.

Regression Analysis. I estimate the effect of Pell Grant reductions on college completion using the BPS 2011–2017 cohort. Regression analyses focus on students with high unmet need (COA - EFC > $10,000) to ensure small changes in parental income or COA do not affect Pell amounts per Pell formula. The sample includes students who received at least $4,000 in Pell aid in Year 1, a threshold which constituted 37% of full-time, first-time dependent students. This threshold minimizes variation in family wealth and partly addresses confounding concerns noted by Bettinger (2004). Among this group, only 22.5% retained a Pell award at or above the initial

Table 4: Grants Transition: Year 1 to Year 3

(a) Full Sample

Year 1	B1	B2	B3	B4	B5
B1	0.55	0.07	0.07	0.04	0.26
B2	0.27	0.20	0.11	0.08	0.34
B3	0.20	0.12	0.14	0.10	0.45
B4	0.10	0.09	0.07	0.15	0.59
B5	0.03	0.01	0.01	0.01	0.94

(b) Eligibility-Restricted Sample

Year 1	B1	B2	B3	B4	B5
B1	0.71	0.08	0.07	0.03	0.12
B2	0.31	0.31	0.11	0.05	0.22
B3	0.14	0.09	0.23	0.09	0.45
B4	0.12	0.16	0.09	0.10	0.52
B5	0.03	0.01	0.01	0.01	0.94

Notes: The sample includes dependent students enrolled full-time in a four-year Bachelor's degree program during the 2011–12 academic year, with at least 8 months of enrollment. Panel (a) reports transition probabilities in Pell Grant amounts from Year 1 to Year 3 without conditioning on eligibility. Panel (b) restricts the sample to students who meet academic and financial eligibility criteria: annual income below $6,501 in 2013–14, completion of at least 24 credits in 2012–13, and a GPA of 2.0 or higher in their second year. Grant brackets are defined as follows: Bracket 1 = $4,500+, Bracket 2 = [$3,500, $4,500), Bracket 3 = [$2,500, $3,500), Bracket 4 = [$1,500, $2,500), Bracket 5 = [$0, $1,500). Students who dropped out before Year 3 are excluded. *Source:* U.S. Department of Education, BPS (2012–2017).

level by Year 3. I estimate how reductions in Pell awards in Year 3 affect dropout from any four-year institution within six years.[12] Dropouts are defined as students who fail to complete a Bachelor's degree within six years of enrolling in a four-year program–the maximum observable period in BPS. This definition follows the federal 150% time-to-degree rule and closely approximates completion outcomes for first-time, full-time, dependent students. Furthermore, due to the unavailability of financial aid data for non-enrolled individuals, students not enrolled in Year 3 are excluded from the sample. Since some early leavers may have dropped out in anticipation of aid loss, this restriction likely leads to a conservative estimate of the impact of grant reductions.

Equation 2 models the dropout outcome Y_i as a function of Pell Grant loss. Students are grouped into three categories based on their Year 3 Pell amount: (i) $0–$2,000, representing a loss of more than two-thirds; (ii) $2,001–$4,000, indicating a loss of one-third to two-thirds; and (iii) $4,001–$5,645, signifying a maintained full grant, which serves as the reference group.[13]

The control vector Θ_i includes factors that affect Pell eligibility and award size: the number of siblings in college during the initial and current year, full-time enrollment status, lagged earnings, and lagged GPA. Including lagged academic performance helps mitigate reverse causality, as students anticipating dropout may already reduce effort. I also control for total loan uptake in Year 3, including parental PLUS loans. Additional controls include high school GPA, race, and gender.

$$\mathrm{Y}_i = \beta_1 \mathrm{Pell}_{[0,\$2,000],i} + \beta_2 \mathrm{Pell}_{[\$2,001,\$4,000],i} + \beta_3 \Theta_i + \epsilon, \tag{2}$$

Table 5 reports the regression results. Students whose Pell awards fall to $0–$2,000 are 14 percentage points more likely to drop out, while those whose aid declines to $2,001–$4,000 face a 13.2 percentage point increase in dropout risk. Both effects are statistically significant at the

[12]The BPS tracks students across institutions, thus I also capture students who transfer.

[13]The maximum Pell award slightly varies across years.

Table 5: Regression: Pell Grant Reduction and 6-Year Dropout

Variable	Coefficient	(Std. Error)
Pell Grant $\leq$ \$2,000	0.140***	(0.040)
Pell Grant \$2,001–\$4,000	0.132***	(0.060)
Earnings (t–1) $\leq$ \$6,499	0.019	(0.024)
GPA 2014 $>$ 2.25	–0.280***	(0.071)
Loan Amount (2013–14)	–0.000	(0.000)
Enrolled $\leq$ 7 mo. in 2013–14	0.332	(0.033)
Sibling in College (2013–14)	–0.022	(0.039)
Sibling in College (2011–12)	–0.033	(0.036)
HS GPA $<$ 3.5	0.125***	(0.033)
Male	0.012	(0.016)
Nonwhite	0.014	(0.032)
R^2	0.237	
Observations (coarsened)	1200	

Notes: Outcome is an indicator for failing to complete a Bachelor's degree within six years. Regressors include Pell Grant bracket in Year $t = 3$, prior earnings, GPA, loan amounts, and family structure. Sample restricted to dependent, first-time full-time students enrolled in 4-year programs in 2011–12 with \$4,000+ Pell aid in Year 1. See text for full eligibility and coding. Data: U.S. Department of Education, BPS: 2012–2017. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Following NCES disclosure protocols, the BPS regression sample uses coarsened microdata to preserve respondent anonymity (NCES 2023).

1% level. Because the sample is limited to those who re-enroll in Year 3, these estimates likely understate the full impact of aid volatility.

The inability of students to compensate for lost grants is evident: the estimated dropout effects remain large and significant even after controlling for concurrent loan uptake. Although BPS does not report EFC in all years, this limitation is mitigated by focusing on students with high initial Pell awards and unmet need above \$10,000. For these students, small changes in family income or college costs rarely affect eligibility, as Pell awards are determined by $\min(\text{COA} - \text{EFC}, \text{Max Pell})$. The results align with the evidence from the NLSY97, where it is shown that losing grants is not compensated by other sources (Table 2). Together, these findings support the interpretation of Pell volatility as an exogenous, uninsurable financial shock from the student's perspective. The NLSY97 shows that grant volatility is not specific to Pell; rather, when all grants are pooled together, and as empirical literature indicates, even Merit-based grants (though a minor part of total grants, up to ten percent) are also frequently lost by students due to certain frictions (**carruthers2016**, **henry2004**, Scott-Clayton 2011). Carruthers and Özek 2016 Henry, Rubenstein, and Bugler 2004

To conclude, the results challenge earlier influential findings by Carneiro and Heckman (2002) on limited borrowing constraints in college attainment. Using nationally representative longitudinal datasets (NLSY and BPS), I show that (1) family wealth plays an increasing role in college participation, (2) students rely heavily on a grant system that exhibits year-to-year volatility, and (3) losing grants significantly increases dropout risk. These findings align with robust empirical, experimental, and quasi-experimental evidence: Denning, Marx, and Turner (2019) document higher dropout risk from Pell reductions using a regression kink around the federal EFC threshold;

Bettinger et al. (2012) demonstrate FAFSA assistance enhances enrollment and persistence; Dynarski et al. (2021b) show guaranteed scholarships increase completion for high-ability, low-income individuals, confirming stable grants' role in persistence; Bettinger (2004) shows that policy-driven reductions in state grant aid in Ohio increase college stop-out; and Castleman and Long (2016) find that eligibility for Florida's need-based FSAG program increases credit accumulation and six-year graduation using a regression discontinuity design. Based on these empirical findings, incorporating this mechanism into structural models of college choice is essential for capturing the financial dimension of college attrition, its macroeconomic consequences, and its implications for policy design. This mechanism contributes to the macroeconomic literature, which typically treats subsidies as deterministic, and to the dropout literature, which primarily explains attrition through learning about ability—thus underestimating the role of the financial, policy-relevant channels.

3 The Model Economy

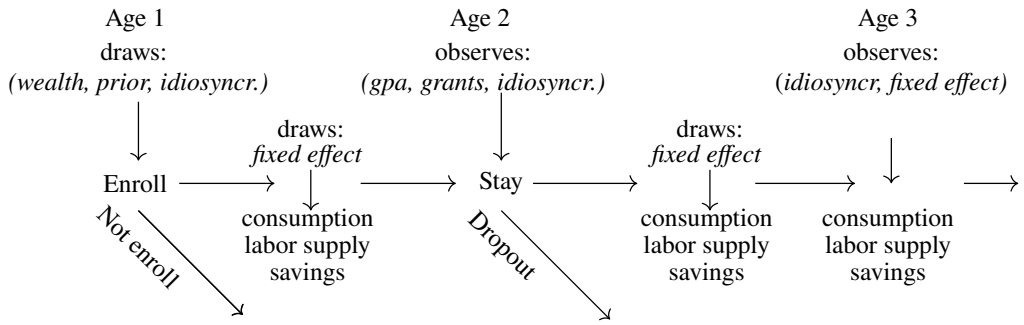
I consider an overlapping generations general equilibrium model in which individuals differ by age, wealth, academic ability, education, and labor productivity. Firms produce a final good using capital and labor in competitive markets, and the government operates a tax and pension system.

The key innovation of the model is the introduction of a two-period college stage with endogenous dropout, shaped by beliefs about academic ability, labor market productivity, and time-varying financial aid. Unlike standard macroeconomic models of education, this framework endogenizes the mid-college continuation decision and incorporates a financial dropout channel—grant volatility—alongside academic and labor market uncertainty. While some prior models allow for dropout based on learning about ability, they abstract from the instability of financial aid, which I document to be widespread and strongly associated with attrition.

Individuals make two education-related decisions: (i) whether to enroll in college, based on initial wealth and prior beliefs about ability, and (ii) whether to continue after the first period. The dropout decision depends on an academic signal (GPA), realized labor market productivity, and grant availability in the second period. Departing from the conventional assumption of fixed aid, I model second-period grants as a function of both GPA and an exogenous stochastic shock. This design is motivated by empirical evidence showing substantial within-college volatility in aid—an uninsurable financial shock largely ignored in existing models.

This structure captures dropout as a dynamic, forward-looking choice shaped jointly by academic and financial uncertainty. As shown in the data, grants often decline between college years, making the continuation decision a critical margin of adjustment. I also model post-college working and retirement phases to quantify the full lifecycle consequences of college investment, which are essential for evaluating long-run welfare and the general equilibrium effects of policy reforms.

Figure 1: Timeline of Schooling Decisions



Notes: This timeline summarizes lifecycle decisions in the first three periods of college years.

3.1 Demographics

Time is discrete, indexed by t, and it goes forever. The economy is populated at any given time by J overlapping generations indexed by $j = 1, 2, \cdots, J$, where J denotes the maximum age. Individuals survive from age j to $j+1$ with probability φ_{j+1}. For simplicity, I assume that the survival rate before retirement is equal to one; agents face a death hazard once they retire, i.e., $\varphi_j \in [0, 1)$ for $j \geq j_r$, where j_r denotes the retirement age. Let N_t denote the initial size of the cohort born in period t; $N_t = (1+n)N_{t-1}$. The relative share of each age cohort in the population is constant over time since the population growth rate is constant, and the age-specific survival rates are time-invariant. To ease aggregation later on, I define m_j as the population size of the age cohort j relative to the youngest cohort alive in the current period:

$$m_j := \frac{N_{t-j+1}\left(\prod_{k=1}^{j}\varphi_k\right)}{N_t}.$$

3.2 Timeline

Individuals enter the economy as high school graduates at age 1, drawing a prior on ability and receiving an education-contingent initial wealth endowment. Based on this information, they choose whether to enroll in college. Those who enroll observe their labor market productivity and make consumption–leisure–savings decisions.

College lasts two periods. At age 2, individuals reassess their academic ability, grants, and labor productivity. Based on updated beliefs, they choose whether to continue or drop out. Those who remain complete college at age 3, while others exit with dropout status.

At age 3, all individuals have finalized their education level—high school graduates, college dropouts, or college graduates—and begin working. They remain in the labor market for 24 periods

(until age 66), after which they retire and live on capital income and pension benefits. Retirees face mortality risk and exit the economy by age 98.

3.3 Beliefs about Academic Ability

Each individual enters the model with a normally distributed prior belief about their unobserved academic ability e_i. The mean of the prior is given by $\mu_{e_0,i} = e_i + \alpha_e + \epsilon_{e_0,i}$, where α_e is a population-wide optimism parameter and $\epsilon_{e_0,i} \sim \mathcal{N}(0, \sigma^2_{e_0})$ is idiosyncratic noise. This implies that $\mu_{e_0,i}$ and σ_{e_0} fully characterize each student's initial belief.

At the end of the first period of college, each student observes their GPA, which serves as a signal about true ability. GPA is contingent on heterogeneity, luck, and effort toward college. The first is captured by true ability, e_i, the second by noise, ψ_i, and the third by one minus the time spent working in the labor market in period 1, $1 - l_{1,i}$. The assumption that working while in college may be detrimental to academic performance aligns with the large literature that isolates the causal impact of working hours on education attainment, including Scott-Clayton and Minaya (2016), Stinebrickner and Stinebrickner (2003), Wenz and Yu (2010), Darolia (2014), Bozick (2007). The GPA of an individual i is thus given by:

$$GPA_i = e_i + \lambda_l \max(l_{1,i} - \underline{l}, 0) + \psi_i, \quad \psi_i \sim \mathcal{N}(0, \sigma^2_\psi), \tag{3}$$

where $\lambda_l < 0$ captures how working affects GPA, and $\underline{l}$ is the hours threshold beyond which academic performance deteriorates.

The GPA signal is adjusted for work effort to yield:

$$\hat{S}_i = GPA_i - \lambda_l \max(l_{1,i} - \underline{l}, 0). \tag{4}$$

Given $\hat{S}_i$, individuals update their beliefs using Bayes' rule:

$$\mu_{e_1,i} = \frac{\sigma^2_\psi}{\sigma^2_{e_0} + \sigma^2_\psi}\mu_{e_0,i} + \frac{\sigma^2_{e_0}}{\sigma^2_{e_0} + \sigma^2_\psi}\hat{S}_i, \tag{5}$$

$$\sigma^2_{e_1,i} = \frac{\sigma^2_\psi}{\sigma^2_{e_0} + \sigma^2_\psi}\sigma^2_{e_0}. \tag{6}$$

I assume that the variance of the prior, $\sigma^2_{e_0,i}$, is the same across all individuals, i.e., given the latter, $\mu_{e_0,i}$ is a sufficient statistic for capturing the distribution of the prior beliefs across individuals.

3.4 College Costs, Grant Mechanisms, and Parental Transfers.

Each period of college attendance incurs a resource cost, represented by a fraction ι of the skilled labor wage rate $w_{t,c}$. The fraction of that cost covered by the government in the first college period

is denoted $z_1(a_c, \mu_{e_0})$, where a_c represents parental transfers for college purposes and μ_{e_0} denotes the individual's ability prior.

I model merit-based and need-based grants as separable components of z_1, as they have distinct eligibility criteria:

$$z_1(a_c, \mu_{e_0}) = z_1^{\text{need}}(a_c) + z_1^{\text{merit}}(\mu_{e_0}). \tag{7}$$

The government is assumed to observe μ_{e_0} as a high school GPA. Thus, the individual's out-of-pocket cost to attend college in the first period is $(1 - z_1(a_c, \mu_{e_0}))\iota w_{t,c}$.

In the second period, the grant amount is no longer deterministic. Instead, it depends on two factors: academic performance (measured by GPA) and a stochastic grant shock ζ. This formulation is motivated by the empirical findings in Section 2, which show substantial unexplained year-to-year volatility in observed grants, even after controlling for eligibility criteria.

Second-period grants are determined by:

$$z_2(a_c, \zeta, GPA) = z_1^{\text{need}}(a_c)\mathbb{1}_{GPA \geq \overline{GPA}_{\text{need}}}\zeta + z_1^{\text{merit}}(\mu_{e_0})\mathbb{1}_{GPA \geq \overline{GPA}_{\text{merit}}}\zeta, \tag{8}$$

where $\overline{GPA}_{\text{need}}$ and $\overline{GPA}_{\text{merit}}$ are GPA thresholds for maintaining need- and merit-based grants, respectively.

Parental Transfers. I use heterogeneity in initial wealth to capture the role of family wealth in shaping college attendance. Individuals draw a college-contingent transfer from an exogenous distribution that reflects the gradient of parental contributions observed in the data. Importantly, students who remain enrolled receive the same transfer amount in the second period of college.

Modeling parental transfers as per-period, college-contingent support is critical for analyzing dropout behavior. This approach departs from most of the macro-education literature, which typically models transfers as a one-time gift at college entry. That simplification is problematic in a dropout context for two reasons. First, transferring all funds at age 18 understates the financial constraints faced during college. Second, it introduces a moral hazard: students may enroll solely to access the transfer and then drop out strategically.[14]

While modeling fully endogenous, multi-period transfers is computationally infeasible, I approximate the empirical distribution of parental transfers by wealth quintiles. Once a student receives an initial transfer, the same amount is provided in subsequent college periods conditional on enrollment. Therefore, I use data to directly discipline the distribution of parental transfers, matching average contributions across wealth quintiles.

This setup addresses two potential concerns related to the absence of endogenous parental transfers. First, parents might adjust support in response to financial shocks. However, this

[14]For example, Colas, Findeisen, and Sachs (2021) address this issue by introducing a pecuniary cost of dropout to deter strategic behavior.

adjustment appears limited: in the NLSY97, students who lose grants receive minimal additional family contributions (Table 2, Panel B). Second, crowd-out of parental support in response to public subsidies is not a concern in this framework, as the policy experiments hold per-period grants fixed by design.

3.5 Labor Productivity.

Labor productivity for an individual i at age j with education status s is defined as:

$$h_{j,i} = \epsilon_j \cdot \exp\left(\theta_i + \eta_i\right), \quad \text{where} \quad \eta_i \in \mathcal{H}_s, \quad \theta_i \in \Theta_s, \quad s \in \{h, d, c\}.$$

The three components are: (1) a deterministic lifecycle productivity profile, ϵ_j; (2) a productivity fixed effect, θ_i; and (3) a stochastic component, η_i. The distribution of the shock η_i is education-specific, denoted $\mathcal{H}_s$, where $s = h$ refers to high school graduates, d to college dropouts, and c to college graduates.

The idiosyncratic shock η_i follows an education-specific Markov process $\pi_s(\eta'|\eta)$ and is redrawn whenever an individual's education status changes. At age 1, all individuals draw η_i from the high school distribution $\mathcal{H}_h$; at age 2, college enrollees redraw from the dropout distribution $\mathcal{H}_d$; and at age 3, college graduates draw from the distribution $\mathcal{H}_c$.

The fixed effect θ_i is also education-specific, drawn from distribution Θ_s that depends on both education level s and the individual's true (unobserved) ability. All individuals draw an initial θ_i at age 1,[15] and those whose education status changes during college redraw from the corresponding distribution. Once education is finalized—i.e., the individual becomes a dropout or graduate—the fixed effect remains fixed for the remainder of the lifecycle. Following Krueger and Ludwig 2015, each Θ_s consists of two values: $\theta_s \in \{\exp(-\sigma_{\theta_s}),\ \exp(\sigma_{\theta_s})\}$.

The probability of drawing the higher fixed effect increases in ability and education level:

$$\pi\left(\theta_s = \exp(\sigma_{\theta_s})\right) = \omega_s e, \tag{9}$$

where e denotes true ability and $\omega_h < \omega_d < \omega_c$. That is, conditional on ability, individuals with higher education are more likely to draw a higher fixed effect. This modeling choice ensures that education and ability are complementary and that labor market returns increase with ability within each education group. It follows Krueger and Ludwig (2016) and allows ability to be dropped as a state variable after college, thereby reducing computational complexity.

[15] Individuals who enroll in college draw $\theta_i \in \Theta_h$ independently of ability. This assumption prevents learning about academic ability from labor market outcomes.

3.6 Government

The government collects taxes on household consumption, capital income, and labor income in order to finance public expenditure G_t and education subsidies. Consumption and capital income are taxed at flat rates, τ_c and τ_k, respectively. Following Heathcote, Storesletten, and Violante (2010), I adopt a potentially progressive labor income tax schedule:

$$\tau_l(y) = 1 - \lambda y^{-\lambda_m}, \tag{10}$$

where $\tau_l(y)$ is the tax rate at income level y, $\lambda_m > 0$ governs the degree of progressivity, and λ determines the average tax rate for a given level of progressivity.

The pension system operates on a pay-as-you-go basis: it collects contributions from current workers and distributes the revenues directly to retirees. In period t, working individuals contribute a fraction τ_p of their labor income to the pension system. Retirees receive a benefit that is proportional to their average lifetime income:

$$pen_t(s,\theta) = \kappa_s w_{t,s} \bar{L}_t(s,\theta),$$

where $\bar{L}_t(s,\theta)$ denotes the average labor supply (in efficiency units) of working-age cohorts with characteristics (s,θ), and $\theta \in \Theta_s$. The pension system's budget constraint is:

$$\sum_{s\in\{h,d,c\}} \tau_p w_{t,s} L_{t,s} = \sum_{s\in\{h,d,c\}} \sum_{\theta\in\Theta_s} \sum_{j=j_r}^{J} pen_t(s,\theta)\cdot m_j(s,\theta), \tag{11}$$

where $m_j(s,\theta)$ is the relative size of cohort j with skill s and fixed productivity component θ.

Finally, the government collects accidental bequests in the economy, which are redistributed as initial parental wealth. This modeling choice allows for intergenerational transfers without explicitly modeling dynastic links. The full government budget constraint is presented in equation (31) in Appendix H.

3.7 The Individual's Problem

At age $j = 1$, an individual observes an idiosyncratic productivity shock η, forms a prior belief μ_{e_0} about her innate ability, and receives education-contingent initial wealth (a_c, a_h)—where a_c is the per-period parental transfer upon college enrollment and a_h if she does not enroll. She then chooses whether to enroll if the expected value of life-time utility of going to college, $W_c^1(a_c,\eta,\mu_{e_0})$, is higher than $W_h^1(a_h,\eta,\mu_{e_0})$, where

$$W_c^1(a_c,\eta,\mu_{e_0}) = \mathbb{E}_{\theta'\in\Theta_h} V_c^1\big(a_c,\theta',\eta,\mu_{e_0}\big),$$

$$W_h^1(a_h, \eta, \mu_{e_0}) = \mathbb{E}_{\theta' \in \Theta_h | \mu_{e_0}} V_h^1\big(a_h, \theta', \eta\big),$$

where $W_c^1(a_c, \eta, \mu_{e_0})$ and $W_h^1(a_h, \eta, \mu_{e_0})$ denote the expected present values of life-time utilities, respectively, of going to college or not; $V_c^1\big(a_c, \theta, \eta, \mu_{e_0}\big)$ and $V_h^1\big(a_h, \theta, \eta\big)$ are the lifetime utility value functions for college-attendance and non-attendance, respectively. The non-college value function, $V_h^1\big(a_h, \theta, \eta\big)$, does not take an ability prior as a state variable, because beliefs become redundant after drawing the fixed effect. Similarly, for enrolled individuals, the first period fixed effect is independent of ability. This assumption is necessary to avoid learning about ability in the labor market.

After the enrollment decision at age 1, individuals observe a fixed effect in the noncollege wage market, θ_n, and then solve a standard consumption–leisure–savings problem. For those who choose not to enroll, their problem until retirement follows the consumption–leisure–savings problem defined in equation (13). For college-bound individuals, the Bellman equation—formulated recursively—is as follows:

$$\begin{aligned} V_c^1(a_c,\theta, \eta, \mu_{e_0}) = \max_{a',c,l} \Bigg\{ & u(c, 1 - \xi(\mu_{e_0}) - l) + \beta \int_{\hat{S}} \int_{\zeta} \int_{\eta' \in \mathcal{H}_d} \\ & \max \Bigg(W_c^2\big(a'(a_c), \eta', z_2(a, \zeta, GPA(l, \hat{S})), \mu_{e_1}(\mu_{e_0}, \hat{S})\big), \\ & W_d^2\big(a'(a_h), \eta', \mu_{e_1}(\mu_{e_0}, \hat{S})\big) \Bigg) d\eta d\zeta d\hat{S} \Bigg\}, \end{aligned} \tag{12}$$

$$\text{s.t.} \quad (1 + \tau_c)c + a' + (1 - z_1(a, \mu_{e_0}))\iota w_{t,c} = (1 + (1 - \tau_k)r_t)a_c + (1 - \tau_p)y - y\tau_l(y) + T,$$

$$\mu_{e_1} = \frac{\sigma_\psi^2 \mu_{e_0} + \sigma_{e_0}^2 \hat{S}}{\sigma_{e_0,i}^2 + \sigma_\psi^2}, \qquad \sigma_{e_1} = \frac{\sigma_{e_0}^2 \sigma_\psi^2}{\sigma_{e_0}^2 + \sigma_\psi^2}, \qquad a' \geq -\underline{A}_1.$$

The expectations are taken with respect to the distribution of the ability signals, $\hat{S}$, shocks to college subsidies, ζ, as well as the future idiosyncratic labor market shocks, η'. The continuation value for college-bound individuals is the maximum expected utility between two scenarios: (a) stay in college, $W_c^2\big(a'(a_c), \eta', z_2(a_c, \zeta, GPA(l, \hat{S})), \mu_{e_1}(\mu_{e_0}, \hat{S})\big)$, or (b) dropping out, $W_d^2\big(a', \eta', \mu_{e_1}(\mu_{e_0}, \hat{S})\big)$.[16] Note that a' depends on parental transfers: if a student remains enrolled, she expects to receive a_c in the next period (the ongoing parental contribution for college), whereas if she drops out, she instead receives a_h. Therefore, students internalize that parental transfers are conditional on their college enrollment decision. The GPA is determined by working hours and ability signals, $(l, \hat{S})$, and grants depend on assets, shocks, and academic performance, $(a, \zeta, GPA(l, \hat{S}))$, as defined in equations (3) and (8), respectively. Finally, earnings in period 1 are given by $y_1 = w_c h_{1,c}(\theta, \eta) l(1, a_c, \theta, \eta, \mu_{e_0})$.

[16] Note that once an individual decides to drop out, the signal, $\hat{S}$, and the subsidies shock, ζ, become redundant.

Decisions at age $j = 2$. At the beginning of period 2, students make a dropout decision based on their GPAs, the stochastic part of the grants, ζ, and an idiosyncratic part of the labor productivity process, η, now drawn from a dropout wage distribution. The GPA affects posterior beliefs about one's true ability, while simultaneously affecting grant allocation. Therefore, a high GPA enhances the value of college through the following channels (1) lowering the instantaneous utility cost of staying in college; (2) increasing expected college returns; and (3) decreasing the probability of losing grants (through GPA requirements). The stochastic shock ζ affects the affordability of college (and, therefore, average returns of college). When $\zeta < 1$, the budget constraint is tightened, and when $\zeta > 1$, college becomes more affordable and, as a consequence, incentivizes more college attendance. Finally, the idiosyncratic wage shock, η, affects an individual's budget constraint as well as the outside option of college: high η may induce students to drop out as the opportunity cost of college increases, but at the same time, it might motivate students to stay in college as college becomes more affordable. Therefore, the impact of η on college attendance cannot be isolated, and it depends on the other components of state space.

With the realized state vector $(GPA(l, \hat{S}), \zeta, \eta)$, an individual compares the value of college to the value of dropping out and optimally decides whether or not to stay in college. Formally, the decision is summarized as follows:

$$\mathbb{1}\big(2, a, \eta, z_2, \mu_{e_1}\big) = \begin{cases} 1, & \text{if } W_c^2\big(a'(a_c), \eta', z_2, \mu_{e_1}\big) > W_d^2\big(a'(a_h), \eta', \mu_{e_1}\big), \\ 0, & \text{otherwise,} \end{cases}$$

where $W_c^2\big(\cdot\big) = \mathbb{E}_{\theta' \in \Theta_d | \mu_{e_1}} V_c^2(\theta', \eta, z_2, \mu_{e_1})$, $\quad W_d^2\big(\cdot\big) = \mathbb{E}_{\theta' \in \Theta_d | \mu_{e_1}} V_d^2(a, \theta', \eta)$ denote the expected present values of the life-time utilities of staying in college and dropping out, respectively. The probabilities are taken with respect to the fixed labor productivity shocks, $\theta \in \Theta_d$. It leads the indicator function, $\mathbb{1}\big(2, a, \eta, z_2, \mu_{e_1}\big)$, to take the value of 1 if the individual decides to remain in college.

After the dropout decision, individuals make consumption-leisure-savings decisions. This problem is formulated as follows for college-bound individuals:

$$V_c^2\big(a, \theta, \eta, z_2, \mu_{e_1}\big) = \max_{a', c, l} \left\{ u(c, 1 - \xi(\mu_{e_1}) - l) + \beta \int_{\eta' \in \mathcal{H}_c} \mathbb{E}_{\theta' \in \Theta_c | \mu_{e_1}} V_c(3, a', \theta', \eta') d\eta \right\},$$

$$\text{s.t.} \quad (1+\tau_c)c + a' + (1 - z_2(a, \zeta, GPA(l_{-1}, \hat{S})))\iota w_{t,c} = (1 + (1-\tau_k)r_t)(a + a_c) + (1-\tau_p)y - y\tau_l(y) + T,$$

$$z_2\big(a_c, \zeta, GPA(l_{-1}, \hat{S})\big) = \big(z_1^{\text{need}}(a_c, \mu_{e_0}) \mathbb{1}_{GPA \geq \overline{GPA}_{\text{need}}} + z_1^{\text{merit}}(a_c, \mu_{e_0}) \mathbb{1}_{GPA \geq \overline{GPA}_{\text{merit}}}\big)\zeta, \qquad a' \geq -\underline{\mathrm{A}}_2.$$

For those individuals who decide to drop out, beliefs about their ability become redundant. Their recursive problem becomes the standard consumption-leisure-savings problem defined in equation (13).

Decisions at age $j >= 3$. College graduates draw their wage components from the college wage distribution. From age $j = 3$ onward,[17] the problem of an individual with an education level $s = \{h, d, c\}$ is as follows:

$$V_s(j, a, \theta, \eta) = \max_{a', c, l} \{u(c, 1 - l) + \beta \int_{\eta'|\eta} V_s(j + 1, a', \theta, \eta') d\eta\}, \tag{13}$$

$$\text{s.t.} \qquad (1 + \tau_c)c + a' = (1 + (1 - \tau_k)r_t)a + (1 - \tau_p)y - y\tau_l(y) + T, \qquad a' \geq -\underline{\mathrm{A}}_j.$$

Decisions at age $j >= j_r$. Upon retirement, individuals' labor productivity drops to zero, and, therefore, they live on capital income and pension benefits. The associated Bellman equation is given by:

$$V(j, a, \theta, 0) = \max_{a', c} \{u(c, 1) + \beta \varphi_{j+1} V(j + 1, a', \theta, 0)\}, \tag{14}$$

$$\text{s.t.} \qquad (1 + \tau_c)c + a' = (1 + (1 - \tau_k)r_t)a + pen_t(s, \theta) + T.$$

Individuals after retirement face mortality risk φ_{j+1} in each period. They die with probability 1 at age $j = J$.

3.8 Production

Firms operate in a perfectly competitive environment, hiring capital and labor in spot markets to produce a final good. Output is produced using a Cobb–Douglas technology:

$$Y_t = A K_t^{\alpha} L_t^{1-\alpha},$$

where A denotes total factor productivity and α governs the elasticity of output with respect to capital. Labor is composed of two skill types: workers with a college degree (skilled) and those without (unskilled), the latter including both college dropouts and high school graduates. These labor types are imperfect substitutes, with elasticity of substitution ϑ. Aggregate labor efficiency is defined as:

$$L_t = \left(\upsilon (L_{t,h} + L_{t,d})^{\vartheta} + (1 - \upsilon) L_{t,c}^{\vartheta}\right)^{1/\vartheta}, \tag{15}$$

where $L_{t,s}$ denotes labor (in efficiency units) supplied by education group s, and $1 - \upsilon$ is a parameter governing the relative demand for skilled versus unskilled labor.[18]

Under perfect competition and constant returns to scale, the firm size distribution is indeterminate. Without loss of generality, I assume a representative firm that takes the skilled wage $w_{t,c}$, the

[17] For high school graduates, who never enroll, the optimization problem reduces to equation (13) from age $j = 1$, and for college dropouts their problem reduces to equation (13) from age $j = 2$ onward.

[18] The assumption of two skill types reflects the distribution of job postings by education. Most individuals with some college experience work in jobs requiring only a high school diploma; only 5% of listings explicitly target "Some college, no degree" Torpey and Watson (2014). Similarly, 6% of jobs require postsecondary non-degree awards, which are excluded from the model.

unskilled wage $w_{t,h}$, and the interest rate r_t as given.

Competitive Equilibrium. Given market prices, firms rent capital and hire labor competitively, households optimize savings, labor supply, and education decisions, and the government collects taxes while operating the education and pension systems under a balanced budget. The full definition of the recursive competitive equilibrium is presented in Appendix H.

4 Calibration

This section discusses the model calibration. Most parameters are either estimated directly from U.S. data, calibrated internally by matching aggregate moments, or taken from the existing literature.

Demographics. A period in the model corresponds to two years. New generations enter the economy at the age of 18 and it takes two model periods (four years) to complete college. Individuals retire at the age of 66, and the maximum age is 96. The population grows at a constant rate of $n = 1\%$ annually, which is consistent with the long-term population growth rate in the U.S. Likewise, survival probabilities φ_j are computed from the actuarial life tables for the US.

Preferences. The model adopts a conventional utility function:

$$u(c, 1-l) = \frac{\left[c^{\nu}(1-l)^{1-\nu}\right]^{1-\frac{1}{\gamma}}}{1-\frac{1}{\gamma}}, \tag{16}$$

where ν reflects the preference for consumption relative to leisure, and γ governs the intertemporal elasticity of substitution (IES). The parameter ν is calibrated to ensure individuals allocate, on average, one-third of their time to labor. The parameter γ is fixed at 0.25, which implies a coefficient of relative risk aversion of approximately 2—a standard value in the literature. These parameters jointly determine average labor supply, the intertemporal elasticity of substitution, and the Frisch elasticity of labor supply.

Technology. The aggregate production function is a Cobb-Douglas form. The capital share α is set to 0.33. Total factor productivity A is normalized to 1. The elasticity of substitution between skilled and unskilled labor is borrowed from Card (2009) and set to 3.33. This estimate is in line with the estimate in Abbott et al. (2019) and those in literature. The discount factor is internally calibrated to target a capital-output ratio of around 3 as in Krueger and Ludwig (2016). Finally, υ is calibrated internally to match the college wage premium of about 80%, reported in Table 4.[19]

Utility Cost of College. The utility cost of college attendance is a key determinant of enrollment heterogeneity across ability levels.[20] I specify the utility cost in period t as $\xi_t(\mu_{e_{t-1},i}) = \exp(b_0 -$

[19]The college wage premium is defined as the ratio of the (age-composition-adjusted) average wage between those with a college degree and those with only a high school degree.

[20]Other determinants include expected earnings in the college and non-college sectors and the time devoted to work while enrolled, all of which depend on true ability.

Table 6: Internally Calibrated Parameters

Parameter	Description	Value	Target
Discount Factor			
β	Discount factor	0.99	K/Y
Production Function			
υ	Skill-level productivity	0.94	College wage premium
Utility Cost of College			
b_0	Constant in $\xi(\cdot)$	0.45	Total enrollment
b_1	Slope in $\xi(\cdot)$	-0.16	Enrollment by ability quintiles
Education Costs			
ι	Cost parameter ($\frac{\iota w_{t,c}}{\bar{Y}}$)	0.196	Tuition as a share of GDP
GPA Thresholds			
$\overline{GPA}_{need}$	Need-based threshold	0.1	% with GPA < 2
$\overline{GPA}_{merit}$	Merit-based threshold	0.3	% with GPA < 3
Generalized Pareto Dist.			
p_k	Shape parameter	0.08	Avg. family contribution
p_σ	Scale parameter	0.94	Avg. family contribution
Labor Productivity			
ω_h	Scale, high ability	0.28	Section 4
ω_d	Scale, dropout	0.84	Dropout wage premium
σ_{θ_d}	Fixed effect, dropout	0.072	Total dropout rate
σ_{θ_c}	Fixed effect, graduate	0.084	Grad rates by ability
Government Policy			
τ_p	Payroll tax	0.07	Pension-budget balance
$1-\lambda$	Flat tax on earnings	0.19	Gov. budget balance

$b_1\mu_{e_{t-1,i}}$), where $\mu_{e_{t-1,i}}$ is the belief about ability at the time of decision. The parameters b_0 and b_1 are held constant across periods to prevent mechanically induced dropout behavior unrelated to learning. Allowing utility costs to rise over time, as in some prior studies, would mechanically inflate dropout through the ability channel—despite limited empirical evidence for increasing college disutility. The parameters are calibrated internally: b_0 matches overall enrollment, and b_1 targets enrollment by ability quintiles. The resulting values are reported in Table 6; model fit is shown in Figure 2.

Resource Cost of College. The resource cost of college is denoted by ιw_c, where ι is a cost parameter calibrated to match the empirical education-to-GDP ratio, and w_c is the college graduate wage. This cost is disciplined using data from the Digest of Education Statistics.

The reported average annual education cost per student in four-year institutions was $24,000 (in 2016 dollars) for the 2011–2012 academic year.[21] This figure is representative of nonprofit colleges, which account for 95 percent of undergraduate enrollment.[22] The resulting value for ι is reported in Table 10.

[21] https://nces.ed.gov/fastfacts/display.asp?id=76.

[22] Public and private nonprofit institutions enroll 78 and 17 percent of students, respectively; private for-profit colleges, which enroll only 5 percent, are excluded to avoid overstating average education costs, as they are typically much more expensive.

Table 7: Initial Wealth as a Share of the Student Budget: Model vs. Data

	Q1	Q2	Q3	Q4	Q5
Data	0.00	0.08	0.31	0.60	0.89
Model	0.05	0.17	0.31	0.53	0.86

Note: Entries report average parental transfers as a share of student budget by wealth quintile. Model calibrated using BPS 2011–2012 cohort.

Borrowing Limits. Borrowing constraints for $j \geq 3$ are set such that borrowers repay at least a minimum amount P each period, so that the loan is fully repaid within 10 years after graduation.
Initial Wealth for College Students. Using BPS data on expected family contributions among enrolled students, I calibrate the initial wealth distribution for college entrants using a modified generalized Pareto function. Parameters are chosen to match the average parental contribution in the third and fifth wealth quintiles. Non-enrollees are assigned zero initial wealth by construction, as the focus is on early transfers conditional on enrollment. Table 7 reports the average parental transfers for college costs by wealth quintile, which closely mirror the observed data. Because the model is calibrated on the college-going population—and the very poorest students tend not to enroll—it slightly overstates parental contributions in the bottom two quintiles.

As for the correlation between ability and family wealth, Table D.1 (Appendix D) shows that parental contributions, expressed as a share of student budgets, are stable across ability quintiles (approximately 0.50), but vary widely across wealth quintiles (from 0.00 to 0.89). This pattern supports the decision not to impose a correlation between student ability and family wealth in the baseline calibration, as ability does not appear to be systematically related to parental transfers—which proxy for family wealth in the model.

Details on the calibration of the GPA function's parameters related to working hours and government policy parameters are provided in Appendix E.

Calibration of the Dropout Channels. This section outlines the calibration of dropout-relevant uncertainty: grant shocks, GPA-contingent eligibility, learning about ability, and labor productivity shocks. Grant policies are calibrated directly from BPS data. Belief parameters are pinned down using Stinebrickner and Stinebrickner (2012). Productivity shocks are partly brought in from the literature and partly calibrated internally to match college outcomes.

To calibrate the grant function, I use data from the BPS 2011-2012 cohort, which provides detailed records of total grants received by students across ability and wealth quintiles. The data indicate that grants are weakly differentiated by ability (32% of costs on average) but strongly differentiated by wealth, covering 49% of costs for the lowest wealth quintile and only 19% for the highest quintile (Table 8). Following these patterns, I calibrate need-based grants using a step function that matches its empirical distribution by wealth quintile, while merit-based grants are

Table 8: Merit-Based and Need-Based Grants as a Share of Cost of Attendance by Ability and Wealth: Model vs. Data

Panel A: Total Grants					
Quintiles	Q1	Q2	Q3	Q4	Q5
By ability	0.35	0.31	0.32	0.34	0.35
By wealth	0.49	0.42	0.23	0.20	0.19
Panel B: Merit-Based Grants					
Ability Quintiles	Q1	Q2	Q3	Q4	Q5
Data	0.14	0.16	0.13	0.12	0.14
Model	0.13	0.13	0.13	0.13	0.14
Panel C: Need-Based Grants					
Wealth Quintiles	Q1	Q2	Q3	Q4	Q5
Data	0.38	0.25	0.10	0.06	0.04
Model	0.40	0.26	0.12	0.05	0.03

Notes: Grant shares are presented as a fraction of cost of attendance (student budget). Wealth quintiles are based on Expected Family Contribution (EFC), and ability quintiles are based on SAT scores of enrolled students. Source: National Center for Education Statistics, BPS 2011–2012 cohort.

weakly increasing with ability (13% on average). The model successfully replicates observed grant shares across ability-wealth categories (Appendix E Table F.1).

Grants in the Second Period of College. The calibration of the second-period grant function (equation 8) involves two key components: GPA thresholds for grant eligibility and a stochastic process capturing grant volatility.

GPA Thresholds. The need-based threshold, $\overline{GPA}_{\text{need}}$, is set at 2.00, to follow Satisfactory Academic Progress (SAP) requirements for Pell Grants. The merit-based threshold, $\overline{GPA}_{\text{merit}}$, is set at 3.00, a conservative lower bound for merit-based grant eligibility. These thresholds are calibrated to match the BPS dataset, in which 9 percent of students fall below 2.00 and 29.9 percent fall below 3.00. The model scales these thresholds so that the simulated fraction of students losing grants aligns with observed failure rates.

GPA Thresholds. For full-time students, GPA thresholds are used as a sufficient proxy for Satisfactory Academic Progress (SAP), which typically combines academic performance and credit accumulation. This simplification is further detailed in Appendix E.1. The need-based threshold, $\overline{GPA}_{\text{need}}$, is set at 2.00, following Satisfactory Academic Progress (SAP) requirements for Pell Grants. The merit-based threshold, $\overline{GPA}_{\text{merit}}$, is set at 3.00, a conservative lower bound for merit-based grant eligibility. These thresholds are calibrated to match the BPS dataset, in which 9 percent of students fall below 2.00 and 29.9 percent fall below 3.00. The model scales these thresholds so that the simulated fraction of students losing grants aligns with observed failure rates.

Grant Volatility. Volatility is modeled using residual year-to-year variation in Pell Grants after

conditioning on eligibility criteria. Because Pell comprises roughly 50% of all U.S. need-based grant and shares administrative infrastructure with other programs, its variation is used to proxy for volatility across grant types. To simplify computation and avoid tracking continuous parental wealth, grant amounts are discretized into five brackets. Panel (b) in Table 4 reports empirical transitions from Year 1 to Year 3 in the BPS data, where bracket 1 corresponds to the maximum grant (covering 38% of the student budget) and bracket 5 to near-zero awards. These transitions determine the stochastic shock grid ζ_{ij} (equation 17) and associated probabilities $\pi_{\zeta_{ij}}$ (equation 18), where i indexes the initial grant bracket and j the realized bracket in the second period. When $i = j$, the grant remains unchanged.

$$\zeta_{ij} = \begin{bmatrix} 1.00 & 0.67 & 0.25 & 0.16 & 0.00 \\ 1.48 & 1.00 & 0.37 & 0.24 & 0.00 \\ 3.95 & 2.67 & 1.00 & 0.65 & 0.00 \\ 6.06 & 4.09 & 1.53 & 1.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 1.00 \end{bmatrix} \quad (17)$$

Stochastic Grant Grid

$$\pi_{\zeta_{ij}} = \begin{bmatrix} 0.71 & 0.08 & 0.07 & 0.03 & 0.12 \\ 0.31 & 0.31 & 0.11 & 0.05 & 0.22 \\ 0.14 & 0.09 & 0.23 & 0.09 & 0.45 \\ 0.12 & 0.16 & 0.09 & 0.10 & 0.52 \\ 0.03 & 0.01 & 0.01 & 0.01 & 0.94 \end{bmatrix} \quad (18)$$

Transition Probabilities

Ability and Beliefs. The optimism parameter, α_e, is defined as the difference between students' mean belief about their future college GPA (which is proxied by their high school GPA before enrollment (Stinebrickner and Stinebrickner 2012)) and their realized GPA after the first half of college. In the data, these are 3.21 and 2.97, respectively, yielding $\alpha_e = \frac{3.21-2.97}{4} = 0.06$. The denominator rescales the optimism gap to the model's normalized GPA scale (ranging from 0 to 1). For the standard deviation of the prior, I impose the restriction $\sigma_{e_0} = \sigma_{\mu_{e_0}}$.[23] The parameter $\sigma_{\mu_{e_0}}$ represents the standard deviation of students' beliefs about their academic performance, averaged across the enrolled population. Based on estimates in Stinebrickner and Stinebrickner (2014), I set $\sigma_{e_0} = \sigma_{\mu_{e_0}} = \frac{0.52}{4} = 0.13$, again adjusting to the normalized GPA scale. After specifying the prior distribution, I calibrate the signal-to-noise ratio by recovering the signal variance σ_ψ. To do so, I rely on empirical estimates from Stinebrickner and Stinebrickner (2014), which document the relative weights students assign to prior beliefs versus observed academic signals after each year. Using their first-year estimates—where belief updating is strongest—and applying equation (5), I derive the value of σ_ψ. This choice of using first-year estimates ensures that the ability channel reflects its maximum contribution to dropout, yielding a conservative calibration relative to other mechanisms such as grant volatility. Table 9 summarizes the calibrated parameters governing the prior and posterior distributions.

Labor Productivity. The wage process combines a deterministic age profile with an idiosyn-

[23]This assumption is necessary due to the lack of reliable data on the distribution of individual priors based on student characteristics like wealth or ability.

Table 9: Parameters of Prior and Posterior Belief Distributions

Parameter	Definition	Value
σ_{e_0}	Std. dev. of prior belief	0.13
α_e	Optimism parameter	0.06
SNR	Signal-to-noise ratio $(1 + \sigma^2_{\mu_{e_0}}/\sigma^2_{\psi_i})$	1.34

Table 10: Externally Calibrated Parameters

Panel A: Demographics, Preferences, and Technology			**Panel B: Education, Labor, and Government Policy**		
Param.	**Description**	**Value**	**Param.**	**Description**	**Value**
Demographics			**Education Costs and Subsidies**		
n	Population growth rate	1%	z_1	Subsidy rate, period 1	Section 4
j_r	Retirement age (66 years)	25	z_2	Subsidy rate, period 2	Section 4
J	Maximum age (94 years)	40	Φ_1	Student loan size (Year 1)	0.396
φ	Survival probabilities	Actuarial Life Tables	Φ_2	Student loan parameter (Year 2)	0.791
Preferences			**Labor Productivity**		
γ	Risk aversion	0.25	σ_{θ_n}	Fixed effect for non-college	0.059
ν	Leisure (hours worked)	0.374	ρ_c	Persistence parameter, college	0.933
Technology			η_c	Stochastic shock, skilled	0.033
α	Capital share of output	0.33	$\rho_{n,d}$	Persistence parameter, nonskilled	0.906
A	Total factor productivity	1	$\eta_{n,d}$	Stochastic shock, nonskilled	0.032
δ	Depreciation rate	0.05			
ϑ	Elasticity of substitution	0.69			
Government Policy					
g_y	G. Govt spending to GDP	17%			
τ_c	Consumption tax	7.3%			
τ_k	Capital income tax	28.3%			
κ_s	Pension benefits	35%			
m	Progressivity	0.1			

cratic AR(1) shock, following estimates from the data. I calibrate the deterministic component, ϵ_j, to be normalized at 1 upon college graduation and to increase by a factor of two by age 50. This schedule aligns with observed wage profiles across the lifecycle (see Ludwig, Schelkle, and Vogel 2012). The AR(1) shock process is calibrated using estimates from Abbott et al. (2019), separately for skilled (college) and unskilled (high school and dropout) groups. The fixed effect of high school graduates is pinned down using the initial cross-sectional dispersion in earnings within that group. The remaining four parameters governing fixed effects in the wage process—ω_h, ω_d,[24] σ_{θ_d}, and σ_{θ_c} (see equation 9)—are calibrated internally to match eight data targets: the college wage premium, the dropout wage premium, the overall dropout rate, and graduation rates by ability quintiles. These four targets overidentify the parameter set. The resulting lifecycle earnings profiles are shown in Figure 7 in Appendix G.[25]

[24] Without loss of generality, ω_c is set to 1.

[25] *Note:* In an alternative calibration, I estimate the wage process exogenously and calibrate grant stochasticity internally. The results are robust both quantitatively and qualitatively. The policy-relevant role of grant volatility in explaining dropout remains stable across specifications. The relative contribution of learning and productivity to dropout varies slightly, with ability beliefs playing a somewhat larger role when wage heterogeneity is fully fixed.

Table 11: Targeted Moments

Description	Model	Data	Source
Capital-Output Ratio	3	3	Fernandez-Villaverde and Krueger (2011)
College Wage Premium	1.8	1.8	Lee, Shin, and Lee (2015)
Dropout Wage Premium	1.2	1.2	Lee, Shin, and Lee (2015)
Tuition as a Share of GDP	0.5	0.5	NCES
Total Enrollment	49.4%	49.4%	NLSY97
Total Dropout	36.2%	36.3%	NLSY97
Average Working Time	0.3	0.3	PSID
Student Budget to GDP per Capita	0.5	0.5	NCES
Initial Wealth	Table 7	–	NCES
Enrollment Rates by Ability	Figure 2	–	NLSY97
Graduation Rates by Ability	Figure 2	–	NLSY97

5 Model Fit

5.1 Targeted Moments

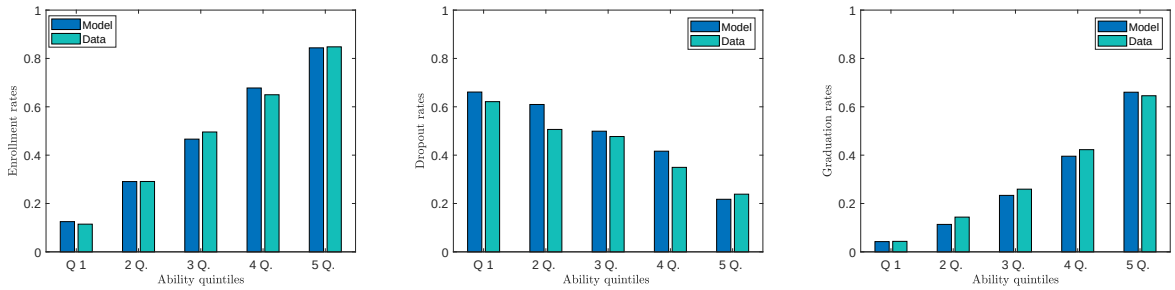
Model fit to the targeted moments is presented in Figure 2, and Table 11. Figure 2 shows that the model closely replicates college participation margins by ability: both enrollment and graduation rates increase monotonically with ability. This increasing pattern is driven by several channels. As ability rises, (i) students are less likely to receive negative signals that affect grant eligibility; (ii) they form higher posterior beliefs that reinforce the decision to stay enrolled; (iii) they face lower time costs, enabling them to allocate more hours to work and self-insure against financial shocks; and (iv) they expect higher returns to college due to the complementarity between ability and education. These mechanisms together result in lower dropout and higher graduation rates for higher-ability students.

Table 11 shows that the model replicates key aggregate moments closely. The average college wage premium is 80 percent, consistent with the data. The model also matches the 20 percent wage premium for college dropouts observed empirically. In addition, the capital-output ratio and average labor supply, measured as the share of total time allocated to market work, are in line with their data counterparts.

5.2 Untargeted Moments

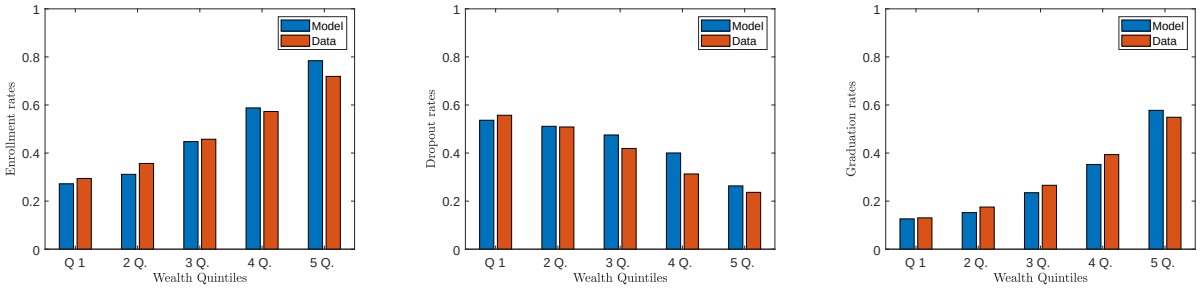
To assess the model's performance beyond the targeted moments, I evaluate its fit to a set of untargeted moments. First, I examine how well the model reproduces college participation margins across the wealth quintiles. Second, I assess the model's elasticities of enrollment and completion with respect to changes in subsidies, using estimates from the micro-empirical literature. This validation is particularly important given the central role of grant policy in the model's counterfactual analysis. Finally, I compare the model's implied earnings distribution to the data; these results are reported in Appendix F.

Figure 2: Targeted Moments. College Participation by Ability Quintiles. Model vs. NLSY97 Data



(a) Enrollment rates **(b)** Dropout rates **(c)** Graduation rates

Figure 3: Untargeted Moments. College Participation by Wealth Quintiles. Model vs. NLSY97 Data



(a) Enrollment **(b)** Dropout **(c)** Graduation

College Participation by Wealth Quintiles. Figure 3 shows enrollment, dropout, and graduation by wealth quintile. Although untargeted, the model replicates the empirical patterns well, with both enrollment and graduation increasing in wealth. These gradients are driven by three forces: wealth reduces the effective cost of college, enables consumption smoothing during enrollment, and provides insurance against financial shocks—each of which lowers the incentive to exit college before completion.

Elasticities of College Participation to Subsidy Changes. I next test the model's responsiveness to changes in college subsidies, benchmarking against quasi-experimental estimates. Most existing studies estimate enrollment effects, while fewer capture the effects on degree completion. I therefore evaluate enrollment and completion responses separately, drawing on distinct empirical sources. The simulation is conducted in partial equilibrium.

Scott-Clayton (2011) studies the West Virginia PROMISE scholarship, introduced in 2002, using administrative data and exploiting eligibility thresholds. The $2,900 scholarship was awarded to students with a high school GPA above 3.00—a threshold met by 40% of entrants—and could be retained by maintaining a GPA above 3.00 in college, which 50% of recipients maintained through year four. The program raised graduation by 7 percentage points. To replicate this experiment, I

Table 12: Elasticities of Enrollment and Graduation to Subsidy Increases

	Empirical Estimate	Model (Partial Eq.)
Panel A: \$2,900 **Merit-Based Grant**		
Δ Enrollment Rate	–	3.6%
Δ Graduation Rate	7.5% (Scott-Clayton 2011)	5.0%
Panel B: \$1,000 **Unconditional Grant**		
Δ Enrollment Rate	3% – 6% (Deming and Dynarski 2009)	4.0%
Δ Graduation Rate	–	2.8%

Notes: The table reports changes in enrollment and graduation rates in response to increases in college subsidies. Model simulations are compared to reduced-form estimates from Scott-Clayton (2011) and Deming and Dynarski (2009). All simulations are conducted in partial equilibrium.

assign a \$2,900 merit-based grant to students in the top 40% of the ability distribution and impose a GPA threshold requiring recipients to remain in the top 50% of that group. The model predicts a 5 percentage point increase in graduation—comparable to the 7.5 percentage point effect in Scott-Clayton (2011).

To assess the enrollment elasticity to aid, I follow Deming and Dynarski (2009), who finds that a \$1,000 reduction in college cost increases enrollment by 3–6 percentage points. In the model, a \$1,000 grant increases enrollment by 4 percentage points and graduation by 2.8 percentage points—both within empirical bounds. Table 12 summarizes the results of both experiments, showing that the model's elasticity estimates align closely with quasi-experimental findings.

6 Model Mechanism

6.1 Initial wealth, ability, and the decision to Drop Out

This section examines how students' initial ability and wealth shape their response to dropout-relevant shocks. In the model, college attrition arises from three sources of uncertainty: (i) noisy signals about academic ability (e.g., GPA), (ii) shocks to grant aid, and (iii) idiosyncratic productivity shocks. Whether these shocks lead to dropout depends jointly on academic ability and financial resources, which determine both exposure to risk and capacity to absorb it. To isolate each channel, Figure 4 (Panels a and b) displays dropout policy functions under high and low realizations of each shock, holding other state variables fixed.[26] Each panel shows decisions for students at the 10th, 50th, and 90th percentiles of the initial wealth distribution across the full support of ability priors. In each panel, the shaded region denotes the set of students who choose to enroll in college. The darker shaded area identifies students whose continuation decision depends on the realization of the shock; conversely, students in the unshaded region on the far left do not enroll, while those

[26]The role of productivity shocks is discussed in Appendix I.

in the lighter shaded area on the right deterministically complete college regardless of the shock.

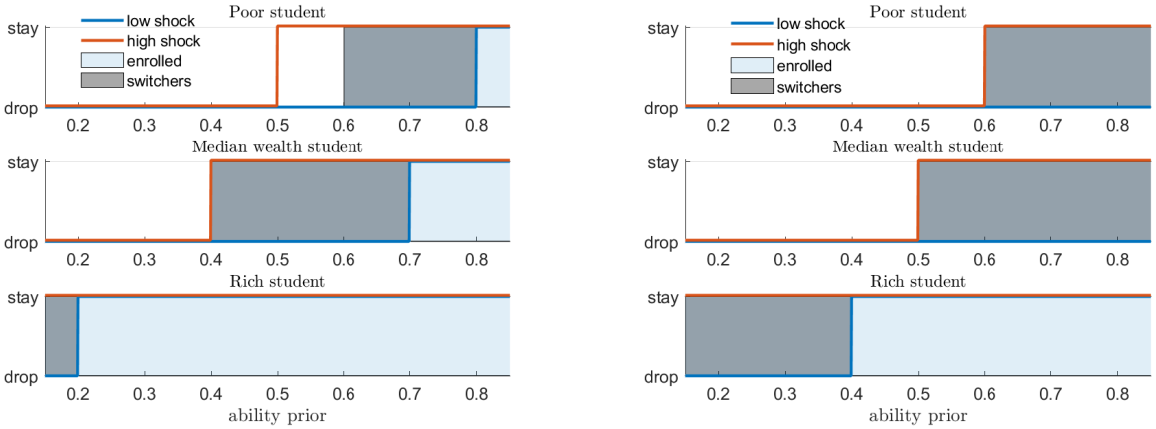
Figure 4a illustrates how dropout behavior responds to stochastic variation in grant aid, holding other state variables fixed. As shown in equation 8, grant receipt is uncertain due to GPA-contingent eligibility and a stochastic component, ζ. The figure isolates the effect of ζ. The shaded region shows enrollment policy functions for poor, median-wealth, and high-wealth individuals. The minimum ability required to find college enrollment optimal decreases with wealth: poor students enroll only if their ability prior exceeds 0.6, median-wealth students require a prior above 0.4, and high-wealth students enroll across the full ability distribution. This pattern confirms empirical findings that enrollment is strongly wealth-dependent. Within the enrolled population, the darker shaded region identifies students whose continuation depends on the realization of the grant shock—that is, they remain in college only if they receive a positive grant draw. Conditional on enrollment, dropout risk remains highly wealth-dependent: the ability threshold required to persist after grant loss declines with wealth. For poor students, this threshold is approximately 0.8—students with priors between 0.6 and 0.8 will enroll, but drop out if they lose their grant. For median-wealth students, the threshold falls to roughly 0.7. High-wealth students are largely unaffected unless their priors are very low. Thus, the cutoff at which grant loss induces dropout declines monotonically with wealth, implying that high-return students from lower-wealth backgrounds are disproportionately excluded from college completion due to adverse financial shocks.

This pattern illustrates how wealth and ability operate as substitutes along the college continuation margin under financial risk. High-ability students persist due to higher expected returns and lower disutility, which allow them to allocate more time to the labor market. Wealth, by contrast, relaxes borrowing constraints, insures against grant loss, and reduces the need to supply labor, thereby mitigating the utility cost of working while in college. As a result, adverse financial shocks induce dropout among students with moderate to high ability from lower-wealth backgrounds—despite their strong college potential—introducing misallocation in the formation of human capital.

Figure 4b illustrates how dropout behavior responds to noisy ability signals. A low signal reduces the value of college by increasing disutility (via lower GPA), lowering expected returns (through posterior beliefs), and raising the probability of grant loss.[27] As with grant shocks, dropout responses to ability signals become less sensitive as wealth increases. Poor students exit following a negative signal unless their priors are high, while high-wealth students remain enrolled even at lower priors. The underlying mechanisms mirror those seen with grant shocks: ability increases the value of college (through higher expected returns and lower disutility), while wealth enhances persistence by smoothing consumption and providing insurance against GPA-dependent grant loss. As a result, high-ability students from low-wealth backgrounds who receive a negative academic signal are more likely to drop out—even when their long-run returns are high—whereas wealthier

[27] Grants are lost if GPA falls below thresholds $\overline{GPA}_{\text{need}}$ and $\overline{GPA}_{\text{merit}}$.

Figure 4: Dropout Policy Functions by Ability Prior and Initial Wealth



(a) Grant Shocks

(b) Ability Signals

Notes: Each panel displays dropout decisions by ability prior (x-axis) for students at the 10th, 50th, and 90th percentiles of initial wealth. The y-axis denotes dropout (0) vs. continuation (1) in the second college period. The red (blue) lines show policy functions under high (low) realizations of the respective shock. The blue shaded region marks priors for which students find it optimal to enroll in period one. The gray region marks priors for which dropout depends on the realization of the shock. Poor students are more exposed to negative realizations of both signal and grant shocks.

peers with similar signals persist, again generating misallocation in human capital formation.

Unlike grant and ability shocks, idiosyncratic productivity shocks do not produce a clear directional effect on dropout. These shocks create opposing forces: they raise the opportunity cost of college by improving outside options, but also increase in-college earnings, making college more affordable. This distinction highlights the importance of the source of financial uncertainty. Shocks originating within the college system—such as grant loss—predictably reduce persistence, while external financial shocks, such as those from the labor market, generate heterogeneous responses that depend on students' broader state space.

In summary, students with either greater financial resources or stronger academic ability are better equipped to absorb shocks, reflecting the substitutability between wealth and ability. Adverse shocks disproportionately induce exit among high-ability students from low-wealth backgrounds and mid-ability students from middle-wealth backgrounds, leading to misallocation in the formation of human capital. The next section quantifies the share of attrition attributable to each source of risk.

6.2 Decomposing the channels of dropping out

This section decomposes the contribution of each source of dropout risk—stochastic grant shocks, GPA-contingent grant loss, imperfect information about ability, and labor market productivity

shocks—to overall college attrition. To isolate the role of each channel, I compute dropout rates under a sequence of counterfactual experiments in which one source of uncertainty is removed at a time, holding all other elements fixed at their benchmark values. These experiments are conducted in partial equilibrium, with skill prices and taxes held constant. The resulting decomposition provides a clear mapping from dropout mechanisms to observed attrition and establishes the scope for targeted policy interventions aimed at increasing completion rates.

The first three experiments target grant risk. In the first, stochastic variation in grants is eliminated by setting $\zeta = 1$, removing exogenous shocks. The second removes GPA-based eligibility by fixing grant receipt independent of academic performance. The third combines both: students receive the same grant amount as in their first year with certainty. The fourth experiment eliminates uncertainty over ability by allowing students to observe their true type before enrollment—removing belief updating and optimism. The fifth and final experiment isolates the role of productivity shocks by shutting down all other risks: grants are fixed and ability is known. In this case, dropout occurs only when favorable wage realizations increase the value of the outside option or when the dropout wage premium makes early exit strictly optimal. Table 13 summarizes the results for each experiment, including changes in enrollment, dropout, graduation, and aggregate labor efficiency.

The first two experiments highlight the central role of grant volatility in driving college attrition. Removing stochastic grant shocks reduces dropout by 33.7%, while eliminating GPA-contingent renewal reduces it by only 4.5%. The grant-shock experiment also yields a notable rise in average efficiency units of labor, driven by improved sorting: high-ability students from low-wealth backgrounds and mid-ability students from middle-wealth families are more likely to graduate when grant is stable. By contrast, relaxing GPA thresholds primarily increases graduation among low- to mid-ability students—a margin that remains quantitatively limited for two reasons. First, few low-ability students enroll in the first place, especially among the poor. Second, the college wage premium is lower for students with weaker academic ability, limiting the gains from retention.

The third experiment, which removes both grant stochasticity and GPA-contingency, generates the largest effects. Dropout falls by 40.9%, while graduation rises to 45%. The effect exceeds the sum of Experiments 1 and 2, indicating that many students are jointly exposed to both risks. Only when both are removed does enrollment increase significantly—by 8 percentage points—raising graduation by 13.5 percentage points. The expansion in skilled labor raises aggregate productivity by 4%, reflecting both the larger number and higher quality of graduates. This result underscores the complementarity between ability and education, and shows that eliminating grant-related uncertainty—holding prices and taxes fixed—can increase college attainment by nearly one-fourth.

Experiment 4, which removes ability uncertainty, leads to a slight decline in enrollment. Low-ability students opt out due to low expected returns, while high-ability students enroll with certainty. These offsetting effects would leave total enrollment unchanged, but the removal of optimism lowers

participation slightly. Dropout falls by 10.1%, while graduation declines by 1 percentage point due to the smaller entering class. Average efficiency units fall marginally (-0.8%) as improved sorting partially offsets the decline in overall graduates.

Experiment 5 isolates productivity shocks by shutting down all other dropout channels. Dropout falls by 49.6%, to 18.2%. The remaining exits reflect selection, not risk: students with low to mid ability leave when favorable wage shocks make work more attractive than graduation. Enrollment remains roughly unchanged: the removal of grant volatility encourages some students to enroll, while the absence of optimism discourages others. These effects nearly offset, resulting in only a 1.8% increase in enrollment. Graduation rises by 10.1 percentage points, and average efficiency units increase as both the quantity and quality of college completers improve.

Before concluding, it is useful to revisit why ability learning alone cannot explain most college attrition and how this model relates to findings from Stinebrickner and Stinebrickner (2012). In the data, enrollment varies sharply by ability: only 12% of students in the lowest AFQT quintile enroll, compared to 86% in the top quintile (Table A.2). This suggests that students enter college with relatively accurate beliefs about their academic potential. Indeed, students in the bottom two ability quintiles represent just 16% of enrollees in the NLSY97. As a result, learning-based dropout among low-ability types cannot account for the observed 40% attrition rate. If students had substantially more uncertainty about their ability, the model would overpredict enrollment among low-ability students and underpredict the strong ability gradient seen in the data (Figure 3).

Stinebrickner and Stinebrickner (2012) estimate that learning explains 40–45% of dropout in the first two years of college. Their estimate comes from Berea College, where students receive full tuition and living support, effectively removing financial constraints and grant volatility. While this setting isolates learning effects, it is not representative of the broader college population, where financial uncertainty remains central. Even in their sample, however, 55–60% of attrition arises from non-learning channels. In contrast, the model here is calibrated to a representative population with realistic financial conditions—uncertain aid, limited insurance, and borrowing constraints. In this setting, learning plays a limited role, consistent with strong sorting at entry, while grant-related uncertainty accounts for roughly one-third of all dropouts.

7 Policy

This section evaluates three general equilibrium policy reforms targeting the structure of the college grant system. General equilibrium analysis is necessary to capture the long-run impact of reforms, as equilibrium adjustments in wages, taxes, and relative returns endogenously influence human capital investment decisions. Each policy is modeled as a permanent reform, financed by adjusting the flat component of the labor-income tax schedule to keep the government budget balanced. Policy 1, the No Reapplication policy, removes the stochastic component of grants (ζ) while

Table 13: College Outcomes Across Dropout Channels (Partial Equilibrium)

		Counterfactual Experiments				
	Bench.	No Grant Shocks (1)	No GPA Threshold (2)	Fixed Grants (3)	No Ability Uncertainty (4)	Residual Dropout (5)
Δ Dropout rate (%)	0.0	-33.7	-4.5	-40.9	-10.1	-49.6
Dropout rate (%)	36.1	24.0	34.5	21.4	32.5	18.2
Enrollment rate (%)	49.4	55.2	49.5	57.3	44.7	51.2
Graduation rate (%)	31.5	42.0	32.4	45.0	30.2	41.8
Δ Efficiency units $\hat{L}$ (%)	0.0	4.0	0.4	4.9	-0.8	3.8

Notes: Each counterfactual removes a specific dropout channel while holding skill prices and tax policy fixed (partial equilibrium). Efficiency units $\hat{L}$ refer to average productivity-weighted labor.

retaining GPA-contingent eligibility. It mirrors simplified grant systems that automatically renew grants based on academic progress, as seen in some state scholarship programs and in proposals to reform the federal FAFSA process. Policy 2, No GPA Requirement, removes GPA-based eligibility but retains the stochastic component. This isolates the share of dropouts attributable to GPA-related grant loss. Policy 3, Fixed Grants, eliminates both sources of uncertainty—students retain the grant they receive in the first year with certainty as long as they do not drop out. Table 14 summarizes the general equilibrium effects of these reforms. Panel (a) reports changes in college participation—enrollment, graduation, and dropout rates, Panel (b) presents macroeconomic outcomes, and Panel (c) displays welfare effects. Figures 5 and 6 show how participation responses vary across the ability and wealth distributions, respectively.

Panel (a) of Table 14 shows that all three policies increase college enrollment and graduation, though the effects are more muted in general equilibrium than in partial equilibrium (see Section 6.2). Enrollment rises by 1 to 3 percentage points, and graduation increases by 3 to 4 percentage points, while overall dropout rates remain stable. These average changes, however, mask substantial shifts in selection. As financial risk is reduced, high-ability students from low-wealth backgrounds are more likely to enroll and persist. At the same time, a compressed college wage premium lowers the net return to marginal students, prompting exit among low-ability individuals from high-wealth families. As a result, college participation becomes increasingly concentrated among students with higher expected returns, improving selection on both ability and financial need.

Figures 5 and 6 illustrate these composition effects. Figure 5 shows that No Reapplication policy and Fixed Grants policy increase enrollment and graduation rates among high-ability students. Figure 6 confirms that many of these individuals come from low-wealth backgrounds and would drop out under financial uncertainty. The mechanism is intuitive: because ability and returns to college are complementary, high-ability students stand to gain the most from completing

a degree. Removing the risk of grant loss reduces their exposure to liquidity shocks, allowing them to persist and realize those high returns. In contrast, low-ability students respond less to the removal of stochastic grant risk. This group remains exposed to other dropout channels—such as poor academic performance or negative ability signals—and is disproportionately drawn from high-wealth families, who are relatively insensitive to grant volatility (see Section 6). At the upper end of the wealth distribution, graduation rates decline modestly, primarily due to the exit of low-ability students who no longer find college completion worthwhile under a compressed wage premium. Thus, the reforms improve sorting along both margins: they enable high-ability, low-wealth students to persist, while encouraging exit among low-ability, high-wealth students with low expected returns to college.

Importantly, among the three reforms, the No Reapplication policy delivers nearly all of the sorting gains. This policy removes stochastic shocks but retains academic requirements, and closely mirrors real-world interventions that eliminate grant reapplication burdens. The result suggests that retaining GPA-contingency while removing reapplication requirements is sufficient to improve educational sorting, particularly among high-ability, low-wealth students. This is in line with rigorous experimental evidence, as Dynarski et al. (2021b) demonstrate that reducing complexity and uncertainty in college pricing, akin to eliminating reapplication burdens, significantly improves the persistence of low-income, high-ability students, thereby enhancing ability sorting.

Better sorting by ability has strong implications for aggregate productivity. Panel (b) Table 14 reports changes in key macroeconomic variables under each reform relative to the benchmark. Average labor productivity increases under all policies, with the largest effects under Policies 1 and 3—2.1% and 2.9%, respectively. Importantly, these gains are not driven by increases in labor supply: hours worked remain flat or decline slightly. Instead, the improvements reflect better matching between ability and educational attainment. Improvements in labor productivity translate into higher output and consumption: aggregate output rises by 2.2% under No Reapplication policy and 2.9% under Fixed Grants policy, with consumption following a similar pattern. No GPA Requirement policy generates only modest gains across all macroaggregates, consistent with its limited effect on sorting. The gains under the Fixed Grants policy exceed the sum of those under the No Reapplication and No GPA Requirement policies. This indicates complementarity between the two risk margins: jointly removing both stochastic and GPA-based uncertainty reduces perceived college risk for a broader set of students. As a result, Fixed Grants reaches students who would not have responded to either reform in isolation.

In general equilibrium, changes in skill prices reinforce the macro and welfare effects of improved sorting. These wage adjustments are a key mechanism underlying the divergence between partial and general equilibrium results. As the supply and composition of college-educated and dropout workers shift, the returns to education adjust endogenously. These general equilibrium

price changes affect both enrollment incentives and the distribution of gains from reform. Panel (c) in Table 14 reports changes in the college and dropout wage premiums relative to the benchmark. The college wage premium declines by 1.7%, 0.7%, and 2.8% under the No Reapplication, No GPA Requirement, and Fixed Grants policies, respectively. These declines reflect the expansion of skilled labor supply induced by higher college completion. At the same time, the dropout wage premium rises by 4.9%, 1.1%, and 8.7%. This increase is driven by improved ability sorting: as more high-ability, low-wealth students enter college and some drop out, the average productivity—and thus earnings—of the dropout group rises.

Welfare improves alongside gains in productivity and consumption. Table 14 reports utilitarian welfare gains for newborns, expressed as consumption-equivalent variation (ω_{CEV}). Welfare rises by 2.4%, 0.1%, and 3.4% under the No Reapplication, No GPA Requirement, and Fixed Grants policies, respectively. The gains under the first and third policies are driven by co-movement in macro aggregates: an increase in skilled labor raises productivity, which boosts output and average consumption. Simultaneously, the compressed college wage premium reduces pre-tax income inequality among ex-ante identical individuals, further contributing to welfare gains.

To identify the underlying drivers of the welfare gains, I apply the decomposition framework of Floden (2001) and Domeij and Heathcote (2004), separating the total effect into level, uncertainty, and inequality components. Level effects capture gains from increased aggregate resources. Uncertainty effects measure welfare improvements from reduced consumption volatility. Inequality effects reflect changes in the dispersion of consumption across households.[28] The results show that welfare gains are primarily driven by level effects: 2.1%, 0.2%, and 2.8% under the three policies, respectively. These closely track the gains in output and consumption, confirming that aggregate efficiency is the dominant channel. Finally, I examine conditional welfare gains across the wealth–ability distribution. High-ability, low-wealth individuals benefit the most from the reduction in financial risk, while low-ability, high-wealth individuals may experience modest welfare losses due to compressed skill premiums. This heterogeneity highlights the redistributive nature of grant stabilization reforms and underscores the importance of general equilibrium effects in evaluating welfare outcomes. Full decomposition results and conditional distributions are presented in Appendix J.1.

A key feature of these reforms is that they are self-financing: although government spending increases, the larger tax base created by a more productive workforce fully offsets the additional outlays. Table 14 reports changes in both the absolute cost of subsidies and their share of GDP. Government spending on education rises by 18.6%, 1.8%, and 25.1% under the No Reapplication, No GPA Requirement, and Fixed Grants policies, respectively. However, these increases are partially offset by gains in output: the education-to-GDP ratio increases by only 16.1%, 1.6%,

[28] Details of the decomposition are provided in Appendix J.1.

and 21.6%, respectively. Neglecting the output response would therefore lead to an overstatement of the fiscal cost of reform. Despite higher education spending, the equilibrium labor income tax rate declines under No Reapplication and Fixed Grants—by 0.9 and 1.1 percentage points, respectively. This reflects an expansion in the tax base driven by higher labor earnings, capital income, and consumption.[29] These results highlight that eliminating uncertainty in the grant system—particularly its stochastic component—yields large efficiency gains without increasing net fiscal burden. In fact, by increasing the productivity and participation of high-return students, stabilizing grants can expand the tax base and reduce the long-run fiscal burden.

Figure 5: Relative Changes in College Participation Rates Compared to the Benchmark by Ability

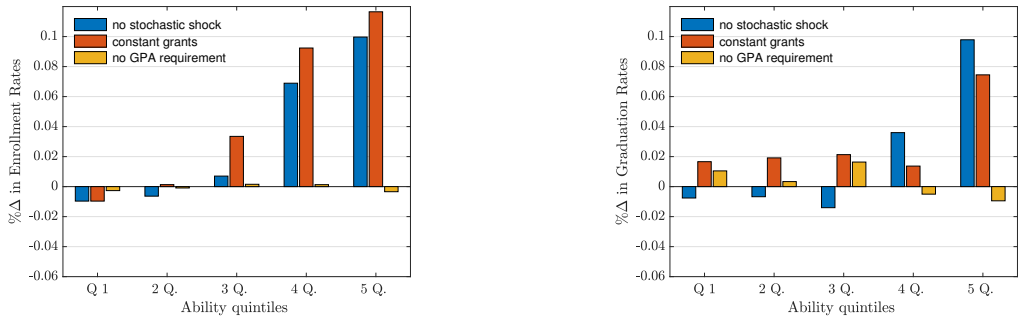
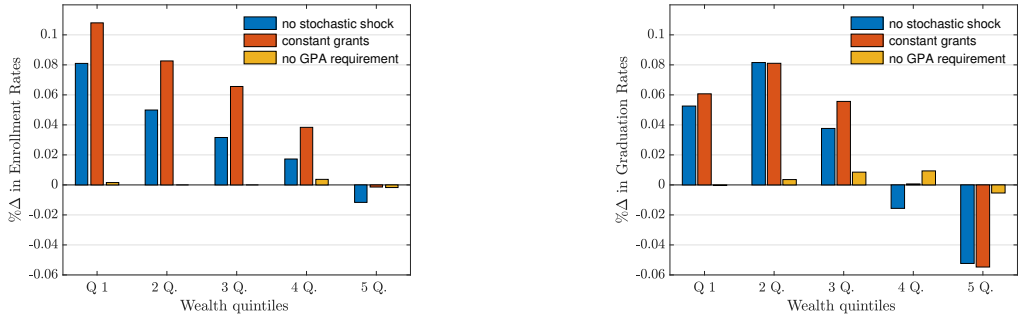


Figure 6: Relative Changes in College Participation Rates compared to the Benchmark by Wealth



Hiring Professional Assistance for Grant Reapplication I also consider a lower-cost alternative tested in Bettinger et al. (2012), which provides professional assistance during annual FAFSA submissions. Following their H&R Block intervention, I assume that guided support reduces perceived uncertainty to the same extent as eliminating the reapplication requirement. The direct cost of professional support is estimated at $87.50 per applicant, or $137.40 per graduate after accounting for dropout. In the model, this policy raises graduation rates and increases average annual earnings among college graduates by 1.7%—approximately $744. At a conservative 20% income tax rate, this implies an annual fiscal return of $148.80 per graduate, exceeding the program's cost. These estimates are conservative, excluding additional gains from higher earnings among

[29]The tax rate remains unchanged under the No GPA Requirement policy, consistent with its limited effect on aggregate outcomes.

Table 14: Macro and Distributional Effects of Grant Reform Policies

	No Reapplication	No GPA Requirement	Fixed Grants
College Participation & Skill Prices			
Enrollment rate (%)	52.5	49.3	54.0
Graduation rate (%)	33.6	31.8	34.4
Dropout rate (%)	36.0	35.4	36.3
College wage premium ($\Delta\%$)	-1.7	-0.7	-2.8
Dropout wage premium ($\Delta\%$)	4.9	1.1	8.7
Aggregate Outcomes ($\Delta\%$)			
Efficiency units (labor)	2.1	0.2	2.9
Hours worked	-0.1	0.0	-0.2
Output	2.2	0.2	2.9
Capital stock	0.2	0.0	0.3
Consumption	2.1	0.2	2.8
Interest rate (pp)	-0.3	-0.1	-0.6
Flat tax rate (τ_w, pp)	-0.9	0.0	-1.1
Public Finance ($\Delta\%$)			
Education spending	18.6	1.8	25.1
Education share of GDP	16.1	1.6	21.6
Efficiency by Education Group ($\Delta\%$)			
Graduates	3.0	-0.1	2.4
Dropouts	2.0	1.0	4.9
High school only	-2.6	-0.2	-3.1

This table summarizes the general equilibrium effects of three grant reform policies relative to the benchmark calibration. Panel sections report changes in college participation, skill prices, aggregate macroeconomic outcomes, public finance, and efficiency by education group. All values are percentage changes ($\Delta\%$) unless otherwise noted.

non-graduates and broader tax channels, such as consumption and capital.

Appendix J.3 provides full implementation details. Appendix J.4 further shows that even partial reductions in grant uncertainty yield meaningful welfare gains—1.6% for low-wealth students—highlighting that simplifying administrative procedures can deliver sizable benefits. In sum, modest, scalable interventions can achieve outcomes close to full uncertainty elimination, making them a cost-effective tool for boosting college attainment and fiscal efficiency.

8 Conclusions

This paper asks why roughly 40 percent of full-time students at four-year U.S. colleges leave without a degree, and whether policy can narrow that gap. Using four longitudinal data sets, I document three empirical facts. First, the family-wealth gradient in college outcomes has widened across cohorts: students from low-wealth families are now both less likely to enroll and more likely to drop out, even after conditioning on measured ability. Second, grant is strikingly volatile from one academic year to the next. Third, losing grant support is a strong predictor of attrition. These patterns motivate a quantitative general equilibrium lifecycle model that embeds grant volatility

alongside the two dropout mechanisms emphasized in earlier work–learning about ability and labor-market shocks.

Calibrated to U.S. micro data, the model shows that who is exposed to grant shocks matters. High-ability students in the bottom half of the wealth distribution are the marginal group: lacking self-insurance, they are less likely to enroll when grant is risky and more likely to drop out when grants fall. Stabilizing grant therefore raises their completion rate by 9 percentage points and accounts for three-quarters of the aggregate graduation gain. Decomposing the dropout channels reveals that eliminating grant uncertainty cuts attrition by 34 percent, removing GPA-contingent grant rules lowers it by a further 5 percent, and shutting down the learning channel reduces dropout by only 10 percent.

The paper then evaluates the general equilibrium implications of reforming the grant system, specifically by modeling a multi-year Pell award that eliminates annual reapplication requirement while retaining academic monitoring by colleges. In this general equilibrium framework, the policy increases aggregate output by 2.2 percent, compresses the skill premium, and raises newborn welfare by 2.4 percent—a gain representing about 70 percent of that obtained when GPA thresholds are also relaxed. The reform proves fiscally self-financing: the larger stock of skilled labor expands the tax base sufficiently to reduce the balanced-budget labor income tax rate. Attrition consequently falls among low-wealth, high-ability students, while rising slightly among wealthier, lower-ability peers due to the reduced skill premium, thus improving sorting in college at both the upper and lower ends of the ability distribution and underscoring the importance of endogenous prices in policy analysis.

These findings contribute to the micro literature on financial constraints and college outcomes, the macro literature on education policy, and the dropout literature, which emphasizes ability learning. By embedding grant volatility in a general equilibrium framework with endogenous dropout, the paper highlights a critical margin often omitted from structural models. In doing so, the analysis shows that dropout—frequently attributed to non-financial factors—reflects aggregate inefficiencies linked to short-run liquidity risk. This perspective is increasingly relevant given the rising importance of family wealth in determining college success.

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Appendix

A NLSY Surveys

The NLSY79 sample consists of individuals born between 1957 and 1964. At the time of the first interview, respondents' ages ranged from 14 to 22. The respondents were 49 to 58 at the time of their last interview, in 2018. Originally, there were 12686 respondents in the sample, out of whom 6111 belong to a representative, cross-sectional sample designed to represent the civilian segment of people living in the US in 1979 and born between 1957 and 1964.[30]

The NLSY97 surveys 8984 individuals who were born between 1981 and 1984. It began in 1997 and is still ongoing. From 1997 to 2011, the survey rounds were taking place annually, and biannually afterwards. Each round thoroughly surveys the respondents about information on their family characteristics, education process, and labor market outcomes.

A.1 Data cleaning

Below I carefully describe the methodology I used to construct the dataset.

Financing College. Respondents are supposed to report the amounts they receive from each source for each academic semester. There are 6 main sources: grants, family aid, loans, out of pocket, family loans, and other finances. The finances reported in the NLSY97 are biannual. I convert them into an annual level by considering the overall money students got and the years they attended undergraduate studies.[31]

Ability. Throughout the empirical analysis, I measure ability using two scores: the ASVAB math verbal percentile score and the PIAT (for the Mathematics Assesment subtest[32]) percentile score. While using the first measure, I drop 918 individuals who did not take the ASWAB test. On the other hand, while working with the second measure, I drop 2940 individuals whose PIAT test scores are missing.

Weekly hours. As the measure of hours worked, I take the number of hours students work in the second week of October (week 41) and in the second week of April (week 14) conditional on being enrolled in college. The reason for selecting the middle week of an academic semester as the reference week is to capture the workload during the study period.

[30] In my analysis, I focus on a cross-sectional sample consisting of 5295 oversampled minorities, including Hispanic or Latino, Black, and economically disadvantaged non-Black/non-Hispanic individuals. An additional 1280 respondents were specifically selected to represent the population serving in one of the four branches of the US military.

[31] I construct an average measure of college finances from each source by collecting the total amount they report during their time spent in college, and dividing it by the number of years during which they are enrolled for a degree (excluding years enrolled in a masters or higher degrees).

[32] One of the PIAT subtests, the Mathematics Assessment, was given in Round 1 to all respondents 9th grade or lower, regardless of age.

A.2 Sample selection in the NLSY79 and NLSY97

The questionnaires within the two surveys are not identical.Therefore, the variables I use in the regressions slightly differ across samples. For the NLSY79, parental education is measured as the number of years they spend in schooling;[33] while the NLSY97 parental education is measured as a binary variable, high school graduate or higher.[34] As for the place of residence, in the NLSY79, I include two variables, urban/rural and south/nonsouth, in the NLSY97 only one variable, urban/rural, as there is no information about south/nonsouth. Furthermore, in the NLSY97, an intact family is measured by whether a youth is living with both parents at age 14. For the NLSY79, the actual number of siblings are reported, while I use the number of youth under 18 for the younger cohort. Finally, as a measure of financial situation in the NLSY97, I use family wealth rather than family income, because it captures the financial state of the household more comprehensively.[35] However, the qualitative findings are robust to the choice between those two measures.

A.3 Graduation & Enrollment Rates in the NLSY97

Enrollment & dropout rates. To capture college enrollment and dropout rates in the NLSY datasets I proceed as follows. If a respondent is coded as enrolled in a college in the months of October and April,[36] then she is considered as a college enrollee. I define a dropout as someone who has attended college for at least one semester but has not earned any degree, whether it be a 2-year or 4-year degree. Finally, I summarize all college participation margins in Table A.2 for the cohort of NLSY97, and A.3 for the cohort NLSY79.

Inconsistency in Table A.1. 22 individuals are not coded as enrolled in a 4-year degree institution, however, their degree is reported to be higher than a 2-year college degree. Therefore, when I sum up the dropouts in the lowest row, I find that 22 people are missing. I drop these 22 individuals while restricting my analysis to bachelor degree recipients only.

Table A.1: Education Attainment in the NLSY97 Data

	2-year[37]	4-year	Any degree
Enrollments	20.10 (1806)	42.87% (3852)	62.97% (5658)
Dropouts	78.02% (1409)	39.72% (1530)	46.06% (2606)
Graduates	21.98% (397)	60.28% (1530)	53.94% (3052)

[33] There is no information what degrees parents actually earned.

[34] I only control for mothers' education, since there are lots of missing information about fathers' education, particularly in NLSY97.

[35] There is no information about family wealth in NLSY79.

[36] The middle of autumn and spring semesters.

Table A.2: Enrollment, Graduation, and Dropout Rates by Ability and Wealth (NLSY97)

College participation rates by ability quintiles						
	Quint 1	Quint 2	Quint 3	Quint 4	Quint 5	All
Bachelor degree						
Enrollment rates	0.12	0.30	0.52	0.66	0.86	0.49
Graduation rates	0.05	0.15	0.29	0.44	0.65	0.31
Dropout rates	0.57	0.52	0.45	0.33	0.25	0.36
Any degree						
Enrollment rates	0.33	0.60	0.73	0.84	0.94	0.69
Graduation rates	0.10	0.24	0.39	0.55	0.72	0.40
Dropout rates	0.69	0.60	0.47	0.35	0.23	0.42
College participation rates by wealth quintiles						
Bachelor degree						
Enrollment rates	0.29	0.36	0.46	0.57	0.72	
Graduation rates	0.13	0.18	0.27	0.39	0.55	
Dropout rates	0.56	0.51	0.42	0.31	0.24	
Any degree						
Enrollment rates	0.51	0.57	0.67	0.75	0.87	
Graduation rates	0.21	0.26	0.36	0.49	0.63	
Dropout rates	0.60	0.55	0.46	0.34	0.27	

Table A.3: Enrollment, Graduation, and Dropout Rates by Ability and Wealth (NLSY79)

College participation rates by ability quintiles						
	Quint 1	Quint 2	Quint 3	Quint 4	Quint 5	All
Bachelor degree						
Enrollment rates	0.22	0.41	0.57	0.73	0.91	0.57
Graduation rates	0.05	0.12	0.20	0.34	0.58	0.26
Dropout rates	0.78	0.70	0.64	0.53	0.37	0.54
Any degree						
Enrollment rates	0.22	0.41	0.57	0.73	0.91	0.57
Graduation rates	0.10	0.20	0.32	0.47	0.65	0.35
Dropout rates	0.57	0.50	0.43	0.36	0.29	0.39
College participation rates by family income quintiles						
Bachelor degree						
Enrollment rates	0.46	0.49	0.53	0.62	0.75	
Graduation rates	0.17	0.19	0.22	0.29	0.43	
Dropout rates	0.63	0.62	0.59	0.53	0.43	
Any degree						
Enrollment rates	0.46	0.49	0.53	0.62	0.75	
Graduation rates	0.25	0.27	0.30	0.40	0.52	
Dropout rates	0.46	0.45	0.43	0.35	0.31	

A.4 The Role of Family Income on College Participation Margins

To examine how the relationship between family wealth and college participation has evolved, I draw on two nationally representative longitudinal datasets, the NLSY79 and NLSY97, which

track cohorts born roughly two decades apart. The NLSY79 follows individuals born between 1957 and 1964, while the NLSY97 surveys those born between 1980 and 1984. Both datasets provide detailed longitudinal records on parental background, cognitive ability, and postsecondary enrollment and completion, enabling a systematic analysis of how financial constraints shape educational attainment. By comparing these cohorts, I document changes in this relationship over time, leveraging the most recent survey waves, which observe respondents through age 33 in the NLSY97 and age 49 in the NLSY79.

By leveraging the rich longitudinal structure of these datasets, I estimate how family wealth shapes college participation across cohorts. Specifically, I regress a college participation margin—measured as enrollment or dropout—on a set of family wealth quartile indicators, partitioning the sample into three groups based on ability terciles.[38] This approach follows the methodology outlined in Carneiro and Heckman (2002). The highest wealth quartile serves as the reference category, and the specification includes a vector of control variables, Z_i, comprising ex-ante family characteristics—parental education, household structure, residential location, and number of siblings—alongside demographic controls for gender and race. Observations with missing AFQT scores or incomplete family income data at baseline (or at age 17) are excluded. A detailed description of the control variables and variable construction is provided in Appendix A.2. The regression equation is given by:

$$Y_i = \alpha + \beta X_i + \gamma Z_i + \epsilon_i, \tag{19}$$

where Y_i represents the college participation outcome, X_i denotes the family wealth quartile dummies, and includes individual and household-level controls.

Tables A.4 and 1 present the results. Panel A in Table A.4 shows the gaps in college enrollment, while Panel B shows the gaps in college dropout rates for the NLSY79 sample. Table A.5 provides the same information for the NLSY97 sample, accounting for college quality. Panel A (B) presents the estimates for enrollment at (dropout from) a 4-year college, and Panel C (D) shows the corresponding estimates for any college, without distinguishing between 2- and 4-year institutions.

Comparing the two tables, it can be observed that the estimated effects of family income are significant for the younger cohort but generally insignificant for the older cohort. In the NLSY79 sample (Appendix A.4, Table A.4), family income plays a minimal and statistically insignificant role in determining college enrollment and completion among high-ability students from low-income families. The estimated probability gap of dropping out for this group is 0.13 percentage points higher compared with their richest counterparts, as we can see from Column (3) in Panel B. Nevertheless, a joint F-test – in the last row of each panel – shows that the overall effects are insignificant, as the null hypothesis that all gaps are equal to zero cannot be rejected. This finding

[38] Ability is measured using AFQT scores, as detailed in Appendix A.1. Robustness checks confirm the validity of the results using alternative measures, such as the Peabody Individual Achievement Test (PIAT) scores.

is consistent with Carneiro and Heckman (2002), who show that controlling for family background characteristics leaves family income redundant in explaining college participation margins.

Table A.4: NLSY79 Representative Sample: Gaps in Enrollment and Completion of 4-Year Degrees Conditional on Parental Education, Number of Siblings, Urban, Gender, and Race Dummies.

	AFQT Tercile 1	AFQT Tercile 2	AFQT Tercile 3	All
		Panel A _ College Enrollment		
q1	-0.0025	0.0236	0.03740	-0.0842^{***}
Std.Err.	(0.0501)	(0.0443)	(0.0310)	(0.0238)
q2	-0.0141	-0.0843^{**}	-0.0100	-0.0976^{***}
Std.Err.	(0.0490)	(0.0397)	$(.0.0260)$	(0.0218)
q3	-0.0269	-0.0127	-0.0127	-0.0424^{**}
Std.Err.	(0.0494)	(0.0365)	(0.0221)	(0.0202)
All Gaps = 0	$F(3, 1180) = 0.1034$	$F(3, 1377) = 0.5258$	$F(3, 1487) = 0.959$	$F(2, 2876) = 16.4260^{***}$
		Panel B _ College Dropout, Bachelor degree		
q1	0.0543	0.0810	0.1329^{***}	0.1363^{***}
Std.Err.	(0.0846)	(0.0575)	(0.0483)	(0.0329)
q2	0.0552	0.0026	0.0620	$0.0666**$
Std.Err.	(0.0836)	(0.0531)	(0.0402)	(0.0298)
q3	0.0171	0.0277	0.0409	0.0504^{*}
Std.Err.	(0.0829)	(0.0464)	(0.0338)	(0.0261)
All Gaps = 0	$F(3, 339) = 0.3148$	$F(3, 768) = 0.7448$	$F(3, 1269) = 6.3666^{**}$	$F(3, 2396) = 12.5304^{***}$

Notes: Ability is measured by Armed Force Qualification Test (AFQT) scores. Within each ability tercile, I regress college enrollment (dropout) on family background and dummies of family wealth quartiles. All gaps are measured relative to the highest family wealth quartile within each ability tercile. q1(q2,q3) denotes gaps in enrollment (dropout) between quartiles 4 and 1 (2,3). Each of the first three columns in these Tables represents a different AFQT tercile. The last column with the title "All" shows the gaps in college enrollment (dropout) for the entire population, without dividing it into different AFQT terciles. The last line of each panel presents a joint F-test that all gaps are equal to zero. *, **, *** denote statistical significance at the 10, 5, and 1 percent, respectively. The methodology is taken from Carneiro and Heckman (2002).

In contrast to the older cohort, the role of financial background is instead more pronounced in the younger cohort. In the bottom ability – bottom family wealth group, individuals have a 16 percentage point lower probability of enrollment at a 4-year college relative to the bottom ability – highest wealth quartile family group. For individuals with abilities in the middle and highest terciles, these gaps amount to 26 and 17 percentage points, respectively. Not surprisingly, at the same time, it can be observed that the higher is the income group the lower the gap of college participation margins are relative to the reference category.

Next, in panel B, Table 1, I examine the probability of dropping out for a bachelor's degree. The table shows that individuals from the middle ability tercile are affected largely by their family income: they are 40% less likely to stay enrolled in college than their rich counterparts. As for the highest ability group, their dropping out probability is still 12% more as compared to their rich counterparts. It is worth noting that significant wealth effects on college dropout probabilities

Table A.5: NLSY97 Gaps in Enrollment Across Family Wealth, Dropout, 2-Year and 4-Year Colleges, Conditioning on Parental Education, Number of Siblings, and Urban.

	AFQT Tercile 1	AFQT Tercile 2	AFQT Tercile 3	All
		Panel A _ College Enrollment, Bachelor degree		
q1	-0.1604^{***}	-0.2676^{***}	-0.1728^{***}	-0.2845^{***}
Std.Err.	(0.0459)	(0.04918)	(0.0405)	(0.0267)
q2	-0.1668^{***}	-0.2239^{***}	-0.0359	-0.2162^{***}
Std.Err.	(0.0448)	(0.0437)	(0.0332)	(0.0241)
q3	-0.1518^{***}	-0.1154^{***}	-0.0469^{*}	-0.1227^{***}
Std.Err.	(0.0479)	(0.0410)	(0.0276)	(0.0227)
All Gaps = 0	$F(3, 951) = 14.8261^{***}$	$F(3, 1031) = 29.4676^{***}$	$F(3, 1338) = 11.0536^{***}$	$F(3, 3144) = 105.5945^{***}$
		Panel B _ College Dropouts, Bachelor degree		
q1	0.1178	0.4016^{***}	0.1251^{**}	0.2550^{***}
Std.Err.	(0.1182)	(0.0716)	(0.0543)	(0.0396)
q2	0.1569	0.2630^{***}	0.0850^{**}	0.1662^{***}
Std.Err.	(0.1138)	(0.0618)	(0.0410)	(0.0333)
q3	-0.0691	0.1876^{***}	0.0382	0.0912^{***}
Std.Err.	(0.1192)	(0.0530)	(0.0333)	(0.0282)
All Gaps = 0	$F(3, 175) = 0.4683$	$F(3, 521)^{***} = 32.4386$	$F(3, 916)^{***} = 6.6494^{***}$	$F(3, 1636) = 42.0546^{***}$
		Panel C _ College Enrollment, 2 year & 4 year		
q1	-0.1819^{***}	-0.1973^{***}	-0.0711^{**}	-0.2213^{***}
Std.Err	(0.0572)	(0.0429)	(0.0287)	(0.0250)
q2	-0.1370^{**}	-0.1417^{***}	-0.0202	-0.1471^{***}
Std.Err.	(0.0558)	(0.0381)	(0.0235)	(0.0225)
q3	-0.1661^{***}	-0.0974^{***}	-0.0162	-0.0909^{***}
Std.Err.	(0.0596)	(0.0358)	(0.0194)	(0.0212)
All Gaps = 0	$F(3, 951) = 9.796^{***}$	$F(3, 1031) = 20.0448^{***}$	$F(3, 1138) = 3.9061^{***}$	$F(3, 3114) = 65.7215^{***}$
		Panel D _ College Dropout, 2 year & 4 year		
q1	0.1900^{**}	0.3243^{***}	0.1249^{**}	0.2410^{***}
Std.Err.	(0.0820)	(0.0580)	(0.0488)	(0.0331)
q2	0.2129^{***}	0.2409^{***}	0.0698^{*}	0.1851^{***}
Std.Err.	(0.0780)	(0.0504)	(0.0388)	(0.0288)
q3	0.0756	0.1527^{***}	0.0260	0.0890^{***}
Std.Err.	(0.0844)	(0.0463)	(0.0317)	(0.0257)
All Gaps = 0	$F(3, 393) = 5.0246^{**}$	$F(3, 774) = 32.1769^{***}$	$F(3, 1045) = 5.9862^{**}$	$F(3, 2236) = 105.5945^{***}$

Notes: Ability is measured by Armed Force Qualification Test (AFQT) scores. Within each ability tercile, I regress college enrollment (dropout) on family background and dummies of family wealth quartile. All gaps are measured relative to the highest family wealth quartile within each ability tercile. q1(q2,q3) denotes gaps in enrollment (dropout) between quartiles 4 and 1 (2,3). Each of the first three columns in these Tables represents a different AFQT tercile. The last column with the title "All" shows the gaps in college enrollment (dropout) for the entire population, without dividing it into different AFQT terciles. The last line of each panel presents a joint F-test that all gaps are equal to zero. *, **, *** denote statistical significance at the 10, 5, and 1 percent, respectively. The methodology is taken from Carneiro and Heckman (2002).

cannot be observed among poor and low ability students (column (1) of panel B, Table 1). This can be explained by the fact that only a few students enroll at a bachelor's degree from the ability tercile (67, 48, 34, and 38 individuals respectively from the lowest to the highest family

wealth quartiles),[39] and therefore, the estimates for their dropping out probabilities (conditional on enrollment) are imprecise.

When examining participation in any college, including both 2-year and 4-year institutions, a consistent qualitative relationship between family wealth and college outcomes is observed. This is evident from panel C and panel D in Table A.5. Specifically, family wealth plays a significant role in determining whether students attend college, although the effect may be less pronounced for 2-year colleges due to their lower costs. Overall, the data suggest that family wealth becomes a key factor in determining college participation, regardless of the type of institution attended in the recent years.

In conclusion, the analysis of NLSY79 and NLSY97 data indicates that family income's significance in post-secondary education success has significantly increased over the years, even after accounting for ability. Family income's role is mitigated for the highest ability tercile group across all college participation levels, suggesting that ability is a strong asset for college success. However, high ability alone cannot offset the negative effects of a low financial background on college success probabilities, as seen in the early 1980s. Today, low-income students face decreased college success probabilities, including enrollment and graduation, due to their low-level wealth background.

B Grant Reductions and Two–Year Persistence (NLSY97)

To assess how a *decline in total grant aid* shapes persistence, I restrict the NLSY97 sample to students who report a strictly positive grant award in their first year of college and then track whether the award falls in Year 2. This descriptive exercise quantifies the association between mid-program grant cuts and the probability of remaining enrolled beyond the second year.

Persistence is modeled as:

$$\begin{aligned}\Pr\big(\mathit{Enroll}_{i,t>2}=1\big) &= \beta_0 + \beta_1\,\mathit{GrantCut}_i + \mathbf{X}_i'\boldsymbol{\gamma} \\ &\quad + \beta_2\big(\mathit{GrantCut}_i \times \mathit{NonWhite}_i\big) + \beta_3\big(\mathit{GrantCut}_i \times \mathit{LowWealth}_i\big) + \varepsilon_i,\end{aligned} \tag{20}$$

(A.1)

where the dependent variable equals 1 when student i is still enrolled (or has re-enrolled) in the third academic year. $\mathit{GrantCut}_i$ indicates that total grant falls between the first and second years. $\mathbf{X}_i$ contains ability-quartile dummies, a parental-degree indicator, gender, the number of household members younger than 18, and birth-cohort fixed effects. $\mathit{NonWhite}_i = 1$ for students who self-identify as non-White, and $\mathit{LowWealth}_i = 1$ for those whose parental wealth lies in the bottom three quartiles (Q1–Q3).[40]

Table B.1 reports four linear-probability specifications. Column (1) includes no wealth controls;

[39] In the bottom ability tercile, the number of individuals from the lowest to the highest family quartiles are respectively

Table B.1: Grant Reductions and Two-Year Persistence (NLSY97)

	Dependent variable: Enrolled in Year 3 (=1)			
	(1)	(2)	(3)	(4)
Grant cut (D_i)	-0.031*	-0.031*	-0.031*	-0.002
	(0.015)	(0.015)	(0.015)	(0.021)
Low-wealth Dummy (Q1–Q3)			-0.039**	-0.022
			(0.013)	(0.016)
Wealth Q3		-0.033**		
Wealth Q2		-0.044**		
Wealth Q1		-0.048**		
Grant Cut $\times$ low-wealth				-0.054*
Grant cut $\times$ non-White	0.082**	0.081**	0.081**	0.098***
Non-White	-0.027	-0.013	-0.016	-0.022
Ability Q3	-0.036**	-0.033**	-0.033**	-0.032**
Ability Q2	-0.056***	-0.054***	-0.054***	-0.053***
Ability Q1	-0.113***	-0.105***	-0.106***	-0.105***
Parental college	0.037**	0.030**	0.032**	0.032**
Male	-0.051***	-0.052***	-0.052***	-0.052***
Children $<$18 in HH	0.000	-0.001	0.000	-0.000
Birth year 1981	0.023	0.021	0.022	0.022
Birth year 1982	0.018	0.018	0.018	0.019
Birth year 1983	0.010	0.011	0.012	0.012
Constant	0.958***	0.984***	0.982***	0.972***
Observations	1 722	1 722	1 722	1 722
R^2	0.038	0.043	0.043	0.045

Notes: Linear-probability models estimated on NLSY97 respondents with non-missing grant and enrollment data. Wealth quartile Q4, ability quartile Q4, and female are omitted categories. Robust standard errors clustered by individual in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

column (2) adds dummies for wealth quartiles Q_1–Q_3 (with Q_4 as the reference); column (3) replaces those dummies with a single *LowWealth* indicator; and column (4) augments column (3) with an interaction between that indicator and *GrantCut*. All regressions control for the baseline covariates listed above and include an interaction between *GrantCut* and *NonWhite*. Standard errors are clustered at the individual level.

Across columns (1)–(3) the coefficient on *GrantCut* is remarkably stable at roughly -0.031 and statistically significant. Its magnitude rivals the penalties from lower ability, lower wealth, or having parents without a college degree, underscoring economic relevance. Column (4) shows that the average effect is driven entirely by students from the bottom 75 group, a grant reduction lowers the probability of remaining enrolled beyond the sophomore year by about five percentage points, while there is no detectable effect for the top quartile. These patterns point to liquidity constraints—rather than permanent income—as the channel through which grant volatility undermines continuation.

Grant volatility is associated with lower persistence and the effect is concentrated among financially constrained students, consistent with the paper's premise that uninsured grant shocks are an important dropout channel. These reduced-form patterns motivate the model's grant-volatility mechanism and the focus on wealth-heterogeneous responses.

C Institutional Settings

The process of obtaining financial aid[41] begins with the U.S. Department of Education determining the Expected Family Contribution (EFC)[42] upon FAFSA submission.

Central to federal financial aid eligibility is the Expected Family Contribution, derived from data provided via the Free Application for Federal Student Aid (FAFSA). This figure serves as an index of a family's financial strength, incorporating taxed and untaxed income, assets, family size, and the number of household members attending college. ***The EFC depends only on the financial state of the family.***[43]

155, 120, 69, and 61.

[40]The top wealth quartile and ability quartile 4 serve as reference categories. Standard errors are clustered at the individual level to accommodate arbitrary serial correlation in unobserved persistence determinants.

[41]Financial aid includes grants, loans, and work-study (see detailed breakdown in Table C.1).

[42]In 2023, the EFC will be replaced by the Student Aid Index (SAI) under the FAFSA Simplification Act. This change aims to address the confusion associated with the term "Expected Family Contribution," which is commonly misunderstood as either the financial responsibility of the family to fund education or the amount of federal aid a student will receive. The revision of this system is anticipated to clarify these misconceptions and emphasize the actual purpose of this number, which is to assist in financial aid assessments.

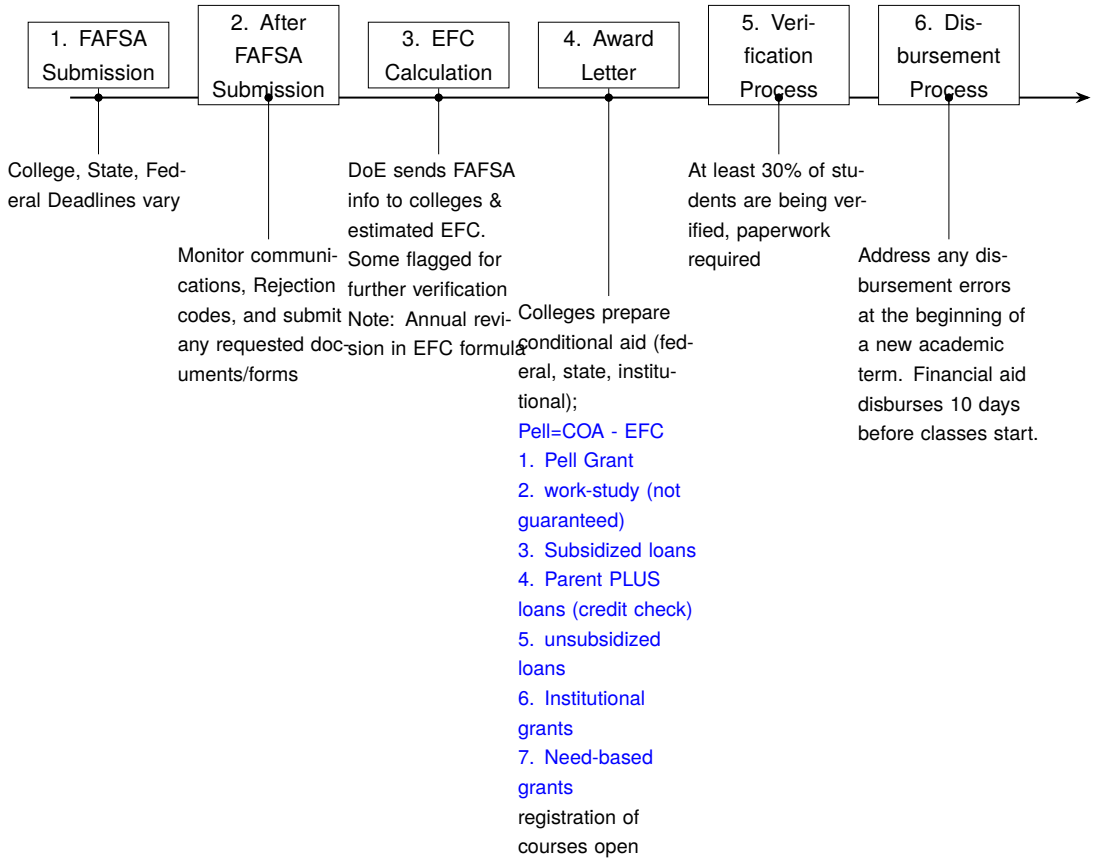
[43]To summarize the process briefly, the computation of the Expected Family Contribution (EFC) starts with evaluating the total income of the family, encompassing both taxable and nontaxable earnings. Subsequently, deductions are made for taxes, essential living expenses, and a safeguarding allowance for savings, resulting in the disposable income, which is then taken into account for college contributions. Furthermore, the assessment includes an examination of assets such as savings, investments, and property (excluding the primary residence). A segment of these assets, based on a safeguarding allowance tied to the parents' age, is exempt from the EFC assessment. The remaining portion is evaluated at a predefined rate to contribute to the EFC. For students, their income and assets play a more significant role

The primary factors influencing a student's Pell Grant amount are the Expected Family Contribution (EFC) and academic performance. However, the EFC is determined by a complex set of rules that consider parental and student assets, income, and other financial factors, many of which are beyond the student's control. The calculation of EFC involves not only current income but also the appreciation of assets, changes in family size, and other nuanced criteria, making it subject to fluctuations due to external economic conditions and federal policy adjustments.

Note that, based on economic fluctuations, the EFC formula is revised annually, thus adding exogenous unpredictability beyond the other bureaucratic processes described below.

After the Department of Education computes the EFC, this value, together with the comprehensive financial and personal details provided through the FAFSA, is disclosed to the colleges. Subsequently, the financial aid office of each college reviews this information to craft a personalized *conditional* financial aid package for the student, including federal, state, and institutional aid. The conditional financial aid award outlines her cost of attendance and the financial resources available to her. There are four categories of federal aid based on financial need (Pell grants, subsidized loans, work-study) and two categories of federal aid not based on need (Direct Unsubsidized Loans, Direct PLUS Loans), as outlined in Table C.1. This package is designed to cover the anticipated cost of attending college, *encompassing tuition, fees, accommodation, meals, textbooks, and other educational expenses.*

in the computation. A student's income, following deductions similar to those for parents but adjusted to individual requirements, influences their EFC. Student assets are appraised at a fixed percentage, directly increasing the EFC, reflecting the expectation that students should allocate a larger share of their savings towards educational expenses. This methodology aims to strike a balance between the family's financial capacity and the need for assistance, ensuring that the EFC truthfully represents their feasible contribution to college costs. Specifically, the financial need is determined as the variance between the cost of college attendance (hereafter COA) and the Expected Family Contribution (hereafter EFC). If this difference is positive, the student qualifies for a financial aid package, comprising Pell grants, federal loans, and work-study opportunities.



After the conditional financial aid and admission, the university then works out the official financial aid offer. Following this, there is an additional step, commonly known as verification, that colleges must complete before students are guaranteed any grants. The Department requires colleges to authenticate the accuracy of the submitted information, flagging 30% of applications for additional verification—a process that colleges are expected to undertake. This verification process may involve confirming income, pension and IRA disbursements, household size, the number of college students in the family, high school completion, and educational objectives. Pell Grant disbursements are withheld until the verification process is completed. While colleges are mandated to verify a portion of flagged applications, many opt to verify all flagged cases to ensure the accuracy and integrity of the financial aid procedure.

The following outlines crucial steps in the financial aid process and potential barriers encountered after FAFSA submission. This post-submission phase, often overlooked, is as complex as the initial application, which has significantly drawn both scrutiny and legislative response, culminating in the FAFSA Simplification Act.

1. **Rejection Codes** Initially, some students are notified by the U.S. Department of Education that their EFC cannot be determined due to "reject codes," indicating missing or conflicting information essential for assessing aid eligibility. Common reasons for reject codes include

absent signatures or reported tax payments surpassing reported earnings. To proceed, students must rectify these discrepancies; 80 percent succeed in resolving these issues and obtaining their EFCs.

2. **Verification Process** (Only 2 percent fail despite being initially eligible based on certain data.) The verification process further complicates the application process. This stage necessitates colleges to gather documents validating the accuracy of information provided through the FAFSA.

3. **Additional Documentation** Some colleges request documents beyond those required by the federal government as part of the financial aid procedure. These may include student surveys, signed acknowledgments of understanding aid eligibility criteria, or copies of driver's licenses, among others.

4. **Eligibility Checks** Before disbursing federal aid, colleges must conduct a final review of a student's eligibility. This involves confirming the student's enrollment in eligible classes and academic programs, as well as satisfactory academic progress. These checks, often automated through college software, can lead to "disbursement errors" if issues are detected. Additionally, some colleges impose their own requirements for aid applicants, such as submitting additional documentation to understand financial aid rules or provide identification to prevent identity theft.

Policy Recognition The complexity inherent in the financial aid application process, including reject codes, verification, extra documentation, and eligibility checks, represents significant hurdles. The "FAFSA Simplification Act of 2019"[44] highlights the recognition of the complexity and unpredictability students face in the financial aid process. The act seeks to streamline the application process, improve predictability, and enhance accessibility to aid by simplifying need analysis, adjusting the Pell Grant program, and establishing clearer guidelines.

D Parental contribution by ability gradient

E Model Calibration

E.1 Measuring SAP in the model

The Satisfactory Academic Progress (SAP) requirements involve qualitative and quantitative measures. The qualitative measure examines the quality of the student's academic performance as

[44]The first rollout of these changes, scheduled for 2024–2025, was unsuccessful due to logistical challenges with the website.

Table C.1: Summary of Federal and Institutional Aid Programs

Aid Program	FAFSA Required	Program Description
Need-Based Aid		
Pell Grants	Yes	For undergraduates with demonstrated need (EFC < $17,395); non-repayable.
SEOG	Yes	Supplemental grants for high-need students at participating institutions.
Direct Subsidized Loans	Yes	Loans for undergraduates; government pays interest during enrollment.
Federal Work-Study	Yes	Part-time campus employment for students with need; positions are not guaranteed.
Institutional Need-Based Grants	Yes	College-specific grants awarded based on EFC.
State Grants	Yes	State-administered need-based awards (e.g., Cal Grant) using EFC.
Non-Need-Based Aid		
Direct Unsubsidized Loans	Yes	Loans available to all eligible students; interest accrues during enrollment.
Direct PLUS Loans	Yes	Loans for graduate students or parents; subject to credit approval.
Institutional Merit-Based Grants	Often	Awards based on academic or other achievements; some use EFC to adjust amounts.

Note: Aid types are based on 2011–12 federal guidelines (NCES 2012). Source: U.S. Department of Education.

Table D.1: Initial wealth as a fraction of student budget

	Student Budget (1)	EFC (2)
Panel (a)		
Ability Quint.		
Q 1	30382	0.36
Q 2	33202	0.47
Q 3	33195	0.47
Q 4	34710	0.50
Q 5	38018	0.47
Panel (b)		
EFC quintiles		
Q 1	27085	0
Q 2	30136	0.08
Q 3	29946	0.31
Q 4	32218	0.60
Q 5	35430	0.89

Source: US Department of Education, National Center for Education Statistics, 2011-12 Beginning Postsecondary Students Longitudinal Study.

measured by grade point average. The quantitative measure assesses the student's advancement towards completing the required credit hours for earning a degree. This requirement is aligned with

being a full-time student, which will be further explained. This allows me to use just a GPA in the model to capture whether students meet the GPA requirements.

In the model, I consider full-time students, i.e., students who attempt full-time credits. The minimum pace requirements, measured earned credits divided by attempted credits, for them to maintain Pell-grants (and most other types of grants) is 67%. Note that failing in 33% of chosen credits yields GPA lower than $\overline{GPA}$ threshold, which, on its own, disqualifies students from grants. Therefore, for full-time students, both the qualitative and quantitative measures of SAP coincide. This enables me to use just GPA requirements in the model to capture whether students are qualified for the grants.

E.2 Working Hours in the GPA Function

To account for the negative impact of working full-time on grades, an important parameter is the working impact on GPA, which is captured by equation (3). This parameter is determined using empirical estimates, which vary in the literature. For a benchmark calibration, I rely on Stinebrickner and Stinebrickner (2008), who estimate the impact of studying time on GPA using a compelling identification strategy. Their findings suggest that studying for one additional hour per day increases GPA by an average of 0.36 points, implying that working for eight hours per day reduces semester GPA by 2.52 (8×0.36). As the time in the model is measured yearly, and only 32 out of 52 weeks are considered as study weeks, increasing work by one hour would reduce GPA by $\frac{32}{52}2.52$. Using a full-time worker hours of 0.35 and a normalized GPA between 0 and 1, I obtain λ_l in equation (3) as -1.11. Additionally, based on studies such as Bozick (2007), I assume that working below $\underline{l} = 0.1$ (i.e., working 15 hours a week) does not harm GPA.[45]

E.3 Government Policy

I set the ratio of government spending to GDP at 17%. The consumption tax rate is estimated to be 7.3% based on the US National Income and Product Accounts data set. The capital income tax rate is taken from Chari and Kehoe (2006). Pension benefits are set to be 35% of the average income within each skill group, consistent with the current social security configuration. The payroll tax rate τ_p is set to balance the pension budget. To parameterize the progressive labor income tax, I rely on the estimate of $\lambda_m = 0.18$ for the measure of progressivity from Ferriere et al. (2023), which is a commonly used value in the literature. The flat part of the labor income tax function, λ, is then set to balance the government budget.

[45] Counterfactual experiments suggest that this particular margin holds limited quantitative significance in explaining the dropout phenomenon within the model. This is attributed to the fact that students internalize the negative consequences of excessive work on their GPA, thereby influencing their eligibility for grants.

F Model Validation

Grant Distribution–As a validation exercise, Table F.1 provides the joint distribution of grants by wealth and ability in the model and data. The model successfully generates comparable shares of college costs financed by grants in each ability-wealth quintile category.

Table F.1: Grants Distribution by Ability and Wealth Quintiles: Model vs. Data

(a) Model

Wealth	Q1	Q2	Q3	Q4	Q5
Q1	0.53	0.56	0.57	0.58	0.60
Q2	0.41	0.43	0.45	0.45	0.48
Q3	0.28	0.31	0.32	0.33	0.35
Q4	0.24	0.26	0.28	0.28	0.31
Q5	0.20	0.22	0.24	0.24	0.27

(b) Data

Wealth	Q1	Q2	Q3	Q4	Q5
Q1	0.48	0.50	0.53	0.58	0.55
Q2	0.40	0.42	0.42	0.42	0.50
Q3	0.27	0.30	0.31	0.31	0.45
Q4	0.22	0.27	0.30	0.30	0.32
Q5	0.24	0.26	0.25	0.25	0.32

Notes: Grant shares are fractions of cost of attendance. Wealth quintiles use Expected Family Contribution (EFC); ability quintiles use SAT scores of enrolled students. Source: National Center for Education Statistics, BPS 2011–2012 cohort (NCES 2012).

Earnings Inequality–In this section, I quantify how far the model goes to generate realistic wage dispersion. This is particularly important as the general equilibrium wages are one of the main drivers of the elasticities of college participation margins in the model. I report different measures of earnings inequality, including wage ratios, Gini coefficients for wage income. I then compare them to pre-tax earnings inequality observed in the data. Table F.2 summarizes the results.

The benchmark model generates a Gini coefficient in line with the data. At the same time, the model slightly overshoots overall earnings inequality when measured by the wage ratio between the 90th percentile and 10th percentile of the wage income distribution. Overall, however, the model matches earnings inequality in the data reasonably well.

Table F.2: Earnings Inequality: Model vs. Data

	Model	PSID
Gini	0.4	0.4
P90/P10	6.4	5.2
P90/P50	2.3	2.4
P50/P10	2.9	2.2

G Lifecycle Profiles

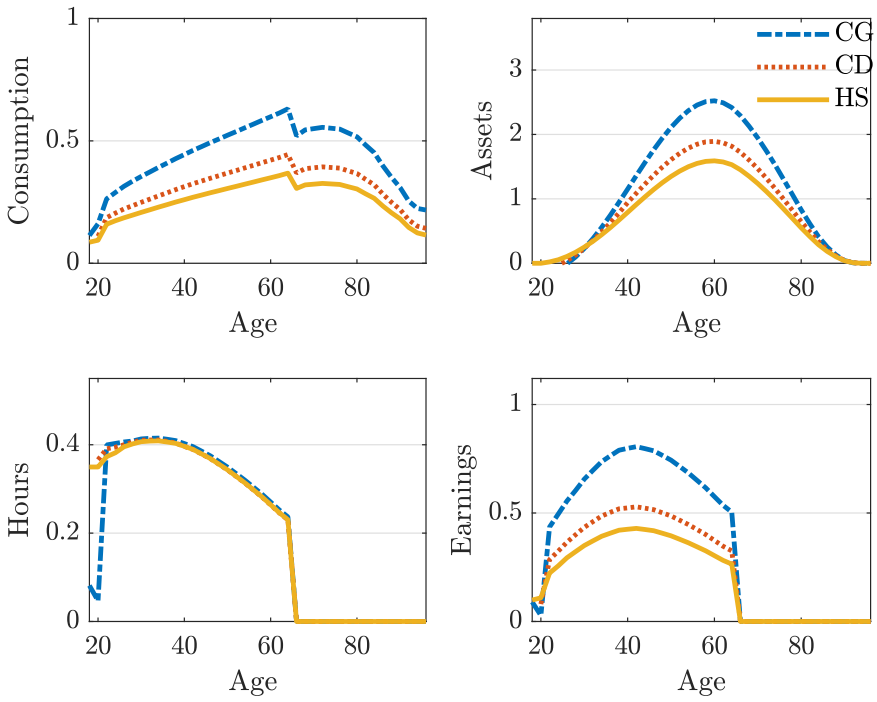
Figure 7 plots the lifecycle profiles of average consumption, asset holdings, hours worked, and earnings for each education level: high school graduates, college dropouts, and college graduates. They exhibit shapes that are typical of any lifecycle model. Consumption rises steadily over the working life for both skilled and unskilled workers. Slightly it dips when workers retire because

pension benefits are only a fraction of average earnings. Gradually consumption decreases as they age and face rising death hazards.

Wealth exhibits the typical hump-shaped profile. For young individuals who are not attending college, the initial wealth is slightly positive. College students, on the other hand, take out loans and, therefore, have negative wealth. On average, it takes about eight years to pay off student loans.

Labor supply does not differ much across skill types. At the age of one, when the young generation enters the workforce, both college-bound and non-college-bound individuals have low labor supply. This is evident in the case of college students as they spend time attending college. For those who are not attending college, the relatively low level of labor supply reflects their low productivity, which is in line with the data. In the second period, college students work less in comparison to the first period. This can be explained by considering that the selection into college already shows up in the second period: richer and more able students remain in college. Consequently, they need to work less to self-finance college.

Figure 7: Lifecycle Profiles of Average Consumption, Asset Holdings, Hours worked, and Earnings for College Graduates, College Dropouts, and High School Graduates



Finally, the lifecycle earnings profile also matches the data pretty well. Earnings are relatively low for young individuals as they enter the economy. Notably, college students have limited time for work, while those who are not in college have low productivity. As a result, college-educated workers experience a more rapid increase in earnings compared to those without a college education

(both high school graduates and dropouts). Average earnings decline gradually before retirement and drop to zero at the time of retirement. Though the wage rate for dropouts is the same as high school graduates, they still earn more than their non-college counterparts. This is because dropouts have higher probabilities of drawing a high fixed effect of θ (see Section 4).

H Competitive Equilibrium

To define a general equilibrium of the model economy, it is useful to introduce some additional notation. In particular, I define the distribution of individuals on the state space. Let $\mathcal{J} = \{1, 2, ..., J\}$, $\mathcal{E} = [0, 1]$, $s = \{h,\ d,\ c\}$, $\mathcal{A} = \mathbb{R}$, $\Theta = \mathbb{R}$ and $\mathcal{H} = \mathbb{R}$ denote the state space for age j, ability e, education level s, wealth a, fixed productivity effect θ and the stochastic productivity component η. And let Σ represent the Borel σ-algebra defined on the product space $\mathbb{X} = \mathcal{E} \times \mathcal{J} \times \mathcal{S} \times \mathcal{A} \times \mathcal{F} \times \mathcal{H}$. Then, for any $X \in \mathbb{X}$, a measure $\phi(X)$ can be properly defined. For ease of notation, let $X(j, s) \in \mathbb{X}$ be the state space of an individual of age j and with education status s, defined by the recursive representation of the individual's problems above.

With this preparation, I now define the stationary recursive competitive equilibrium as follows. A stationary recursive competitive equilibrium is a collection of: (1) decision rules of individuals $\Big\{\ \mathbb{1}(1, a_s, \mu_{e_0}, \eta),\ \mathbb{1}\big(2, a, z, \mu_{e_1}, \eta\big),\ c(X(j,s)), l(X(j,s)), a'(X(j,s))\Big\}$; (2) aggregate capital and labor inputs, $\big\{K, L_h, L_d, L_c\big\}$, on the part of firms; (3) value functions $\big\{V\big(X(j,s)\big)\big\}$; (4) government policies $\{\tau_c, \tau_k, \tau_p, \tau_l(y), pen(s, \theta_s), \kappa_s, z_1, z_2, T\}$; (5) prices $\big\{r, w_h, w_c\big\}$; (6) education system characterized by $\{\iota, \xi(\mu_{e_0}), \xi(\mu_{e_1})\}$; and (7) a vector of measures ϕ, such that:

1. The decision rules of individuals solve their respective lifecycle problems, and $V\big(X(j,s)\big)\big\}$ are the associated value functions.

2. Aggregate capital and labor inputs, $\{K, L_h, L_d, L_c\}$, solve the representative firm's profit maximization problem, which is fully characterized by the following first order conditions:

$$r = \alpha A k^{\alpha-1} - \delta, \tag{21}$$

$$w = (1-\alpha) A k^{\alpha}, \tag{22}$$

$$w_c = (1-\alpha)(1-\upsilon) k^{\alpha} \left(\frac{L}{L_c}\right)^{1-\zeta} = w \left(\frac{L}{L_c}\right)^{1-\zeta}, \tag{23}$$

and

$$w_h = (1-\alpha) k^{\alpha} (\upsilon) \left(\frac{L}{L_h + L_d}\right)^{1-\zeta} = w(1-\upsilon) \left(\frac{L}{L_h + L_d}\right)^{1-\zeta}, \tag{24}$$

where $k = \frac{K}{L}$, $w = (1-\alpha)k^{\alpha}$, and the college wage premium is therefore given by:

$$\frac{w_c}{w_h} = \frac{1-\upsilon}{\upsilon}\left(\frac{L_h + L_d}{L_c}\right)^{1-\zeta}. \tag{25}$$

3. The labor market for each skill type clears:

$$L_s = \sum_{s=\{h,d,c\}} \sum_{j=1}^{j_r-1} \int_{X(j,s)} h_{s,j}(\theta,\eta) l\big(X(j,s)\big) d\phi\big(X(j,s)\big), \tag{26}$$

4. The capital market clears:

$$K = \sum_{s=\{h,d,c\}} \sum_{j=1}^{J} \int_{X(j,s)} a'(X(j,s)) d\phi\big(X(j,s)\big) + A_{init},$$

where A_{init} is the aggregate wealth transfer to the newly arrived generation:

$$A_{init} = \sum_{s=\{h,d,c\}} \int_{X(1,s)} af(s,a)\, d\phi(X(1,s)) + \sum_{s=\{h,d,c\}} \int_{X(2,s)} af(s,a)\, d\phi(X(2,s)), \tag{27}$$

where $\phi(j,s)$ denotes the measure of individuals at age $j = \{1,2\}$ with college decision s and $f(s,a)$ is the distribution from which initial wealth is drawn.

5. The good market clears:

$$Y = C + G + E + I, \tag{28}$$

$$C = \sum_{s=\{h,d,c\}} \sum_{j=1}^{J} \int_{X(j,s)} c\big(X(j,s)\big) d\phi\big(X(j,s)\big), \tag{29}$$

$$E_t = \int_{X(1,c)} \iota w_c d\phi(X(1,c)) + \int_{X(2,c)} \iota w_c d\phi(X(2,c)), \tag{30}$$

where G represents government spending, and I is gross investment.

6. The government budget constraint holds:

$$\tau_c C + \tau_k r A + T_l + (1+r)A_b = G + A_{init} + Z + T, \tag{31}$$

where T_l denotes labor income tax revenues, as given by:

$$T_l = \sum_{s=\{h,d,c\}} \sum_{j=1}^{j_r-1} \int_{X(j,s)} \tau_l(y_s) y_s d\phi(X(j,s)), \tag{32}$$

with $y_s = (1-\tau_s)w_{t,s}h_{s,j}(\theta,\eta)l(j,a,\theta,\eta)$.[46] A_b denotes accidental bequest:

$$A_b = \sum_{s\in\{h,d,c\}}\sum_{j=j_r}^{J}\int_{X(j,s)} a'(X(j,s))\frac{1-\varphi_{j+1}}{\varphi_{j+1}}d\phi(X(j,s)). \tag{33}$$

Z is the aggregate education subsidies:

$$Z_t = \int_{X(1,c)} z_1(\cdot)\iota w_c d\phi(X(1,c)) + \int_{X(2,c)} z_2(\cdot)\iota w_c d\phi(X(2,c)). \tag{34}$$

7. The pension budget constraint (11) holds.

8. Individual behaviors are consistent with aggregate behavior: measure ϕ is a fixed point of $\phi(X) = \Pi(X,\phi)$, for any $X \in \mathbb{X}$, where $\Pi(X,\cdot)$ signifies the transition function generated by the decision rules of individuals, the process of exogenous states, and the survival probabilities.

9. All aggregate per capita variables increase by the population growth rate, n_p.

I The Role of Idiosyncratic Productivity Shocks in Dropout Decisions

This appendix elaborates on how idiosyncratic productivity shocks, η, contribute to college dropout decisions within the model, a channel briefly introduced in Section 6 that complements academic and financial aid uncertainties.

Unlike grant aid shocks or noisy ability signals, which tend to have a clear directional impact on college persistence, idiosyncratic labor market productivity shocks generate opposing forces that complicate their effect on dropout. A favorable productivity shock (e.g., a higher η) can increase the opportunity cost of college by making immediate labor market entry more attractive. Simultaneously, however, such a shock can also increase an individual's potential in-college earnings, thereby making college more affordable and potentially increasing persistence. The net effect on the continuation decision thus depends on the relative strength of these competing income and substitution effects, as well as the individual's broader state space (wealth, ability).

Figure 8 illustrates the policy functions for college continuation in response to idiosyncratic productivity shocks, holding other state variables fixed. The figure reveals heterogeneous responses across different student types:

Among poor students with mid-level ability priors (0.5–0.6), favorable realizations of η tend to increase retention. In this segment, the income effect often dominates, making college more

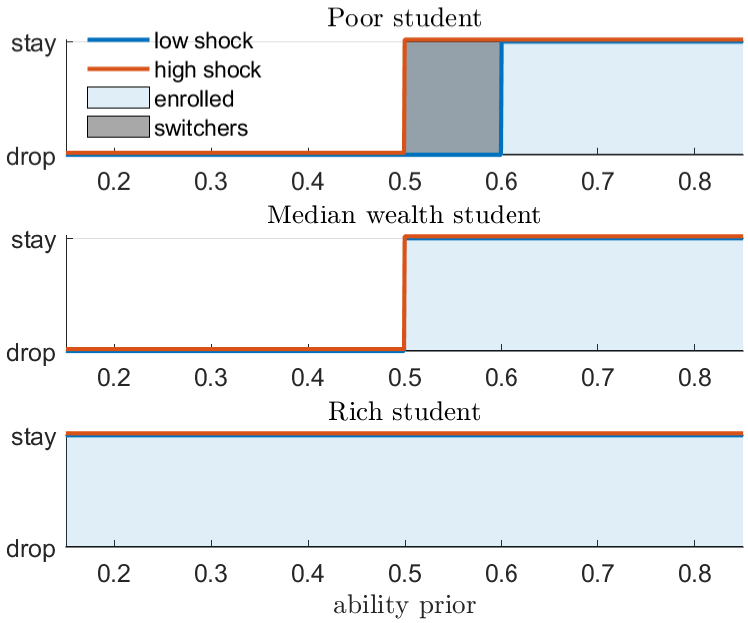
[46] Note that I slightly abuse notation in that for college-bound individuals the state space also incorporates prior, posterior of ability and a shock to the grants.

affordable and thus strengthening the incentive to persist despite an improved outside option. For median- and high-wealth students, dropout behavior is largely unaffected by productivity shocks over the relevant state space. These students have greater financial resources to absorb shocks, or their expected returns to college are already sufficiently high that changes in labor market prospects do not significantly alter their optimal education decision.

The wage process in the model also introduces an additional selection margin through the dropout premium. This means that some low-ability students, even those not facing direct academic or financial aid shocks, may opt to exit college if they experience sufficiently favorable labor market wage draws, making early entry into the workforce more valuable than continued enrollment.

This distinction highlights the critical importance of the source of financial uncertainty when analyzing college attrition. Shocks originating predominantly within the college system itself—such as unexpected grant reductions or unfavorable academic signals—tend to have a clear and predictable negative effect on persistence. In contrast, external financial shocks, like those arising from the labor market, generate more complex and heterogeneous responses that are contingent on students' specific ability, wealth, and the relative returns to immediate employment versus college completion.

Figure 8: Idiosyncratic productivity shocks



J Welfare Analysis

J.1 Decomposition of the Welfare Gains

For the decomposition, it is useful to define certainty-equivalent bundles. The bundle characterizes the constant amount of consumption and work hours an individual can consume and work for throughout her lifetime to achieve the same lifetime utility, $V(\cdot)$, as she has in the uncertain world. Formally, the derivation of certainty equivalent bundles proceeds as follows.

$$\sum_{t=1}^{J} \beta^{t-1} \varphi_t U(\tilde{c}, 1-\tilde{l}) = V(\{c_t, l_t\}_{t=1}^{J}), \tag{35}$$

where for notational simplicity, I suppressed the state space. For each point of a state space of newborns, $(1, a, \eta, \theta, \mu_{e_0})$, there is an associated bundle $(\tilde{c}, \tilde{l})$ that solves equation (35). Since there are two unknowns and one equation, there is a continuous set of $(\tilde{c}, \tilde{l})$ that solves the equation. To tackle this issue, in practice, I set the certainty equivalent working hours, $\tilde{l}$, to average hours in the economy. Then, it becomes possible to easily solve the remaining unknown, $\tilde{c}$, as follows:

$$\tilde{c} = \left(\frac{V(\{c_t, l_t\}_{t=1}^{J})(1-\frac{1}{\gamma})}{\sum_{t=1}^{J} \beta^{t-1} \varphi_t} \right)^{\frac{1}{\nu(1-\frac{1}{\gamma})}} \frac{1}{(1-\tilde{l})^{\frac{1-\nu}{\nu}}}. \tag{36}$$

Finally, it is useful to define average certainty equivalent hours, $\tilde{H}$ and consumption, $\tilde{C}$:

$$\tilde{H} = \int \tilde{l}(1, a, \theta, \eta, \mu_{e_0}) \, d\phi(1, a, \theta, \eta, \mu_{e_0}), \tag{37}$$

$$\tilde{C} = \int \tilde{c}(1, a, \theta, \eta, \mu_{e_0}) \, d\phi(1, a, \theta, \eta, \mu_{e_0}). \tag{38}$$

Given the following variable set in each economy $\left(\tilde{c}, \tilde{l}, \tilde{C}, \tilde{H}, V(\cdot), C, H \right)$, I am equipped to decompose the welfare gains in level, ω_{level}, uncertainty, $\omega_{\text{uncertainty}}$, and, inequality, $\omega_{\text{inequality}}$, effects.

Level effect. To isolate the level effects, I compare the average consumptions between economies A and B, while controlling for the possible differences in leisure across these two economies. To compensate leisure differences, I calculate a 'leisure-compensated' consumption bundle, $\hat{C}^B$, for economy B:

$$V\left(\{\hat{C}^B, L^A\}_{t=1}^{J} \right) = V\left(\{C^B, L^B\}_{t=1}^{J} \right). \tag{39}$$

Given the utility form in equation (16), it can be shown that:

$$\hat{C}^B = C^B \left(\frac{1 - L^B}{1 - L^A} \right)^{\frac{1-\nu}{\nu}}. \tag{40}$$

Then, the gains in welfare due to the level effect is calculated as:

$$\omega_{\text{level}} = \frac{\hat{C}^B}{C^A} - 1. \tag{41}$$

Uncertainty effect. The cost of uncertainty, $p_{uncertainty}$, in economy i is defined as a fraction of consumption an individual would be willing to give up to avoid all uncertainty facing in her consumption path. It solves the following equation:

$$V\left(\left\{(1 - p^i_{uncertainty})C^i, H^i\right\}_{t=1}^J\right) = V\left(\left\{\tilde{C}^i, \tilde{H}^i\right\}_{t=1}^J\right). \tag{42}$$

After calculating $p^i_{uncertainty}$ for $i \in \{A, B\}$, the welfare gain in reduced uncertainty in economy B relative to economy A is defined as follows:

$$\omega_{\text{uncertainty}} = \frac{1 - p^B_{\text{uncertainty}}}{1 - p^A_{\text{uncertainty}}} - 1. \tag{43}$$

Inequality effect. The cost of inequality, $p_{inequality}$, answers what fraction of consumption an individual should give up to be indifferent between being born into economy i and into economy where everyone consumes and works the same amount. For that purpose, the value of average certainty equivalent bundles and average values of certainty equivalent are compared. Formally, this is summarized as follows:

$$V\left(\left\{(1 - p_{\text{ineq}})\tilde{C}, \tilde{L}\right\}\right) = \int V\left(\tilde{c}\left(1, a, \theta, \eta, \mu_{e_0}\right), \tilde{l}\left(1, a, \theta, \eta, \mu_{e_0}\right)\right) d\phi\left(1, a, \theta, \eta, \mu_{e_0}\right) \tag{44}$$

It follows that the welfare gains in reducing inequality in economy B relative to economy A for an individual with a state space $(\cdot)$ is given by:

$$\omega_{\text{inequality}} = \frac{1 - p^B_{\text{inequality}}}{1 - p^A_{\text{inequality}}} - 1. \tag{45}$$

Finally, following Floden (2001), it can be shown that $\omega_{CEV} \approx (1 + \omega_{level})(1 + \omega_{inequality})(1 + \omega_{uncertainty}) - 1$.

J.2 Conditional Welfare Gains

Next, I look at who wins or loses at an individual level. Table J.1 provides conditional welfare gains for newborns of various wealth-ability groups. Specifically, I consider students at the 10th, 50th, and 90th percentiles of wealth and ability distributions, resulting in a total of nine different types. Table J.1 reports the conditional welfare gains for policies 1 (panel (a)), 2 (panel (b)), and 3 (panel (c)).

First, examining panel (a) in Table J.1 indicates that eliminating the stochastic part of the grant system leads all groups but one to win unconditionally on whether they go to college or not. For example, poor and median wealth individuals with low ability, and poor individuals with median ability do not go to college in either case. However, they face welfare gains of about 1.6% in terms of consumption equivalence. In the long term, the benefits are solely due to the rise in their relative wages and the reduction in average labor taxes. The college-bound individuals win as they face less adverse shocks in college, and the reduced uncertainty promotes their utility gains.

As for the case of the elimination of the GPA requirement (policy 2), panel (b) in Table J.1 shows that only two groups, rich - median ability and rich - high ability individuals, lose (by 0.1pp and 0.2pp, respectively). This is because these groups would go to college and graduate in either case. The GPA requirement was not a major concern for them in the benchmark as they have quite a high prior, and the chance of losing grants is minor even in the presence of lower grades. While all other types gain, this group faces a decreased college wage premium (by around 0.7%) as compared to the benchmark case, and this is the driving force of their welfare losses. All other types gain.

Finally, as for the last policy, panel (c) in Table J.1 shows that all groups but the top ability–top wealth group are better off relative to the benchmark economy. College-bound individuals win as the policy greatly reduces adverse shocks at college. Non-college individuals win as their wage rate increases. All individuals also enjoy the fact that the budget-balancing tax rate is reduced.

J.3 Hiring Professional Assistance for Grant Reapplication

Next, I will explore a scenario where the grant reapplication requirement remains intact, but students are provided with professional assistants to simplify the application process. This analysis aims to determine the cost-effectiveness of using professional assistance as an alternative policy to reduce grant uncertainty, as discussed in Bettinger et al. (2012). By comparing the cost per student of hiring an assistant with the potential gains in annual earnings per student and the resulting increase in labor taxes, I can evaluate the effectiveness of this intervention.

Assuming the assistance provided by professional assistants is perfect, implementing this intervention would be as effective as removing the entire reapplication requirements at college. This assumption allows me to work with the same policy functions students have under policy 1. Despite the possibility of partial uncertainty still existing in grant applications under this experiment, further

Table J.1: Conditional Welfare Gains under Policies by Ability and Wealth

	low ability	median ability	high ability
Policy 1 − No Stochastic Shock			
Poor	1.6	1.6	2.7
Median	1.6	1.5	11
Rich	1.6	0.1	0.6
Policy 2 − No GPA Requirements			
Poor	0.1	0.1	0.1
Median	0.1	0.1	0
Rich	0.1	-0.1	-0.2
Policy 3 − Constant Grants			
Poor	1.9	1.9	6.6
Median	1.9	4.3	10.8
Rich	1.9	1	0.3

analysis, as discussed below, is necessary to evaluate the feasibility and potential impact of this intervention. Appendix J.4 demonstrates that the even improving partial uncertainty can generate significant welfare gains, underscoring its effectiveness.

To estimate the cost of hiring professional assistants, I refer to a study conducted by Bettinger et al. (2012). According to their research, the total cost per applicant for this intervention, including expenses associated with software adoption and call centers, amounts to approximately $87.50. Taking into account the fact that not everyone graduates, the cost per graduate is then calculated to be $137.4 per student.

To evaluate the potential benefits of this intervention, the focus is on the projected increase in average annual earnings for college graduates. On average, this intervention is expected to result in increased earnings of 1.7% per year, equating to a roughly $744 raise. Considering a minimum income tax rate of 20%, the cost per student per year is significantly lower than the benefit the government would receive from the expanded labor income tax base. The analysis suggests that reducing grant uncertainty by employing professional assistants for students could yield substantial benefits in comparison to the cost per student.

By focusing solely on college graduates, the estimated benefits provided may be considered conservative, as they serve as an illustrative example rather than an exhaustive analysis of potential outcomes. However, when accounting for the relative earnings gain of high school students and dropouts, as discussed earlier, as well as the potential increase in tax revenue from sources such as consumption and capital gains, it becomes reasonable to anticipate significantly greater financial gains for the government associated with implementing the policy. This further strengthens the justification for supporting the provision of professional assistants to mitigate grant uncertainty.

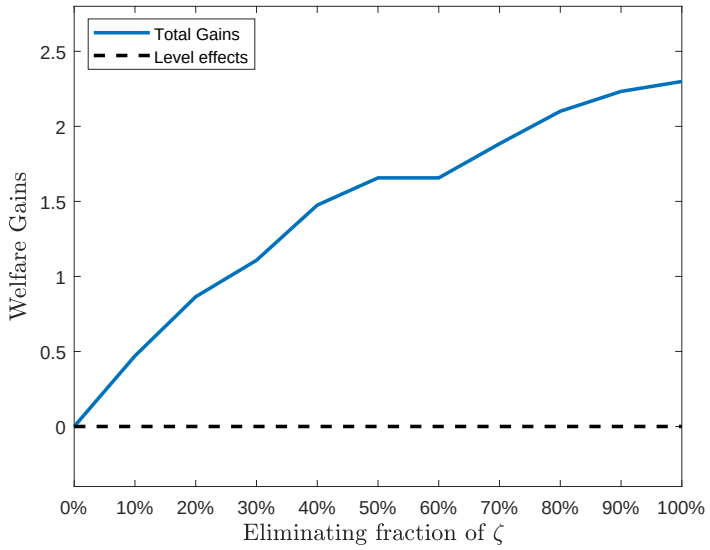
Whether through the removal of reapplication requirements or the provision of professional

assistance during the application process, these interventions aim to alleviate barriers and enhance access to financial aid. Reducing uncertainties associated with grants has the potential to enhance educational opportunities and outcomes for a broader range of college-age individuals, leading to substantial welfare gains through cost-effective policy tools.

J.4 Robustness of Welfare Gains to the Elimination of Grants Uncertainty

In this section, I discuss the robustness of the results on the welfare gains of policy 1. I am mainly interested in how robust the welfare gains are when only the fraction of the stochastic shock, ζ, is eliminated. This clarifies whether a policy that is successful in decreasing at least a partial amount of the uncertainty would still yield welfare gains. Figure 9 summarizes the results. It exhibits the welfare gains as a function of the standard deviation of ζ. Specifically, the X-axis refers to the fraction of the uncertainty eliminated, and Y-axes presents the welfare gains in terms of consumption equivalence. The figure plots the total gains in terms of consumption equivalence. It can be observed that the total and level gains increase as the variance of the stochastic shock decreases.

Figure 9: The Effects of Eliminating Fraction of the Stochastic Shock in the Grant System



J.5 Dropout rates by Year of Exit and Wealth Quartile

Table J.2 presents the distribution of college outcomes, categorized by the year of exit or graduation, across different wealth quartiles (Q1 being the lowest, Q4 the highest). Percentages are calculated based on students who initially enrolled in a bachelor's degree program.

The data highlights that early-year attrition is disproportionately concentrated among lower-wealth students. Cumulative dropout rates in the initial college years show a steep inverse relation-

ship with wealth. For instance, approximately 27.5% of students from the lowest wealth quartile (Q1) drop out within the first three years of college (summing those who drop after Year 1, Year 2, and Year 3). In stark contrast, students from the highest wealth quartile (Q4) experience a much lower cumulative dropout rate of about 10.3% over the same period. This indicates that financially constrained students are more likely to exit the education system in its earliest stages, while their wealthier counterparts exhibit higher persistence through these critical initial years.

Table J.2: College Outcomes by Year of Exit and Wealth Quartile (NLSY97)

Outcome Category	**Q1 (Low)**	**Q2**	**Q3**	**Q4 (High)**	**Overall**
Graduated	42.21	53.22	66.47	75.54	64.10
Dropped after Year 8+	7.38	3.92	3.10	1.14	3.08
Dropped after Year 7	4.92	4.48	2.71	1.72	2.97
Dropped after Year 6	4.10	5.04	2.52	3.00	3.41
Dropped after Year 5	4.92	4.20	5.04	4.58	4.68
Dropped after Year 4	9.02	10.64	3.88	3.72	5.84
Dropped after Year 3	8.20	7.00	6.40	4.86	6.17
Dropped after Year 2	9.43	7.28	5.81	2.43	5.29
Dropped after Year 1	9.84	4.20	4.07	3.00	4.46
Unknown/Other Drop	0.00	0.00	0.00	0.00	0.00

Notes: Percentages of students who enrolled in a bachelor's degree program in Year 1, categorized by their ultimate outcome (graduation) or the last observed college year of enrollment if they did not graduate. Percentages are calculated within each wealth quartile and for the overall sample. Q1 represents the lowest wealth quartile, and Q4 represents the highest wealth quartile.