Annenberg Institute
BROWN UNIVERSITY

EdWorkingPaper No. 24-1073

The Effects of Losing Pell Grant Eligibility on Student Outcomes

Shinyoung Kim
Iowa State University

While initial Pell Grant eligibility is solely determined by financial need, students must achieve Satisfactory Academic Progress to retain it. Students eligible for higher aid are less likely to complete college when they lose eligibility compared to those with lower aid. This non-random attrition introduces bias in the Local Average Treatment Effects. I construct nonparametric bounds on LATE under two monotonicity assumptions. Bound estimates reveal that students eligible for higher aid are up to 4 percentage points more likely to graduate within four years than those with less aid. In the worst case, they are still up to 2 percentage points more likely to graduate.

VERSION: March 2025

Suggested citation: Kim, Shinyoung. (2025). The Effects of Losing Pell Grant Eligibility on Student Outcomes. (EdWorkingPaper: 24 -1073). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/a576-xv04

The Effects of Losing Pell Grant Eligibility on Student Outcomes

Shinyoung Kim*

While initial Pell Grant eligibility is solely determined by financial need, students must achieve Satisfactory Academic Progress to retain it. Students eligible for higher aid are less likely to complete college when they lose eligibility compared to those with lower aid. This non-random attrition introduces bias in the Local Average Treatment Effects. I construct nonparametric bounds on LATE under two monotonicity assumptions. Bound estimates reveal that students eligible for higher aid are up to 4 percentage points more likely to graduate within four years than those with less aid. In the worst case, they are still up to 2 percentage points more likely to graduate.

JEL code: I20, I22

Keywords: Need-based Financial Aid, Educational Finance, Cost of Higher Education

*Iowa State University. E-mail: skim1@ iastate.edu.

I. Introduction

Since the 1970s, the Federal Pell Grant program has been a major source of federally funded, need-based financial aid. As of the 2021-2022 academic year, about 6.1 million undergraduate students in the U.S., approximately 32 percent, received a Pell Grant (U.S. Department of Education, 2022c).[1] Aimed at making higher education more accessible for low-income students, eligibility for the Pell Grant is determined solely by financial need; however, to maintain grant eligibility, students must also demonstrate Satisfactory Academic Progress (SAP) alongside financial necessity. The general requirements for federal SAP include maintaining a cumulative grade point average (GPA) of 2.0 or above and completing at least two-thirds of the cumulative credit hours attempted. Students who fail to meet these academic standards may retain the grant for one additional semester; however, repeated failure results in the loss of eligibility (U.S. Department of Education, 2011).

Existing studies provide mixed evidence on whether educational subsidies affect student outcomes. Some have concluded that need-based financial aid positively affects student outcomes (Seftor and Turner, 2002; Bettinger, 2004; Deming and Dynarski, 2009; Park and Scott-Clayton, 2018; Anderson et al., 2020; Liu, 2020), while others have found little to no impact (Hansen, 1983; Kane, 1995; Angrist et al., 2017; Turner, 2017; Marx and Turner, 2018; Carruthers and Welch, 2019; Rattini, 2023).[2]

Recent studies have leveraged exogenous variation, such as sharp cutoffs in grant amounts: students whose family income falls below a year-specific threshold qualify for the maximum grant amount, while those above the threshold are eligible for adjusted amounts. This eligibility is determined by financial need, measured by Expected Family Contribution (EFC).[3] Students with a $0 EFC are eligible for the maximum grant amount, while those with a

[1]For more information on the Federal Pell Grant program, refer to Title IV of the Higher Education Act of 1965, which authorizes federal student financial aid programs.

[2]Suggested explanations for the diminished impact of Pell Grants include the complexity and administrative burden of applying for financial aid (Bettinger et al., 2012), a lack of awareness regarding eligibility and benefits, and the interaction—whether implicit or explicit—with other forms of financial aid. Dynarski and Scott-Clayton (2013) note that students often do not realize they qualify for aid and do not apply for financial assistance. Additionally, an increase in Pell Grant amounts is associated with reductions in federal loans, state grants, or institutional aid, thereby offsetting the intended impact of Pell Grants (Turner, 2000, 2017; Bettinger and Williams, 2013; Park and Scott-Clayton, 2018; Eng and Matsudaira, 2021). Lastly, the variability of state and institutional aid programs may explain the inconsistent evidence regarding Pell Grants across different studies (Park and Scott-Clayton, 2018).

[3]On December 27, 2020, Congress passed the Consolidated Appropriations Act, amending the FUTURE Act and including the FAFSA Simplification Act to improve federal student aid distribution. One key change is replacing the Expected Family Contribution (EFC) with the Student Aid Index (SAI) for the 2024–25 award year.

positive EFC qualify for adjusted amounts based on their EFC. This discontinuity in grant amounts generates an ideal setup to use the Regression Discontinuity (RD) approach.

Exploiting this cutoff in grant eligibility, Castleman and Long (2016) find that eligibility had a positive effect on attendance, credit accumulation, and completion rates for students at 4-year institutions. Similarly, Denning et al. (2019) show that eligibility for more grant aid positively affects both college outcomes and post-college earnings, marking the first study to investigate the effect of US federal grant programs on post-college earnings. Eng and Matsudaira (2021), employing discontinuities and kinks, suggest that Pell Grant eligibility contributes positively to degree completion rates for up to six years, yet it has no impact on earnings.

Despite significant research on the effect of financial aid on student outcomes, the impact of losing aid due to academic requirements has not been explicitly discussed. Schudde and Scott-Clayton (2016) was the first paper to address the impact of losing Pell Grants on student outcomes, with Scott-Clayton and Schudde (2020) as its follow-up. Their results show that Pell recipients with low GPAs are more likely to leave college compared with academically similar non-Pell recipients among students in 2-year programs. Expanding on previous work, I examine the effect of losing grant eligibility on completion rates among Pell recipients in 4-year programs. I use data from the Beginning Postsecondary Students study (BPS:12/17) which surveyed a nationally representative sample of undergraduates enrolled in 4-year institutions in 2011-2012, tracking the cohort three times over six years after college entry.

Consistent with previous findings, I find that students qualifying for full aid are less likely to complete college after losing their grant compared with those with lower aid. More specifically, among students who lost eligibility, those below the income cutoff are 8 percentage points less likely to to graduate within four years. This non-random attrition from the sample could introduce selection bias, as the students remaining on either side of the income threshold may no longer be comparable (Lee and Lemieux, 2010; Abdulkadiroğlu et al., 2018). To address potential selection bias, I derive two nonparametric bounds on the Local Average Treatment Effects (LATE), each based on a different monotonicity assumption: monotonicity in potential outcomes and monotonicity in dropout process.

Naive RD estimates show no significant effects on completion rates or cumulative GPA, but bounding results find a positive, significant impact on completion rates. The bounding results using monotonicity in potential outcomes show that eligible students are up to 4 percentage points more likely to graduate from a 4-year institution within four years compared with those eligible for less aid. Even in the worst case, they are at least 2 percentage points more likely to graduate. The bound estimates under the monotonicity in dropout rates remain consistent. Eligibility increases four-year, five-year, and six-year graduation rates by up to 6, 12, and 13 percentage points, respectively. Even in the worst-case scenario, recipients are at least 3, 10, and 10 percentage points more likely to graduate. Overall, these results suggest that the previously estimated impact of maximum grant eligibility may be underestimated when not accounting for selection bias.

Need-based financial aid is designed to attract and support low-income students, for whom the benefits of completing college outweigh the costs, especially since the completion gap is more significant than the enrollment gap (Bound et al., 2010).[4] One may argue that this academic requirement enhances aid efficiency by pushing out students whose costs of finishing college may outweigh the benefits of staying. However, evidence suggests that it also discourages students capable of completing and potentially benefiting from college. I find that a substantial number of Pell recipients have SAT math scores exceeding the average of non-Pell recipients who completed college. Thus, the question of whether academic requirements exclude students who are not capable of completing college, and thereby increase aid efficiency, should be carefully evaluated.

My results suggest important policy considerations for institutions. Institutions may benefit from implementing more targeted interventions aimed at Pell recipients who are at high risk of losing their grants but demonstrate potential for completing college. As highlighted by Scott-Clayton and Schudde (2020), students are often unaware of SAP requirements until they lose their aid. Similarly, Baum and Scott-Clayton (2013) argue that the Pell program needs more tailored support services, beyond increasing grant amounts. Institutions may need to provide timely guidance or notifications of SAP failure to students at risk of losing their grants. The sooner students realize they may lose their grant aid, the easier it will be for them to take action to maintain their eligibility, making the SAP policy informative rather than restrictive.

This paper contributes to the extensive literature on the effects of educational subsidies on student outcomes. Specifically, it adds to the literature on the consequences of linking academic requirements to need-based financial aid, a topic that has received little attention despite its significance (Scott-Clayton and Schudde, 2020). Bettinger (2004) highlights that students eligible for aid —often those who enter college but leave without a degree —are a key demographic for educational attainment initiatives aimed at improving educational attainment. Furthermore, Bettinger (2004) argues that policymakers have traditionally focused more on increasing college enrollment, often overlooking college completion rates. However,

[4]On average, students from high-income families are six times more likely to complete a bachelor's degree compared with their low-income counterparts (Bailey and Dynarski, 2011; Goldrick-Rab et al., 2016).

as the gap in completion rates persists while enrollment continues to rise, both policymakers and institutions may need to shift their focus toward promoting student persistence and degree completion.

The remainder of the paper is organized as follows: Section II describes the Pell Grant program design and data. Section III outlines the empirical methods. Section IV presents the results, and Section V concludes.

II. The Pell Grant Program Design and Data

1. The Pell Grant Program

Students must file a Free Application for Federal Student Aid (FAFSA) before the beginning of the academic year to be eligible for a Pell Grant. In order to determine a student's eligibility, the Central Process System calculates the Expected Family Contribution (EFC). The EFC is calculated based on information provided in the FAFSA, primarily considering the family's income and their financial capacity for college expenses.[5] Pell Grant eligibility is then determined by the positive difference between the annual maximum Pell Grant amount set by Congress and the EFC. Students are classified into three groups: dependent, independent with dependents, and independent without dependents.[6] The first two groups can qualify for an Automatic Zero (AZ) EFC if their (or their family's) income falls below the eligibility threshold, whereas the last group of students is subject to a different threshold. This study primarily focuses on financially dependent students and independent students with dependents due to the small sample size of independent students without dependents.

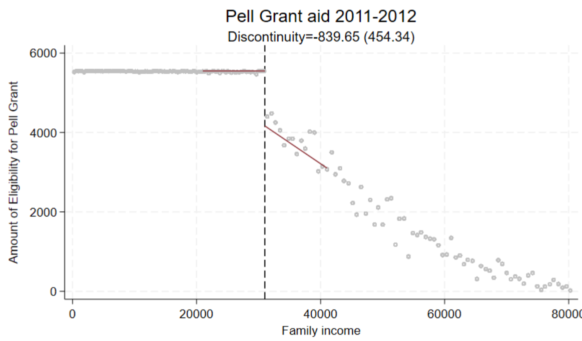
The identification leverages a discontinuity in the federal formula to calculate Pell Grant aid. Students with a $0 EFC receive the maximum Pell Grant amount, while those with family incomes above the AZ income threshold have their Pell Grant amounts adjusted according to their EFC. Students whose income exceeds the AZ threshold may still qualify for a $0 EFC under certain conditions, such as if someone in their household received means-tested benefits two to three years prior to college entry. Additionally, students must file the FAFSA each year to maintain their federal financial aid. Failing to file the FAFSA or

[5] The student's EFC is calculated by the Department of Education based on the family's taxed and untaxed income, assets, benefits, and other factors. It includes parents' contributions as well as the student's contributions from income and assets (U.S. Department of Education, 2022a).

[6] An individual can qualify as an independent student on the FAFSA if they are either 24 years of age or older, married or divorced, have been on active duty in the U.S. Armed Forces, provide primary support for dependents living with them, are classified as an orphan (with both parents deceased), or are enrolling in a graduate program (U.S. Department of Education, 2022b).

missing a federal deadline results in zero Pell Grant aid, and late submission can also reduce the amount of aid received.[7] This paper focuses on the discontinuity in Pell Grant eligibility based on income in the first year of college, as continued eligibility in subsequent years is not observable in this dataset.

Figure 1: Discontinuity in Pell Grant Eligibility at the Automatic-Zero (AZ) Threshold in 2011-2012



Notes: This figure displays the Pell Grant schedule for first-time undergraduate students who entered college in the 2011-2012 academic year and were either dependent or independent students with dependents. A dashed line represents the automatic-zero (AZ) income threshold, set at $31,000 for the 2011-2012 academic year. On average, students with an EFC just below the AZ threshold receive $840 more than those just above it. Pell grant amounts are in 2012 dollars.
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

Figure 1 illustrates the difference in Pell Grant eligibility at the AZ income threshold. In 2011-2012, the threshold was $31,000. Students whose family income fell below $31,000 met one criterion to receive a $0 EFC. Those with a $0 EFC qualify for the maximum grant aid, which was set at $5,500 for the 2011-2012 academic year. However, the Pell Grant eligible amount may not equal the realized grant amounts received by students, as the final amount considers other factors beyond the EFC, such as the cost of attendance and enrollment intensity. For example, students eligible for $5,550 will receive only $2,780 if they enroll as part-time students. Appendix Figure B1 shows the discontinuity in actual grant amounts received by students from the first to the fourth year of college. While measuring the effects

[7]The FAFSA form determines eligibility for three types of financial aid: federal, institutional, and state grants. Each program has its own deadline, with institutional and state grants typically requiring earlier submissions than federal aid. Many institutional and state aid programs operate on a first-come, first-served basis. As a result, filing the FAFSA late may result in missing out on institutional and state grants. McKinney and Novak (2015) find that those who did not file FAFSA or filed FAFSA late were systematically different from those who filed it or filed it early. Students who file the FAFSA late or do not file at all are more likely to enroll as part-time students, less likely to complete their majors, and tend to have lower SAT scores. Although these findings are limited to FAFSA filing in the first year of college, they suggest that failing to account for non-filing or delayed filing could introduce confounding effects into the analysis.

of discontinuity in actual grant amounts is important, estimating the discontinuity in eligible grant amounts is also crucial, as policymakers can only control the eligible amount (further explained in Section II(2)).

Apart from financial need, the Pell Grant program has required students to maintain Satisfactory Academic Progress (SAP) since 1976 to remain eligible for aid, following a federal mandate for 'satisfactory progress' toward degree completion (Scott-Clayton and Schudde, 2020).[8] Students who fail to meet the SAP requirement may receive an academic warning for one semester; however, repeated failure in achieving SAP in the subsequent semester results in the loss of grants.[9] While linking academic requirements to financial aid may encourage improved student performance, unintended consequences have been observed, most notably on student dropouts (Scott-Clayton and Schudde, 2020; Montalbán, 2023).

2. Data

The Beginning Postsecondary Students (BPS) cohorts were drawn from the National Postsecondary Student Aid Study (NPSAS), which provides a nationally representative sample of undergraduate students enrolled in post-secondary institutions participating in Title IV federal financial aid programs. The BPS study collected data on the types and amounts of federal financial aid from the U.S. Department of Education Central Processing System (CPS) and the National Student Loan Data System (NSLDS). The study compiled federal financial aid records for the entire undergraduate period, enabling detailed observations of the relationship between financial aid and student outcomes for each academic year. This study focuses on the cohort who entered college in 2011-2012 (hereafter BPS:12/17) whose progress was tracked over the first, third, and sixth years after college entry.[10] Students

[8]While institutions may have varying policies, their SAP requirements must be at least as strict as their graduation standards, typically requiring a minimum GPA of 2.0 and completion of at least two-thirds of cumulative credit hours attempted (Schudde and Scott-Clayton, 2016). Due to the insufficient number of students in the sample not meeting the SAP credit requirements, this paper only focuses on the GPA requirement.

[9]Students may demonstrate extenuating circumstances and successfully appeal to the school. In the sample, among students eligible for the maximum Pell aid, 49 percent of those who lost their grant in the first year received Pell Grants in the following academic year, though the amounts were significantly lower than what they originally qualified for. This is partially because students switched from being full-time students to part-time students. Similarly, among those with adjusted amounts, 52 percent of students who failed to satisfy SAP in the first year received Pell Grants in the next academic year.

[10]To avoid unacceptably high rates of misclassification, the BPS administrations employ "excessive over-sampling" for the NPSAS study. The first follow-up BPS cohort has a 68 percent response rate, and the second follow-up BPS cohort has a 67 percent response rate. While it is not feasible to analyze the characteristics of non-respondents, BPS sampling weights are used to account for non-response and ensure the analysis is representative (Bryan et al., Washington, DC: U.S. Government Printing Office.).

missing the necessary information to determine their type of financial aid were excluded, reducing the sample size from 10,360 to 8,920 for four-year degrees.

Table 1 presents descriptive statistics for the analyzed sample of first-time students in four-year degree programs. The sample in column 1 is restricted to first-time undergraduate students who enrolled in a 4-year institution during the 2011-2012 academic year. The sample in columns 2 and 3 is narrowed down to those who qualify for AZ EFC and whose income falls within $10,000 below or above the AZ income threshold. The sample in columns 4 and 5 is limited to students who have not completed their degrees six years after entry.

Students eligible for the maximum grant aid come from lower-income backgrounds, measured by adjusted gross income (AGI), and are less likely to have parents who hold at least a bachelor's degree compared with those eligible for less aid. Students below and above the income threshold are equally likely to enroll as full-time students in their first year. However, fewer students maintained full-time enrollment in subsequent years, which partially explains the reduction in Pell Grant amounts over time as the grants are determined by students' enrollment intensity (Park and Scott-Clayton, 2018). Students below the cutoff received about $4,561 in Pell Grants for 2011-2012, covering roughly 36 percent of their tuition, while those above the cutoff received around $2,731, covering about 20 percent of their tuition.

Students below the income cutoff took out more loans in their first, second, and third years, and they received more state or institutional grants. Figure B2 shows a discontinuity in total federal loans (including both subsidized and unsubsidized Stafford loans) from the first to the third year.[11] In the first and second years, students below the cutoff borrowed $877 and $762 more than those above the cutoff; however, these gaps were not significant. In the third year, students below the cutoff borrowed significantly more ($1,121) compared with those above the cutoff. Additionally, students above the cutoff received $2,480 more in total institutional grants. All analyses include all types of grants in the model to account for these differences.

[11]The Federal Family Education Loan Program (FFELP) previously offered Federal Stafford Loans (subsidized and unsubsidized); however, the FFEL Program ended in July 2010, and all federal loans are now issued through the Federal Direct Loan Program (FDLP), replacing Stafford Loans with Direct Subsidized Loans.

Table 1: Summary Statistics of the Data

		Enrolled in 2011-12		Non-completers	
	All	Below cutoff -$10,000	Above cutoff +$10,000	Below cutoff -$10,000	Above cutoff +$10,000
	(1)	(2)	(3)	(4)	(5)
Panel A. Demographics					
Female	.57	.62	.56	.72	.49
Age	18.99	19.33	19.03	20.34	20.44
White	.75	.55	.64	.61	.56
Parental education					
father: bachelor's	.44	.18	.28	.04	.14
mother: bachelor's	.43	.21	.24	.09	.14
Full-time					
2011-2012	.82 (6,550)	.82 (440)	.87 (430)	.76 (130)	.84 (120)
2012-2013	.70 (4,980)	.71 (330)	.78 (350)		
2013-2014	.64 (4,220)	.64 (260)	.67 (270)		
2014-2015	.66 (4,350)	.62 (270)	.68 (270)		
2015-2016	.48 (1,740)	.43 (130)	.49 (120)		
2016-2017	.36 (790)	.43 (80)	.28 (40)		
Time to degree	4.42	4.62	4.54		
Completion	.51	.32	.42		
Grade Average Point					
first-year	2.88	2.73	2.54	2.31	1.40
second-year	2.97	2.67	2.84	2.11	2.12
cumulative	2.96	2.75	2.71		
SAT					
math	540	502	527	481	526
verbal	540	495	519	486	501
Panel B. Labor Market Outcomes					
Earnings	36,442	30,797	33,935	27,619	30,623
Employment status	.64	.59	.54	.53	.47
Panel C. Financial aid					
Adjusted Gross Income (AGI)	86,303	25,838	36,065	25,129	35,095
Tuition (2011-2012)	14,896	12,793	13,957	9,943	9,470
Stafford loans					
2011-2012	3,156	3,212	3,474	4,706	4,564
2012-2013	2,888	3,688	3,214	1,946	2,490
2013-2014	2,868	3,711	2,856	259	1,154
State/Institutional grants					
2011-2012	5,160	6,576	6,077	4,553	2,972
Work-study					
2011-2012	304	690	385	200	231
Pell Grant received					
2011-2012	1,468	4,561	2,731	3,825	2,817
2012-2013	1,290	3,963	2,513	3,322	2,366
2013-2014	1,192	3,379	2,446	872	2,284
2014-2015	1,168	3,171	2,258	603	719
2015-2016	1,087	1,986	1,368	566	635
N (unweighted)	8,920	550	500	180	150

Notes: Column 1 includes first-time undergraduates who enrolled in a 4-year institution in the 2011-2012 academic year. Columns 2 and 3 narrow down to those qualifying for auto-zero EFC with incomes within $10,000 of the $31,000 threshold. Columns 4 and 5 are limited to those who have not completed their degrees. Full-time status, first- and second-year GPAs are conditional on enrollment status, with the number of students enrolled each academic year shown in parentheses. Tuition refers to tuition and fees at the NPSAS institution for students who attended only one institution in 2011-2012. Students who attended more than one institution during this period were excluded from this variable. Loans measure the amount of direct subsidized and unsubsidized Stafford loans received by students during the 2011-2012 academic year. State and institutional grants measure the total amount of state and institutional grants received by students in 2011-2012. The variable cumulative GPA is conditional on degree completion. All dollar amounts are adjusted to 2017 values. The sample size is rounded to the nearest 10.
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

III. Empirical Methods

1. Identification

I use a Regression Discontinuity (RD) approach, which exploits the discontinuity in Pell-eligible amounts generated by the AZ policy to estimate the effect of Pell Grant eligibility on student outcomes. The identification of the RD parameter relies on the assumption that the conditional expectations of potential outcomes are continuous at the threshold. Intuitively, that is, students just below and just above the income threshold should not differ significantly in their characteristics. This reasoning allows one to attribute any observed discontinuous jump in the outcome at the threshold to the causal effect of the Pell Grant (Lee and Lemieux, 2010). If students on either side of the cutoff have similar distributions of all predetermined characteristics, they are assumed to be similar in their underlying characteristics. Then, there should be no reason—other than the Pell eligibility amount—for a discontinuous change in student outcomes at the cutoff. This discontinuity yields the following RD estimand:

$$\Gamma(c) = \lim_{\epsilon \uparrow 0} [Y_i | X_i = c + \epsilon] - \lim_{\epsilon \downarrow 0} [Y_i | X_i = c + \epsilon] \tag{1}$$

where Y_i denotes the observed outcome of student i, X_i is the family income, measured by AGI, and c is the AZ income threshold. The parameter of interest, $\Gamma(c)$, estimates the causal effect of eligibility for the maximum grant aid on student outcomes, such as completion rates and cumulative GPA. Under the continuity assumption, which is further discussed in the next section, $\Gamma(c)$ would equal $E[Y(1) - Y(0) | X = c]$, which is the average treatment effect at the cutoff c, where $Y(1)$ is the potential treated outcome and $Y(0)$ is the potential untreated outcome.

The model estimates the effect of eligibility for the maximum Pell Grant amounts, rather than the actual awards on student outcomes (i.e., Intent-to-Treat (ITT) effects). This is for two reasons: first, enrollment decisions can be influenced by the award amount; second, policymakers can regulate only aid eligibility, rather than the actual aid amounts students receive. While examining the effects of actual award amounts on student outcomes is important, researchers often look into the ITT to evaluate the effect of an aid policy. I estimate local linear regression with a triangle kernel and the coverage error (CE)-optimal bandwidth of $10,000 for each outcome variable. For constructing the confidence intervals, I also use CE-optimal bandwidths.

2. Validity of the identification assumptions

As with other RD design studies, two potential concerns regarding the identification assumption arise. First, estimates may be biased if students underreport their EFC to receive additional Pell Grant awards (the direction of bias is unclear). Misreporting or manipulating family income is possible; however, this poses a minimal threat to identification for two reasons: first, students are generally unaware of the AZ threshold (Eng and Matsudaira, 2021), and second, over half of Pell Grant-eligible students are subject to FAFSA verification, where income is one of the primary factors reviewed (Denning et al., 2019). Nevertheless, to address this concern, I conducted a density test introduced by McCrary (2008), which provides a test for detecting manipulation of EFC. Figure B6 shows the results of the density test using samples within ±\$10,000 of the AZ eligibility cutoff. Any spikes in the density of observations would indicate endogenous sorting. The results show that the density of observations is smooth around the threshold, suggesting that students do not manipulate their EFC to receive additional grants. More specifically, the test yields a discontinuity estimate of -0.11, with a standard error of 0.14. Additional test results for observable predetermined characteristics can be found in Figures B4 and B5.

Another concern involves eligibility-induced enrollment. Marginal students—those who might not have enrolled in college without financial aid—could be systematically different from those who would enroll regardless of financial aid. The BPS study focuses on undergraduate students who have already filed FAFSA and enrolled in college, meaning the dataset does not include students who filed FAFSA but did not enroll; thus, assessing the responsiveness of student enrollment to AZ policies is not directly testable. Although the key identification assumption cannot be tested directly, I employ the following Ordinary Least Squares (OLS) to examine whether students below and above the income threshold respond differently to the loss of a grant due to SAP failure:

$$Y_{y,i} = \beta_0 + \beta_1 maxPell_i + \beta_2 FailSAP_{y,i} + \beta_3 maxPell_i * FailSAP_{y,i} + Z_i\delta + \epsilon_i \qquad (2)$$

where $Y_{y,i}$ denotes student persistence and graduation rates for a specific academic year, y, $maxPell_i$ is a binary variable indicating eligibility for the maximum Pell Grant amount, $FailSAP_{y,i}$ indicates whether a student fails to meet GPA requirements in the academic year, y, and Z_i is a vector of student characteristics. To examine the immediate effect of losing Pell on persistence, I use the cumulative GPA from the first and second years, as well as students' persistence rates in the second and third years. The differences in the effect of losing Pell Grant eligibility between students just below and above the income threshold are captured by $\beta_1 + \beta_3$.

Table 2: The Average Effect of Losing Pell on Persistence Rates Among Pell Grant Recipients

	Persistence			Graduation		
	Second	Third	Fourth	4 years	5 years	6 years
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Second year						
maxPell$_{y_1}$	-.07***	-.05**	.01	-.08***	-.10***	-.12***
	(.02)	(.03)	(.03)	(.03)	(.03)	(.03)
Fail SAP$_{y_1}$	-.22***	-.35***	-.30***	-.18***	-.37***	-.41***
	(.04)	(.04)	(.06)	(.05)	(.06)	(.06)
maxPell$_{y_1}$ * fail SAP$_{y_1}$	-.19***	-.09	-.01	.02	.06	.06
	(.05)	(.06)	(.08)	(.07)	(.08)	(.08)
P-value on joint F-test	.00	.01	.00	.03	.01	.00
N (unweighted)	1,040[a]	1,040[a]	1,040[a]	1,040[a]	1,040[a]	1,040[a]
Panel B. Second and third years						
maxPell$_{y_1}$		.03	.06	-.05*	-.05	-.05
		(.02)	(.04)	(.03)	(.03)	(.03)
Fail SAP$_{y_{1,2}}$		.04	.13	-.22**	-.40**	-.42***
		(.07)	(.12)	(.11)	(.11)	(.11)
maxPell$_{y_1}$ * fail SAP$_{y_{1,2}}$		-.12	-.35*	.11	.10	.06
		(.12)	(.14)	(.19)	(.18)	(.17)
P-value on joint F-test		.23	.54	.21	.29	.29
N (unweighted)		910[b]	910[b]	910[b]	910[b]	910[b]

Notes: This table shows the immediate effect of SAP failure in the second year (2012-2013) and third year (2013-2014) on persistence and completion rates for students both below and above the AZ threshold. Panel A presents the effect of SAP failure in the second year on persistence and completion rates, while Panel B shows the impact in both the second and third years. To determine whether students meet SAP requirements for each year, first-year and second-year cumulative GPAs are used, which both are retrieved from transcripts. All models control for age, gender, enrollment status, tuition and fees in 2011-2012, total institutional aid in 2011-2012 (including institutional grants), total Stafford loans borrowed, parental receipt of federal benefits in 2011-2012, and parental education level. The results of an F-test of the 'maxPell' and 'fail SAP' coefficients are shown. All analyses use BPS sampling weights. The sample size is rounded to the nearest 10.

* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level

Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

[a]Students who transferred to the 2-year institution are included.

[b]Students who transferred to the 2-year institution are included. Those who are not enrolled in their second year are excluded.

The results in Table 2 suggest that students below the income threshold are less likely to persist in the year they lose eligibility compared with those above the threshold on average. Panel A examines the average effect of second-year SAP failure and Panel B shows the average effect of second- and third-year SAP failure, all on persistence and graduation rates.[12]

[12]Students may have transferred from a 4-year institution to a 2-year institution. The BPS studies lack

While SAP failure discourages overall student persistence, this effect is more pronounced for students below the income threshold. Specifically, among students who lost their grant eligibility in their second year, those below the income threshold are 26 percentage points less likely to persist into their second year compared with those above the income threshold. This negative effect on persistence continues until graduation; these students are 8, 10, and 12 percentage points less likely to graduate within four, five, and six years, respectively, compared with those above the income threshold. Similarly, students below the threshold who lost their grant eligibility in the second year and did not regain it in the third year are 5 percentage points less likely to graduate within four years than those above the threshold. Overall, the results suggest that eligible students are less likely to persist in college after losing their grant than those with adjusted grant amounts.

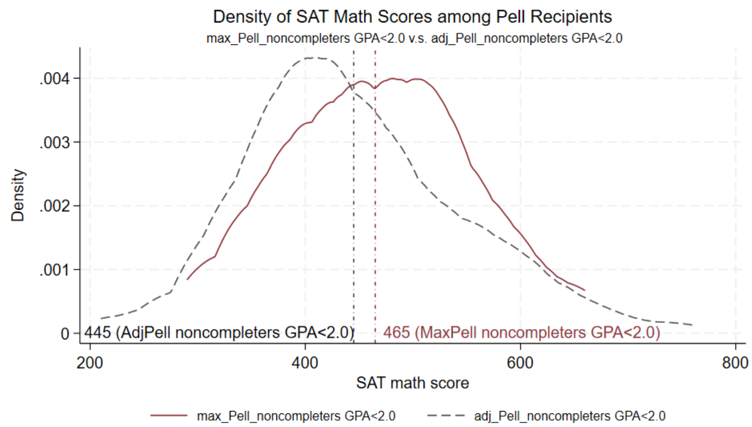
I further examine how these two groups respond differently to the loss of Pell by comparing students at the GPA cutoff separately for those below and above the income cutoff in Table 3.[13] The conventional RD results indicate that among students below the cutoff, those with a first-year GPA just below 2.0 are 23 percentage points less likely to graduate within four years compared with those with a GPA of 2.0 or above. For students above the income cutoff, the loss of the Pell Grant in the second year has a negligible effect. The results are consistent with the findings in Lindo et al. (2010). Using an RD, they find that students just below the minimum GPA cutoff, receiving academic probation, are significantly less likely to enroll the following year compared with students just above the GPA cutoff. Additionally, Figure 2 shows the distribution of SAT math scores for students who lost their grant eligibility and did not persist in college; this group is further decomposed into those who qualified for the maximum Pell Grant to those with less aid. The results indicate that

detailed information on which institutions students transferred to and when these transfers occurred, providing only the overall transfer rates; thus, all samples in Table 2 may include students who transferred and persisted in a 2-year institution. The overall transfer rates to 2-year institutions were similar for students below and above the income cutoff. Specifically, 27 percent of students below the income threshold and 27 percent of students above it transferred to a 2-year institution. Among those who transferred, about 67 percent of students below the income threshold did so within the first three years of college, relative to 75 percent of students above the income threshold. The second-year retention rate, defined as the percentage of students who continue at their initial institution in their second year of college, is 59 percent among the analyzed sample.

[13]GPA may be subject to manipulation, which could invalidate the RD approach. Figure B7 shows the results of the McCrary density test on first-year GPA using the samples within ±\$10,000 of the AZ eligibility cutoff. The test yields a discontinuity estimate of 2.52, with a standard error of 0.87. Similarly, the test on second-year GPA yields a discontinuity estimate of 0.97, with a standard error of 0.41. Although the presence of discontinuity suggests that GPA may be subject to manipulation, students have imprecise control over their GPAs. According to Lee and Lemieux (2010), when the assignment variable cannot be precisely manipulated, even if individuals have some influence over it, RD designs remain valid.

students who were eligible for the maximum grant, lost their aid, and did not complete college have significantly higher SAT math scores than their counterparts with less aid, with the difference significant at the 10 percent level.

Figure 2: Distribution of SAT Math Scores Among MaxPell and AdjustedPell Non-Completers with a GPA Below 2.0



Notes: This figure shows the distribution of SAT math scores among students eligible for the maximum Pell Grant and those eligible for adjusted amounts, all of whom have a GPA below 2.0 and did not complete college. The results of the Kolmogorov-Smirnov test indicate that, on average, students eligible for the maximum Pell Grant who did not complete college with a GPA below 2.0 have higher SAT math scores than academically similar students eligible for less aid. This difference is statistically significant at the 10 percent level, suggesting that these two groups may differ in their underlying characteristics.

Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

Table 3: The Effect of Losing Pell on 4-year Graduation Rates Among Pell Grant Recipients at the GPA Threshold

	Fail SAP in the 2nd year		Fail SAP in the 3rd year	
	Below	Above	Below	Above
	(1)	(2)	(3)	(4)
Conventional	.23**	-.05	-.12	-.02
	(.11)	(.10)	(.17)	(.07)
Robust	.25	-.12	-.10	-.00
	(.21)	(.13)	(.26)	(.09)
CI	[-.16, .67]	[-.39, .14]	[-.60, .40]	[-.17, .17]

Notes: This table shows the effect of losing Pell Grant eligibility in the second and third years on 4-year completion rates. 'Below' represents students below the income threshold, while 'Above' represents students above the income threshold. Among students below the cutoff, 16 percent received a GPA below 2.0 in the first year, compared with 18 percent of students above the cutoff. In the second year, 17 percent of students below the cutoff received a GPA below 2.0, compared with 17 percent of students above the cutoff (this number is similar to findings from Schudde and Scott-Clayton (2016)). All models control for age, gender, enrollment status, tuition and fees in 2011-2012, total institutional aid in 2011-2012 (including institutional grants), total Stafford loans borrowed, parental receipt of federal benefits in 2011-2012, and parental education level. All analyses use BPS sampling weights.
* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

Earlier studies offer several explanations for why reductions or forfeiture of need-based financial aid likely discourage student persistence and why the discouragement effect is more pronounced among students with higher levels of aid. Bettinger (2004) explains after completing the first year, students must decide whether to continue into the next year. Since the initial investment for Pell Grant recipients comes from the federal government, these students may not be as motivated to put in the same effort as those who made more personal investments. Denning (2019) shows that additional aid leads students to reduce their work efforts; thus, students who receive higher financial aid may perform worse, be more vulnerable, and be less likely to persist in college without the aid compared with those with less aid. Similarly, Rattini (2023) argues that lower-aid recipients are more driven to persist and finish college due to the higher initial cost of college than those eligible for higher aid.

3. Bounds on Pell Grant Effects

Even when the continuity assumption holds, non-random attrition from the sample could still introduce selection bias, as the students remaining on either side of the income threshold may not be comparable (Abdulkadiroğlu et al., 2018). The attrition can result in different covariate distributions on both sides of the threshold, resulting in selection bias. To see this, let $Y_i(P^{\max})$ denote the potential outcome for student i, where $P^{\max} = 1$ if the student is eligible for the maximum Pell Grant amount and $P^{\max} = 0$ indicates otherwise. For simplicity, the subscript i is omitted in the following discussion. The potential outcome is given by:

$$Y = Y(0)(1 - P^{\max}) + Y(1)P^{\max} \tag{3}$$

The parameter of interest is the effect of being eligible for the maximum Pell Grant on student outcomes, denoted as $\Gamma(c) = E[Y(1) - Y(0)|X = c]$, where c is a known income threshold. Let $N(P, P^{\max})$ denote the potential non-persistence outcome, where P indicates whether a student retains a Pell Grant, with $P = 1$ indicating that the student retains the grant and $P = 0$ indicates otherwise. Different persistence behaviors among students who lost their grants suggest that the conditional mean of $N(0, P^{\max})$ given X may differ for students below and above the income threshold, i.e., $E[N(0, 1)|X = c] \neq E[N(0, 0)|X = c]$, which implies $\lim_{\epsilon \uparrow 0} E[N(0, P^{\max})|X = c + \epsilon] \neq \lim_{\epsilon \downarrow 0} E[N(0, P^{\max})|X = c + \epsilon]$.

Let the potential outcomes depend on both observed covariates, X, and potential non-persistence. Assuming additive separability between observable characteristics and non-persistence, the general form of the treatment effect model can be written as:

$$Y(P^{\max}) = G_{P^{\max}}(X) - F(N(P, P^{\max})) + \epsilon \tag{4}$$

By maintaining the exogeneity assumption throughout, we have $E[Y(P^{\max})|X, N(P, P^{\max})] = G_{P^{\max}}(X) - F(N(P, P^{\max}))$. $G_{P^{\max}}(X)$ represents the return for students with characteristics X, and $F(N(P, P^{\max}))$ is a function summarizing how persistence is related to student outcomes. I assume that if Pell recipients with a GPA below 2.0 had not lost their grant eligibility, their expected value of non-persistence rates would have been continuous at the cutoff; that is, $E[N(0, P^{\max})|X = c] = E[N(0, 1 - P^{\max})|X = c]$. I further assume that if the expected value of non-persistence is the same, then, the expected relationship between non-persistence and student outcomes is also the same across these groups; that is, $E[F(N(P, P^{\max}))|X = c] = E[F(N(P, 1 - P^{\max}))|X = c] = E[F(N)|X = c]$. Given this general specification, the RD estimand, $\Gamma_{RD}(c)$, can be decomposed as follows:

$$\begin{aligned}\Gamma_{RD}(c) = &\big(E[G_1(X)|X=c] - E[G_0(X)|X=c]\big)\\ &+ \big(E[F(N(0,0))|X=c]E[N(0,0)|X=c] + E[F(N(1,0))|X=c]E[N(1,0)|X=c]\big)\\ &- \big(E[F(N(0,1))|X=c]E[N(0,1)|X=c] + E[F(N(1,1))|X=c]E[N(1,1)|X=c]\big)\end{aligned} \tag{5}$$

In the absence of attrition bias, the RD estimand equals LATE, $E[G_1(X)|X = c] - E[G_0(X)|X = c]$. The difference in persistence behavior among students who lost their grant yields a biased estimate of LATE, shown as $-E[F(N(0,1))|X = c]E[N(0,1)|X = c] + E[F(N(0,0))|X = c]E[N(0,0)|X = c]$. Thus, the RD estimates are confounded by selection bias, as shown in the equation 6:

$$\hat{\Gamma}(c) = \lim_{\epsilon\uparrow 0} E[Y_i|X_i = c+\epsilon] - \lim_{\epsilon\downarrow 0} E[Y_i|X_i = c+\epsilon] + S \tag{6}$$

where $S = -E[F(N)|X = c^-, P = 0]E[P = 0|X = c^-] + E[F(N)|X = c^+, P = 0]E[P = 0|X = c^+]$ denotes the selection effect.

Another issue arises from non-random attrition. Certain academic outcomes, such as cumulative GPA, are only observable for students who graduate. For students who do not persist and complete college, these outcomes become unobserved, and if this attrition is not random, this can result in biased LATE. To see this, consider the following decomposition of the treatment effects:

$$\begin{aligned}\Gamma(c) &= E[Y(1)|X=c] - E[Y(0)|X=c]\\ &= E[Y(1)|X=c, N=1]E[N=1|X=c] + E[Y(1)|X=c, N=0]E[N=0|X=c]\\ &- (E[Y(0)|X=c, N=1]E[N=1|X=c] + E[Y(0)|X=c, N=0]E[N=0|X=c])\end{aligned} \tag{7}$$

where N denotes the observed persistence outcomes, with $N = 1$ if a student does not persist in college and $N = 0$ indicates otherwise. If a student does not persist in completing college, their outcomes become unobservable, as shown below:

$$\hat{\Gamma}(c) = E[Y|X=c, N=0]E[N=0|X=c] - E[Y|X=c, N=0]E[N=0|X=c] \tag{8}$$

As shown in equation 8, the outcomes of those who do not complete college become unobserved.

3..1 Monotonicity in Potential Outcomes

Identifying the treatment effect requires knowledge of the counterfactual outcomes for students who left college due to grant loss, had they retained it. However, disentangling selection bias from the treatment effect is infeasible as the true relationship between student persistence and the outcome variable cannot be directly estimated; thus, the treatment effect can only be bounded. I construct two nonparametric bounds on LATE using the following monotonicity assumptions: one on potential outcomes and the other on the dropout process.

To apply the first monotonicity assumption, I propose the following thought experiment: *What would the completion rates be if students who lost their grant had retained it?* To carry out this experiment, I divide students into three groups: the *always-students*, *induced-students*, and *never-students*. The always-students are those who persist in college regardless of their eligibility for full or partial grant amounts, i.e., $P(N(0, P^{\max}) = 0, N(1, P^{\max}) = 0)$; the induced-students are those who are induced to persist in college due to their grant, $P(N(0, P^{\max}) = 1, N(1, P^{\max}) = 0)$, and the never-students are those who never finish college regardless of grant, $P(N(0, P^{\max}) = 1, N(1, P^{\max}) = 1)$.[14] Each of these groups can be further divided into 12 subgroups based on their GPAs: substantially below 2.0, just below 2.0, just above 2.0, and substantially above 2.0. Students with a GPA of 2.0 or above are not subject to selection, whereas those with a GPA below 2.0 are.

I first estimate the probability of a student with a GPA just below 2.0 being an induced-student. The conditional probability of not persisting in college ($N = 1$), given an income below the threshold and a GPA just below 2.0, can be decomposed as follows:

$$
\begin{aligned}
P(N = 1|X = c^-, G = 2.0^-) = P(N(0,1) = 1, N(1,1) = 0|X = c^-, G = 2.0^-) \\
+ P(N(0,1) = 1, N(1,1) = 1|X = c^-, G = 2.0^-)
\end{aligned}
\tag{9}
$$

Those who leave college despite having a GPA just above 2.0 are the never-students:

$$
P(N = 1|X = c^-, G = 2.0^+) = P(N(0,1) = 1, N(1,1) = 1|X = c^-, G = 2.0^+) \tag{10}
$$

[14] This paper focuses on students who entered college in the 2011-2012 academic year. As these students are already enrolled, the impact of financial aid on enrollment is not covered in this paper.

Assuming that the probability of being never-students is continuous in GPA, one can estimate $P(N(0,1)=1, N(1,1)=0|X=c^-, G=2.0^-)$ by subtracting $P(N=1|X=c^-, G=2.0^+)$ from $P(N=1|X=c^-, G=2.0^-)$. The estimation for the remaining groups can be found in Appendix A.

Researchers must distinguish between students who discontinue college due to grant loss and those who would not have persisted in college regardless of receiving the grant. Induced-students with a GPA below 2.0 fall into the first group, while never-students belong to the second group. The bias arises from these induced-students who made non-persistence decisions because of grant loss. Never-students will not persist in college regardless of whether they receive a grant; thus, their potential completion rates are 0, whether treated or untreated.

To bound LATE, the counterfactual outcomes for induced-students who lost their grants need to be known. To do so, I impose the following monotonicity assumption: the potential outcomes for the always-students are at least as good as those for the induced-students, and the outcomes for the induced-students are at least as good as those for the never-students, conditional on treatment. This assumption is similar to the Monotone Treatment Selection (MTS) assumption introduced by Manski and Pepper (2000), which posits that expected potential outcomes move in a specific direction when comparing individuals in the treatment and control groups, i.e., $E[Y(P^{\max})|N(0,P^{\max})=0, N(1,P^{\max})=0] \geq E[Y(P^{\max})|N(0,P^{\max})=1, N(1,P^{\max})=0] \geq E[Y(P^{\max})|N(0,P^{\max})=1, N(1,P^{\max})=1]$ where $P^{\max}=\{0,1\}$. Under the monotonicity assumption, the observed outcomes of the always-students with GPAs below 2.0 can serve as an upper bound for the counterfactual outcomes of the induced-students with GPAs below 2.0. The upper bound of $E[Y(1)|X=c^-]$ can be obtained as:

$$
\begin{aligned}
&E_{\max}[Y(1)|X=c^-] \\
&\quad = \Big(E[Y|N=0, X=c^-, G<2.0^-](P(N=0|X=c^-, G<2.0^-) \\
&\quad + P(N=1|X=c^-, G<2.0^-))\Big)P(G<2.0^-|X=c^-) \\
&\quad + \Big(E[Y|N=0, X=c^-, G=2.0^-]\big(P(N=0|X=c^-, G=2.0^-) \\
&\quad + P(N=1|X=c^-, G=2.0^-) - P(N=1|X=c^-, G=2.0^+)\big)\Big)P(G=2.0^-|X=c^-) \\
&\quad + E[Y|N=0, X=c^-, G=2.0^+]P(N=0|X=c^-, G=2.0^+)P(G=2.0^+|X=c^-) \\
&\quad + E[Y|N=0, X=c^-, G>2.0^+]P(N=0|X=c^-, G>2.0^+)P(G>2.0^+|X=c^-)
\end{aligned} \tag{11}
$$

The monotonicity assumption does not provide lower bounds; thus, the lower bounds for counterfactual completion rates must be conjectured. While completion rates range between 0 and 1, 0 cannot serve as a lower bound because, under the assumption, induced-students left college due to their grant loss. To construct the lower bound, an additional assumption is required: the counterfactual completion rates for these students are assumed to be similar to those at the 10th percentile of the college completion distribution for observed students with similar GPA and income levels. Finally, the lower bound of $E[Y(1)|X = c^-]$ can be obtained as:

$$\begin{aligned}
&E_{\min}[Y(1)|X = c^-] \\
&\quad = \big(E[Y|N = 0, X = c^-, G < 2.0^-]P(N = 0|X = c^-, G < 2.0^-)P(G < 2.0^-|X = c^-) \\
&\quad + \Big(E[Y|N = 0, X = c^-, G = 2.0^-]P(N = 0|X = c^-, G = 2.0^-) \\
&\quad + \tau_{Y_{10}|N=0,X=c^-,G=2.0^-}\big(P(N = 1|X = c^-, G = 2.0^-) \\
&\quad - P(N = 1|X = c^-, G = 2.0^+)\big)\Big)P(G = 2.0^-|X = c^-) \\
&\quad + E[Y|N = 0, X = c^-, G = 2.0^+]P(N = 0|X = c^-, G = 2.0^+)P(G = 2.0^+|X = c^-) \\
&\quad + E[Y|N = 0, X = c^-, G > 2.0^+]P(N = 0|X = c^-, G > 2.0^+)P(G > 2.0^+|X = c^-)
\end{aligned} \tag{12}$$

where $\tau_{Y_{10}|N=0,X=c^-,G}$ represents the 10th percentile of the college completion distribution for students with similar GPA and income levels who complete college. For other academic outcomes, such as GPA, the worst value of GPA takes a value of 2.0, which is a graduation requirement for most institutions in the U.S.

To obtain the upper bound of LATE, $\Gamma(c) = E[Y(1) - Y(0)|X = c]$, one can subtract the lower bound on $E[Y(0)|X = c^+]$ from the upper bound on $E[Y(1)|X = c^-]$. To obtain the lower bound, subtract the upper bound on $E[Y(0)|X = c^+]$ from the lower bound on $E[Y(1)|X = c^-]$:

$$\Gamma^{\text{UB}}(c) = E_{\max}[Y(1)|X = c^-] - E_{\min}[Y(0)|X = c^+] \tag{13a}$$

$$\Gamma^{\text{LB}}(c) = E_{\min}[Y(1)|X = c^-] - E_{\max}[Y(0)|X = c^+] \tag{13b}$$

3..2 Monotonicity in Response Rates

Bound estimates relying on the monotonicity assumption on potential outcomes often yield wide intervals, particularly when a large portion of the sample requires imputation. Lee (2009) proposes an alternative method for bounding LATE in the presence of attrition, leveraging observed dropout rates and the quantiles of the outcome distribution. The intuition of this method is to trim the sample—either from below or above—so that students who remain in the sample are comparable across the income threshold. The following framework closely follows the approach used in Lee (2009):

$$\begin{aligned} Y &= \mathbb{1}[N^* \leq 0] \cdot Y^* \\ N^* &= (1 - P^{\max}) \cdot \delta \cdot \mathbb{1}[G < 2] + X\Pi_2 + V \\ Y^* &= P^{\max} \cdot \gamma + X\Pi_1 + U \end{aligned} \tag{14}$$

where Y^* is the potential outcome, $P^{\max}$ is the indicator variable of being eligible for the maximum Pell Grant, and X is a vector of baseline characteristics. The variable N^* is a latent variable representing the propensity to not persist in college. Both variables Y^* and N^* is not observed, but the student outcomes conditional on persistence Y is observed. The parameter δ is negative ($\delta < 0$) as students eligible to receive the maximum Pell Grant amount are less likely to persist in college.

The observed means for students receiving the maximum Pell Grant and those with adjusted Pell Grant amounts can be expressed as:

$$\begin{aligned} & E[Y|P^{\max} = 1, N^* \leq 0] \\ & = E[Y|P^{\max} = 1, N^* \leq 0, G < 2.0]P(G < 2.0|P^{\max} = 1, N^* \leq 0) \\ & + E[Y|P^{\max} = 1, N^* \leq 0, G \geq 2.0]P(G \geq 2.0|P^{\max} = 1, N^* \leq 0) \\ & = (\gamma + X\Pi_1 + E[U|P^{\max} = 1, V \leq -X\Pi_2, G < 2.0])P(G < 2.0|P^{\max} = 1, V \leq -X\Pi_2) \\ & + (\gamma + X\Pi_1 + E[U|P^{\max} = 1, V \leq -X\Pi_2, G \geq 2.0])P(G \geq 2.0|P^{\max} = 1, V \leq -X\Pi_2) \end{aligned} \tag{15}$$

$$
\begin{aligned}
&E[Y|P^{\max}=0,N^*\leq 0]\\
&=E[Y|P^{\max}=0,N^*\leq 0,G<2.0]P(G<2.0|P^{\max}=0,N^*\leq 0)\\
&+E[Y|P^{\max}=0,N^*\leq 0,G\geq 2.0]P(G\geq 2.0|P^{\max}=0,N^*\leq 0)\\
&=(X\Pi_1+E[U|P^{\max}=0,V\leq -\delta-X\Pi_2,G<2.0])P(G<2.0|P^{\max}=0,V\leq -\delta-X\Pi_2)\\
&+(X\Pi_1+E[U|P^{\max}=0,V\leq -X\Pi_2,G\geq 2.0])P(G\geq 2.0|P^{\max}=0,V\leq -X\Pi_2)
\end{aligned}
\tag{16}
$$

The underlying assumption is that groups who suffer less attrition—in this case, students eligible for partial grants with a GPA below 2.0—include both always- and induced-students. In contrast, students eligible for full aid consist solely of always-students. Additionally, always-students on either side of the income threshold are assumed to be comparable.[15] This assumption allows the observed difference in non-persistence rates between students below and above the income threshold, among those with a GPA below 2.0, to reflect students who discontinue college because of their grant loss.

Students eligible for partial grants who lost their grants can be decomposed into always-students and induced-students as follows:

$$
\begin{aligned}
&E[Y|P^{\max}=0,N^*\leq 0,G<2.0]\\
&=(1-\phi)\cdot E[Y|P^{\max}=0,V\leq -X\Pi_2,G<2.0]\\
&+\phi\cdot E[Y|P^{\max}=0,-X\Pi_2\leq V\leq -\delta-X\Pi_2,G<2.0]
\end{aligned}
\tag{17}
$$

We cannot identify which observations are always-students ($V \leq -X\Pi_2$) and which are induced-students ($-X\Pi_2 \leq V \leq -\delta - X\Pi_2$).[16] Let ϕ denote the estimated share of induced-students whose GPA is below 2.0 and who are eligible for partial grants, i.e., $\phi = \frac{P(-X\Pi_2<V\leq -\delta-X\Pi_2)}{P(V\leq -\delta-X\Pi_2)} \approx \frac{P(N^*\leq 0|P^{\max}=0,G<2)-P(N^*\leq 0|P^{\max}=1,G<2)}{P(N^*\leq 0|P^{\max}=0,G<2)}$. To construct the worst-case bound for the mean value of always-students with a GPA below 2.0 among those eligible for partial grants, I trim the upper tail of the observed Y distribution by the proportion

[15]The results in Table B2 indicate that students with a GPA above 2.0 are comparable below and above the income threshold, showing no discontinuity at the income threshold in persistence and completion rates, except for enrollment status in the fourth year.

[16]Maximum Pell Grant recipients who persist in college despite having a GPA below 2.0 are assumed to be the always-students, while those eligible for partial grants who did not persist are assumed to be the never-students. The observed difference in non-persistence rates between these groups reflects the induced-students—those whose persistence decisions were directly affected by the loss of their grant.

ϕ, while the best-case bound is obtained by trimming the lower tail of the distribution by ϕ. In other words, under the worst-case scenario, all induced-students who lost their grants among those above the income threshold are assumed to score at the $1-\phi^{th}$ percentile of the observed distribution. Under the best-case scenario, they are assumed to score at the ϕ^{th} percentile of the observed distribution. The upper and lower bounds can be estimated as follows:

$$\begin{aligned} E^{\min}[Y|P^{\max}=0, V \leq -X\Pi_2, G < 2.0] &= E[Y|P^{\max}=0, N^* \leq 0, G < 2.0, Y \leq y_{1-\phi}] \\ E^{\max}[Y|P^{\max}=0, V \leq -X\Pi_2, G < 2.0] &= E[Y|P^{\max}=0, N^* \leq 0, G < 2.0, Y \geq y_{\phi}] \end{aligned} \tag{18}$$

This method produces tighter bounds if the proportion of the sample requiring bounding is smaller.

IV. Results

1. The Effects on Degree Completion and Academic Outcomes

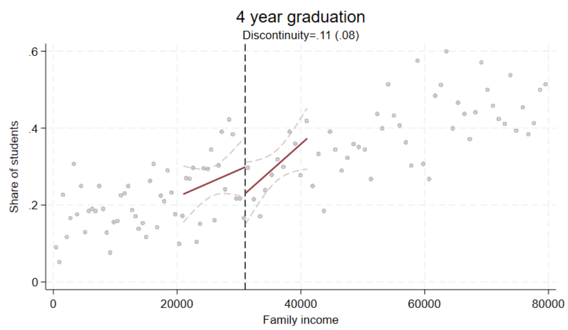
1..1 Naive RD Estimates

Figure 3 and Table 4 present conventional and robust RD estimates on completion and academic outcomes, along with robust bias-corrected (RBC) confidence intervals. The naive RD results show that students qualifying for the maximum grant aid achieve a GPA that is 0.55 points higher in their first year of college compared with those receiving adjusted grant amounts. However, no significant effect is observed on cumulative GPA. Similarly, no significant effects are found on completion rates.

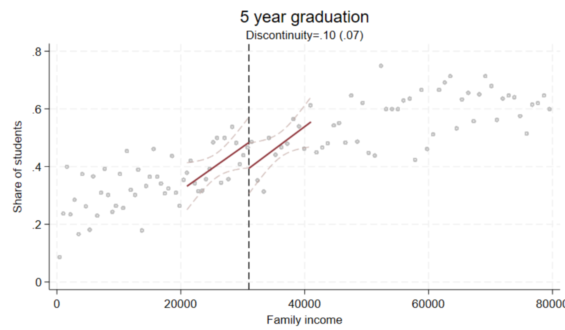
To test the robustness of the estimates, I replicate the results using various bandwidths. Table B1 shows the effects of AZ eligibility on the outcomes of interest using various bandwidths. Columns 1 and 2 use bandwidths that are \$1,000 and \$2,000 narrower, while Columns 4 and 5 apply bandwidths that are \$1,000 and \$2,000 wider. Column 3 reports results using the optimal bandwidth. The estimates remain relatively stable, suggesting that the results are robust to changes in bandwidth length. In Column 6, I test whether the results are sensitive to the functional form of the relationship between the outcomes of interest and the EFC by adding a quadratic term of the EFC and its interaction with the quadratic term. The polynomial specification is not significant, indicating that the relationship between the outcomes and the EFC is locally linear.

Figure 3: The Effect of AZ Eligibility on Student Outcomes

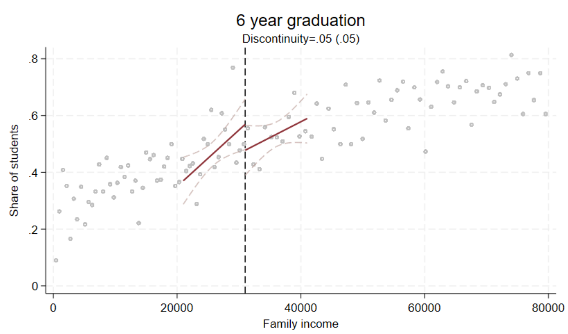
(a) 4-year graduation



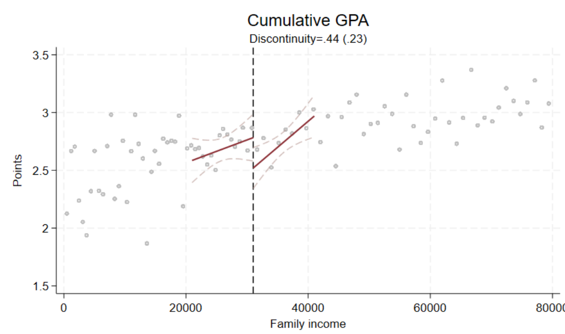
(b) 5-year graduation



(c) 6-year graduation



(d) Cumulative GPA



Notes: Each figure shows bias-corrected RD estimates from a local linear regression of each outcome variable on AGI, noted at the top of each figure, with the standard error shown in parentheses. Solid red lines indicate estimates from local linear regression, and light rose dotted lines represent the robust biased-corrected (RBC) confidence intervals.
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

Table 4: The Effect of AZ Eligibility on Completion Rates

	Completion			Grade Point Average	
	4 years	5 years	6 years	First-year	Cum
	(1)	(2)	(3)	(4)	(5)
AZ eligibility					
Conventional	.03	.10	.09	.55**	.10
	(.08)	(.09)	(.09)	(.25)	(.16)
Robust	.04	.11	.10	.56**	.11
	(.09)	(.10)	(.09)	(.26)	(.17)
CI	[-.13, .21]	[-.08, .30]	[-.08, .28]	[.05, 1.08]	[-.22, .44]

Notes: This table shows conventional and bias-corrected RD estimates of the effect of AZ eligibility on four-, five-, and six-year completion rates, and first-year and cumulative GPA, along with robust bias-corrected (RBC) confidence intervals. 'First-year' GPA refers to a student's cumulative GPA during their first year of enrollment (2011-2012). 'Cumulative' GPA refers to a student's cumulative GPA at the last known institution they attended. All models control for age, gender, enrollment status, tuition and fees in 2011-2012, total institutional aid in 2011-2012 (including institutional grants), total Stafford loans borrowed, parental receipt of federal benefits in 2011-2012, and parental education level. All analyses use BPS sampling weights.
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

While the naive RD analysis finds insignificant effects of Pell Grants on completion rates, the bound estimates show larger positive effects after adjusting for selection. This suggests that earlier estimates might have underestimated the true impact of eligibility for additional grant aid. Table 5 presents the conventional RD estimates, adjusted for selection, along with 95 percent confidence intervals obtained using the percentile method.[17] Panel A shows the bound estimates under the monotonicity assumption on potential outcomes, and Panel B displays the results under the monotonicity assumption on dropout rates.

Under the assumption of monotonicity in potential outcomes, students eligible for the maximum Pell Grant amount are up to 4 percentage points more likely to graduate within four years after college entry compared with those eligible for partial grants. Even in the worst case, they are at least 2 percentage points more likely to graduate within four years. This suggests that previous estimates may have been underestimated.

Similarly, maximum Pell Grant recipients are up to 11 percentage points more likely to graduate within five years. In the worst-case scenario, they are still up to 7 percentage points more likely to graduate within five years. Their likelihood of graduating within six years ranges from 3 to 12 percentage points higher. While the grant also has a positive effect on

[17] Students with GPAs just below and just above the threshold include those with GPAs between 1.0–2.0 and 2.0–3.0, respectively. This bandwidth is based on the results from Table 3.

cumulative GPA, the magnitude is relatively small—maximum Pell Grant recipients graduate with a GPA up to 0.17 points higher.

Assuming monotonicity in dropout rates, the results remain consistent. Eligibility for the maximum Pell Grant increases four-year, five-year, and six-year graduation rates by up to 6, 12, and 13 percentage points, respectively. Even in the worst-case scenario, recipients are at least 3, 10, and 10 percentage points more likely to graduate within four, five, and six years, respectively, relative to those eligible for partial grants.

Notice that the monotonicity assumption in response rates produce wider bounds, as a larger share of the sample requires imputation compared with the monotonicity assumption on potential outcomes. Specifically, under the monotonicity assumption on potential outcomes, between 4 and 8 percent of those eligible for the maximum grant amount and between 2 and 7 percent of those eligible for the partial grants required imputation. In contrast, under the monotonicity assumption on response rates, 16 percent of students who were eligible for partial grants but lost their eligibility must be imputed.

Table 5: Bounding the Effect of AZ Eligibility on Student Outcomes

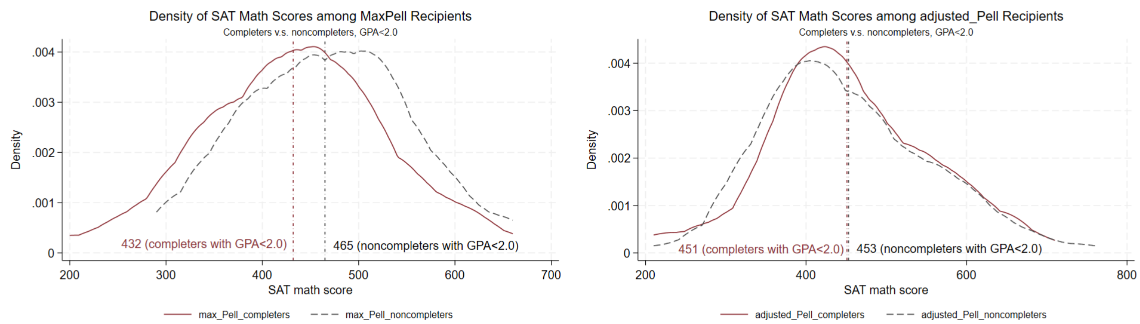
	Completion			Grade Point Average
	4 years	5 years	6 years	
	(1)	(2)	(3)	(4)
Panel A. Monotonicity in potential outcomes				
Bounds	[.016, .041]	[.075, .114]	[.027, .123]	[.008, .170]
CI	[-.009, .074]	[.048, .131]	[.002, .156]	[-.017, .215]
Panel B. Monotonicity in response rates				
Bounds	[.034, .056]	[.097, .122]	[.093, .125]	[.095, .105]
CI	[-.106, .133]	[-.004, .217]	[-.006, .236]	[-.092, .275]

Notes: This table presents conventional RD estimates adjusted for selection effects under different monotonicity assumptions. The lower confidence limit for the lower bound and the upper confidence limit for the upper bound of the estimates are reported. The first row of each panel presents the range of the effect of eligibility for the maximum Pell Grant on four-, five-, and six-year graduation rates, and cumulative GPA, with confidence intervals shown in the second row.
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

One could argue that linking academic requirements to need-based financial aid eligibility may improve aid efficiency by filtering out students whose costs of finishing college may outweigh the benefits. However, evidence suggests that the policy also discourages students who may be capable of completing college. Figure 4 (a) shows the distribution of SAT math scores for maximum-award Pell recipients who failed to meet SAP requirements in their first year, further broken down by students who completed college to those who did not. Figure 4 (b) presents similar distributions for Pell recipients with adjusted awards who did not meet SAP criteria. The results indicate that eligible students who lost their grant and did not

Figure 4: Distribution of SAT Math Scores Between Completers and Non-Completers with a GPA Below 2.0

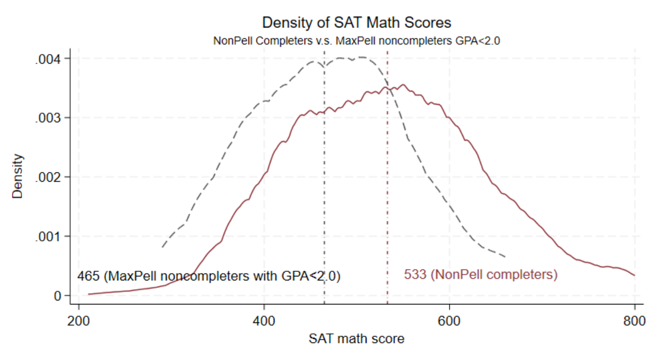
(a) Density SAT Math MaxPell (b) Density SAT Math AdjustedPell



Notes: These figures display the density of SAT math scores for completers and non-completers, separated by eligibility for the maximum Pell Grant and those with less aid, among students who failed to meet Satisfactory Academic Progress (SAP) requirements. The Kolmogorov-Smirnov test results indicate that, among students below the income threshold, those who did not persist and complete college had, on average, higher SAT math scores than those who completed college, with this difference being significant at the 5 percent level. In contrast, no significant difference in SAT math scores was observed among students receiving less aid. These findings suggest that the SAP policy may be pushing out students who are capable of completing college.

Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

Figure 5: Distribution of SAT Math Scores Between Non-Pell Recipients and Max-Pell Recipients with a GPA Below 2.0



Notes: This figure displays the density of SAT math scores for completers and non-completers, separated by eligibility for the maximum Pell Grant and those with less aid, among students who failed to meet Satisfactory Academic Progress (SAP) requirements. The Kolmogorov-Smirnov test results indicate that Non-Pell recipients who completed college have higher SAT math scores, on average, with a difference significant at the 1 percent level compared with Max-Pell recipients who did not complete college and lost their grants. However, a substantial portion of the Max-Pell recipients have SAT math scores above the average of Non-Pell recipients. These findings suggest that the SAP policy may be pushing out students who are capable of completing college.
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

persist in college had, on average, higher SAT math scores than those who lost their grant but completed college. The Kolmogorov-Smirnov test results reveal that the differences between the distributions of these two groups are significant at the 5 percent level. However, no such difference was found among students receiving less aid. Furthermore, Figure 5 compares the SAT score distribution between non-Pell recipients who completed college and maximum-award Pell recipients, particularly those who lost their grant and did not complete college. While non-Pell recipients have a higher average SAT score, a substantial number of eligible students who lost their aid and did not complete college have SAT math scores that exceed the average of non-Pell recipients. This suggests that students who lost grant eligibility but were capable of completing college may have been pushed out due to the SAP policy. If they had continued, it could have led to larger positive effects on student outcomes than previously estimated.

V. Conclusion

Using nationally representative student-level data and a RD design, this paper argues that previous estimates of the effects of maximum grant aid eligibility on student outcomes may be underestimated if selection bias due to grant loss is not considered. While initial Pell Grant eligibility is entirely determined by financial need, students must meet SAP requirements after their first year of college, which typically include maintaining a GPA of 2.0 or higher. Students eligible for the maximum Pell Grant are less likely to persist in college after losing their grant compared with those qualifying for partial grants. This non-random attrition from the sample makes the students who remain below and above the income threshold incomparable. To address this selection bias, I provide bounds on LATE using two monotonicity assumptions.

While naive RD estimates show no effect on graduation rates or academic outcomes, the bounding results find larger positive effects. Students eligible for full aid are up to 4, 7, and 12 percentage points more likely to graduate within four, five, and six years, respectively. Even in the worst-case scenario, they are at least 2, 6, and 3 percentage points more likely to graduate. Under an alternative monotonicity assumption, the results remain consistent: eligible students are up to 7, 11, and 12 percentage points more likely to graduate within four, five, and six years after college entry.

SAP requirements are implement to help students complete their degrees on time and may potentially benefit students by filtering out those who are either not interested in or not capable of completing college. I also find that a substantial portion of Pell recipients who lost their grant and did not persist in college had higher SAT math scores than the average non-Pell recipient who graduated. These findings suggest that not every student who seems to be pushed out due to grant loss is incapable of completing college. As Schudde and Scott-Clayton (2016) discuss, financial factors may cause students to drop out too early. Furthermore, Scott-Clayton and Schudde (2020) note that students are often unaware of SAP requirements until they lose their aid. These students could benefit from timely guidance on both academic and SAP progress. Providing earlier warnings to at-risk students might allow them to retain their grants, potentially leading to greater positive effects of aid on student outcomes than previously estimated.

References

Abdulkadiroğlu, Atila, Parag A Pathak, and Christopher R Walters, "Free to choose: Can school choice reduce student achievement?," *American Economic Journal: Applied Economics*, 2018, *10* (1), 175–206.

Anderson, Drew M, Katharine M Broton, Sara Goldrick-Rab, and Robert Kelchen, "Experimental evidence on the impacts of need-based financial aid: Longitudinal assessment of the Wisconsin Scholars Grant," *Journal of Policy Analysis and Management*, 2020, *39* (3), 720–739.

Angrist, Joshua, David Autor, Sally Hudson, and Amanda Pallais, "Evaluating post-secondary aid: Enrollment, persistence, and projected completion effects," Technical Report, National Bureau of Economic Research 2017.

Bailey, Martha J and Susan M Dynarski, "Gains and gaps: Changing inequality in US college entry and completion," Technical Report, National Bureau of Economic Research 2011.

Baum, Sandy and Judith Scott-Clayton, "Redesigning the Pell Grant program for the twenty-first century," 2013.

Bettinger, Eric, "How financial aid affects persistence," in "College choices: The economics of where to go, when to go, and how to pay for it," University of Chicago Press, 2004, pp. 207–238.

_ and Betsy Williams, "Federal and state financial aid during the great recession," in "How the financial crisis and great recession affected higher education," University of Chicago Press, 2013, pp. 235–262.

Bettinger, Eric P, Bridget Terry Long, Philip Oreopoulos, and Lisa Sanbonmatsu, "The role of application assistance and information in college decisions: Results from the H&R Block FAFSA experiment," *The Quarterly Journal of Economics*, 2012, *127* (3), 1205–1242.

Bound, John, Michael F Lovenheim, and Sarah Turner, "Why have college completion rates declined? An analysis of changing student preparation and collegiate resources," *American Economic Journal: Applied Economics*, 2010, *2* (3), 129–157.

Bryan, Michael, Darryl Cooney, and Barbara Elliott, "2012/17 Beginning Postsecondary Students Longitudinal Study (BPS: 12/17) Data File Documentation. (NCES 2020-522)," *U.S. Department of Education, National Center for Edcuation Statistics.*, Washington, DC: U.S. Government Printing Office.

Carruthers, Celeste K and Jilleah G Welch, "Not whether, but where? Pell grants and college choices," *Journal of Public Economics*, 2019, *172*, 1–19.

Castleman, Benjamin L and Bridget Terry Long, "Looking beyond enrollment: The causal effect of need-based grants on college access, persistence, and graduation," *Journal of Labor Economics*, 2016, *34* (4), 1023–1073.

Deming, D and S Dynarski, "Into college, out of poverty? Policies to increase the postsecondary attainment of the poor (Working Paper No. 15387)," 2009.

Denning, Jeffrey T, "Born under a lucky star: Financial aid, college completion, labor supply, and credit constraints," *Journal of Human Resources*, 2019, *54* (3), 760–784.

_ , Benjamin M Marx, and Lesley J Turner, "ProPelled: The effects of grants on graduation, earnings, and welfare," *American Economic Journal: Applied Economics*, 2019, *11* (3), 193–224.

Dynarski, Susan and Judith Scott-Clayton, "Financial aid policy: Lessons from research," 2013.

Eng, Amanda and Jordan Matsudaira, "Pell grants and student success: Evidence from the universe of federal aid recipients," *Journal of Labor Economics*, 2021, *39* (S2), S413–S454.

Goldrick-Rab, Sara, Robert Kelchen, Douglas N Harris, and James Benson, "Reducing income inequality in educational attainment: Experimental evidence on the impact of financial aid on college completion," *American Journal of Sociology*, 2016, *121* (6), 1762–1817.

Hansen, W Lee, "Impact of student financial aid on access," *Proceedings of the Academy of Political Science*, 1983, *35* (2), 84–96.

Kane, Thomas J, "Rising public college tuition and college entry: How well do public subsidies promote access to college?," 1995.

Lee, David S, "Training, wages, and sample selection: Estimating sharp bounds on treatment effects," 2009.

_ and Thomas Lemieux, "Regression discontinuity designs in economics," *Journal of economic literature*, 2010, *48* (2), 281–355.

Lindo, Jason M, Nicholas J Sanders, and Philip Oreopoulos, "Ability, gender, and performance standards: Evidence from academic probation," *American economic journal: Applied economics*, 2010, *2* (2), 95–117.

Liu, Vivian Yuen Ting, "Is school out for the summer? The impact of year-round pell grants on academic and employment outcomes of community college students," *Education Finance and Policy*, 2020, *15* (2), 241–269.

Manski, Charles F. and John V. Pepper, "Monotone Instrumental Variables: With an Application to the Returns to Schooling," *Econometrica*, 2000, *68* (4), 997–1010.

Marx, Benjamin M and Lesley J Turner, "Borrowing trouble? Human capital investment with opt-in costs and implications for the effectiveness of grant aid," *American Economic Journal: Applied Economics*, 2018, *10* (2), 163–201.

McCrary, Justin, "Manipulation of the running variable in the regression discontinuity design: A density test," *Journal of econometrics*, 2008, *142* (2), 698–714.

McKinney, Lyle and Heather Novak, "FAFSA filing among first-year college students: Who files on time, who doesn't, and why does it matter?," *Research in Higher Education*, 2015, *56*, 1–28.

Montalbán, José, "Countering moral hazard in higher education: The role of performance incentives in need-based grants," *The Economic Journal*, 2023, *133* (649), 355–389.

Park, Rina Seung Eun and Judith Scott-Clayton, "The impact of Pell Grant eligibility on community college students' financial aid packages, labor supply, and academic outcomes," *Educational Evaluation and Policy Analysis*, 2018, *40* (4), 557–585.

Rattini, Veronica, "The effects of financial aid on graduation and labor market outcomes: New evidence from matched education-labor data," *Economics of Education Review*, 2023, *96*, 102444.

Schudde, Lauren and Judith Scott-Clayton, "Pell grants as performance-based scholarships? An examination of satisfactory academic progress requirements in the nation's largest need-based aid program," *Research in Higher Education*, 2016, *57*, 943–967.

Scott-Clayton, Judith and Lauren Schudde, "The consequences of performance standards in need-based aid: Evidence from community colleges," *Journal of Human Resources*, 2020, *55* (4), 1105–1136.

Seftor, Neil S and Sarah E Turner, "Back to school: Federal student aid policy and adult college enrollment," *Journal of Human resources*, 2002, pp. 336–352.

Turner, Lesley J, "The economic incidence of federal student grant aid," *University of Maryland, College Park, MD*, 2017, *1000.*

Turner, Sarah, "Federal Financial Aid: How Well Does It Work? in J.Smart,ed.," *Higher education: Handbook of theory and research*, 2000.

U.S. Department of Education, "Federal Student Aid Handbook, 2011-2012," Technical Report 2011.

_ , "The EFC Formula, 2011-2012," Technical Report 2022.

_ , "The EFC Formula, 2022-2023," Technical Report 2022.

_ , "Student Financial Aid component final data (2008-09 - 2020-21) and provisional data (2021-22)," 2022.

A Appendix: Bounds on LATE Under a Monotonicity Assumption on Potential Outcomes

Identifying the treatment effect requires knowledge of the counterfactual outcomes for students who did not persist in college due to their grant loss, had they completed college. However, disentangling selection bias from the treatment effect is infeasible as the true relationship between student persistence and the outcome variable cannot be directly estimated; therefore, the treatment effect can only be bounded. I construct two nonparametric bounds on the Local Average Treatment Effect (LATE) using the following monotonicity assumptions: one on potential outcomes and another on the dropout process.

To apply the first monotoicity assumption, I propose the following throught experiment: *What would the completion rates be if students who lost their grant had retained it?* To carry out this experiment, I divide students into three groups: the *always-students*, *induced-students*, and *never-students*. The always-students are those who persist in college regardless of their eligibility for full or partial grant amounts, i.e., $P(N(0, P^{\max}) = 0, N(1, P^{\max}) = 0)$; the induced-students are those who are induced to persist in college due to their grant, $P(N(0, P^{\max}) = 1, N(1, P^{\max}) = 0)$, and the never-students are those who never finish college regardless of grant, $P(N(0, P^{\max}) = 1, N(1, P^{\max}) = 1)$. Each of these groups can be further divided into 12 subgroups based on their GPAs: substantially below 2.0, just below 2.0, just above 2.0, and substantially above 2.0. Students with a GPA of 2.0 or above are not subject to selection, whereas those with a GPA below 2.0 are.

I first estimate the probability of a student with a GPA just below 2.0 being an induced-student. The conditional probability of not persisting in college ($N = 1$), given an income below the threshold and a GPA just below 2.0, can be decomposed as follows:

$$\begin{aligned} P(N = 1|X = c^-, G = 2.0^-) &= P(N(0, 1) = 1, N(1, 1) = 0|X = c^-, G = 2.0^-) \\ &\quad + P(N(0, 1) = 1, N(1, 1) = 1|X = c^-, G = 2.0^-) \end{aligned} \tag{19}$$

Those who leave college despite having a GPA just above 2.0 are the never-students:

$$P(N = 1|X = c^-, G = 2.0^+) = P(N(0, 1) = 1, N(1, 1) = 1|X = c^-, G = 2.0^+) \tag{20}$$

Assuming that the probability of being never-students is continuous in GPA, one can estimate $P(N(0, 1) = 1, N(1, 1) = 0|X = c^-, G = 2.0^-)$ by subtracting $P(N = 1|X = c^-, G = 2.0^+)$ from $P(N = 1|X = c^-, G = 2.0^-)$. The probability of a student with a GPA significantly above 2.0 being a never-student can be estimated as $P(N(0, 1) = 1, N(1, 1) = 1|X = c^-, G > 2.0^+) = P(N = 1|X = c^-, G > 2.0^+)$. The probability of a student with a GPA just below 2.0 being a never-student can be estimated as follows: $P(N(0, 1) = 1, N(1, 1) = 1|X = c^-, G = 2.0^-) = P(N = 1|X = c^-, G = 2.0^+)$. Similarly, the probability of a student with a GPA just above 2.0 being a never-student can be estimated as follows: $P(N(0, 1) = 1, N(1, 1) = 1|X = c^-, G = 2.0^+) =$

$P(N=1|X=c^-,G=2.0^+)$. Lastly, the probabilities of being a never-students and an induced-students with a GPA significantly below 2.0 cannot be distinguished from one another and can only be estimated together: $P(N(0,1)=1,N(1,1)=1|X=c^-,G<2.0^-)+P(N(0,1)=1,N(1,1)=0|X=c^-,G<2.0^-)=P(N=1|X=c^-,G<2.0^-)$.

I next estimate the probability of a student who persists in college and has an income below the income threshold. Assuming that the probability of being always-students is continuous in GPA, one can estimate $P(N(0,1)=1,N(1,1)=0|X=c^-,G=2.0^+)$. The conditional probability of staying in college (N=0), given an income below the threshold and a GPA just above 2.0, can be decomposed as follows:

$$\begin{aligned} P(N=0|X=c^-,G=2.0^+) &= P(N(0,1)=0,N(1,1)=0|X=c^-,G=2.0^+) \\ &\quad + P(N(0,1)=1,N(1,1)=0|X=c^-,G=2.0^+) \end{aligned} \tag{21}$$

Those who persist in college despite having a GPA just below 2.0 are the always-students:

$$P(N=0|X=c^-,G=2.0^-)=P(N(0,1)=0,N(1,1)=0|X=c^-,G=2.0^-) \tag{22}$$

Then, the probability of a student with a GPA just above 2.0 being an induced-student, $P(N(0,1)=1,N(1,1)=0|X=c^-,G=2.0^+)$, can be estimated by subtracting $P(N=0|X=c^-,G=2.0^-)$ from $P(N=0|X=c^-,G=2.0^+)$. The probability of a student with a GPA significantly below 2.0 being an always-student can be estimated as $P(P(0,1)=0,N(1,1)=0|X=c^-,G<2.0^-)=P(N=0|X=c^-,G<2.0^-)$. Similarly, the probability of being a student with a GPA just below 2.0 can be estimated as follows: $P(N(0,1)=0,N(1,1)=0|X=c^-,G=2.0^-)=P(N=0|X=c^-,G=2.0^-)$. The probability of being a student with a GAP just above 2.0 being an always-student can be estimated as follows: $P(N(0,1)=0,N(1,1)=0|X=c^-,G=2.0^+)=P(N=0|X-c^-,G=2.0^-)$. Lastly, the probabilities of being an always-students and an induced-students with a GPA significantly above 2.0 cannot be distinguished from one another and can only be estimated together $P(N(0,1)=0,N(1,1)=0|X=c^-,G>2.0^+)+P(N(0,1)=1,N(1,1)=0|X=c^-,G>2.0^+)=P(N=0|X=c^-,G>2.0^+)$. The probability of a student being always-students, induced-students, or never-students across various GPA levels with incomes above the threshold can be similarly estimated.

Students from the induced-students and the never-students groups with a GPA substantially below 2.0 are indistinguishable; thus, let ϕ_1 represent $P(N(0,1)=1,N(1,1)=0|X=c^-,G<2.0^-)$. Similarly, students from the always-students and the induced-students groups with a GPA substantially above 2.0 are indistinguishable; thus, let ϕ_2 represent $P(N(0,1)=0,N(1,1)=0|X=c^-,G>2.0^+)$. Similarly, let ϕ_3 represent $P(N(0,0)=1,N(1,0)=0|X=c^+,G<2.0^-)$ and let ϕ_4 represent $P(N(0,0)=0,N(1,0)=0|X=c^+,G>2.0^+)$.

The expected value of potential outcomes for students with income below the threshold and a

GPA substantially below 2.0 can be rewritten as follows:

$$
\begin{aligned}
&E[Y(1)|X=c^-,G<2.0^-] \\
&= E[Y|N=0,X=c^-,G<2.0^-]P(N=0|X=c^-,G<2.0^-) \\
&+ E[Y(1)|N(0,1)=1,N(1,1)=0,X=c^-,G<2.0^-]\phi_1 \\
&+ E[Y(1)|N(0,1)=1,N(1,1)=1,X=c^-,G<2.0^-](P(N=1|X=c^-,G<2.0^-)-\phi_1)
\end{aligned}
\tag{23}
$$

Researchers must differentiate between students who discontinue college due to grant loss and those who would not have persisted in college regardless of receiving the grant. Induced-students with a GPA below 2.0 fall into the first group, while never-students belong to the second group. The bias arises from these induced-students who withdraw college because of grant loss.

I impose the following monotonicity assumption: the potential outcomes for the always-students are at least as good as those for the induced-students, and the outcomes for the induced-students are at least as good as those for the never-students, conditional on treatment. This assumption is similar to the Monotone Treatment Selection (MTS) assumption introduced by Manski and Pepper (2000), which assumes that expected potential outcomes shift in a particular direction when individuals are treated, i.e., $E[Y(P^{\max})|N(0,P^{\max})=0,N(1,P^{\max})=0] \geq E[Y(P^{\max})|N(0,P^{\max})=1,N(1,P^{\max})=0] \geq E[Y(P^{\max})|N(0,P^{\max})=1,N(1,P^{\max})=1]$ where $P^{\max}=\{0,1\}$. Under the monotonicity assumption, the observed outcomes of the always-students with GPAs below 2.0 can serve as an upper bound for the counterfactual outcomes of the induced-students with GPAs below 2.0. The upper bound of $E[Y(1)|X=c^-]$ can be obtained as:

$$
\begin{aligned}
&E_{\max}[Y(1)|X=c^-] \\
&\quad= \Big(E[Y|N=0,X=c^-,G<2.0^-](P(N=0|X=c^-,G<2.0^-) \\
&\quad+ P(N=1|X=c^-,G<2.0^-))\Big)P(G<2.0^-|X=c^-) \\
&\quad+ \Big(E[Y|N=0,X=c^-,G=2.0^-]\big(P(N=0|X=c^-,G=2.0^-) \\
&\quad+ P(N=1|X=c^-,G=2.0^-)-P(N=1|X=c^-,G=2.0^+))\Big)P(G=2.0^-|X=c^-) \\
&\quad+ E[Y|N=0,X=c^-,G=2.0^+]P(N=0|X=c^-,G=2.0^+)P(G=2.0^+|X=c^-) \\
&\quad+ E[Y|N=0,X=c^-,G>2.0^+]P(N=0|X=c^-,G>2.0^+)P(G>2.0^+|X=c^-)
\end{aligned}
\tag{24}
$$

The monotonicity assumption does not provide lower bounds; thus, the lower bounds for counterfactual completion rates must be conjectured. While completion rates range between 0 and 1, 0 cannot serve as a lower bound because, under the assumption, induced-students left college due to their grant loss. To construct the lower bound, an additional assumption is required: the counterfactual completion rates for these students are assumed to be similar to those at the 10th percentile of the college completion distribution for observed students with similar GPA and income levels. Finally, the lower bound of $E[Y(1)|X = c^-]$ can be obtained as:

$$\begin{aligned}
&E_{\min}[Y(1)|X = c^-] \\
&\quad = \big(E[Y|N = 0, X = c^-, G < 2.0^-]P(N = 0|X = c^-, G < 2.0^-)P(G < 2.0^-|X = c^-) \\
&\quad + \Big(E[Y|N = 0, X = c^-, G = 2.0^-]P(N = 0|X = c^-, G = 2.0^-) \\
&\quad + \tau_{Y_{10}|N=0,X=c^-,G=2.0^-}(P(N = 1|X = c^-, G = 2.0^-) \\
&\quad - P(N = 1|X = c^-, G = 2.0^+))\Big)P(G = 2.0^-|X = c^-) \\
&\quad + E[Y|N = 0, X = c^-, G = 2.0^+]P(N = 0|X = c^-, G = 2.0^+)P(G = 2.0^+|X = c^-) \\
&\quad + E[Y|N = 0, X = c^-, G > 2.0^+]P(N = 0|X = c^-, G > 2.0^+)P(G > 2.0^+|X = c^-)
\end{aligned} \tag{25}$$

where $\tau_{Y_{10}|N=0,X=c^-,G}$ represents the 10th percentile of the college completion distribution for students with similar GPA and income levels who complete college. For other academic outcomes, such as GPA, the worst value of GPA takes a value of 2.0, which is a graduation requirement for most institutions in the U.S. Similarly, the upper and the lower bound of $E[Y(0)|X = c^+]$ can be obtained as follows in a similar manner.

To obtain the upper bound of LATE, $\Gamma(c) = E[Y(1) - Y(0)|X = c]$, one can subtract the lower bound on $E[Y(0)|X = c^+]$ from the upper bound on $E[Y(1)|X = c^-]$. To obtain the lower bound, subtract the upper bound on $E[Y(0)|X = c^+]$ from the lower bound on $E[Y(1)|X = c^-]$:

$$\Gamma^{\text{UB}}(c) = E_{\max}[Y(1)|X = c^-] - E_{\min}[Y(0)|X = c^+] \tag{26a}$$

$$\Gamma^{\text{LB}}(c) = E_{\min}[Y(1)|X = c^-] - E_{\max}[Y(0)|X = c^+] \tag{26b}$$

B Appendix: Additional Tables and Figures

Table B1: Robustness of the Effect of AZ Eligibility on Student Outcomes

	Bandwidth widths					Functional form
	-2,000	-1,000	Optimal	+1,000	+2,000	
	(1)	(2)	(3)	(4)	(5)	(6)
4-year completion rate						
Conventional	.03	.04	.03	.02	.02	.03
	(.09)	(.09)	(.08)	(.08)	(.07)	(.09)
Robust	.05	.03	.04	.01	.01	.02
	(.13)	(.13)	(.09)	(.11)	(.11)	(.09)
CI	[-.31, .21]	[-.27, .22]	[-.13, .21]	[-.21, .23]	[-.20, .22]	[-.16, .21]
5-year completion rate						
Conventional	.10	.10	.10	.10	.09	.12
	(.10)	(.09)	(.09)	(.08)	(.08)	(.10)
Robust	.13	.11	.11	.10	.10	.13
	(.14)	(.13)	(.10)	(.12)	(.11)	(.10)
CI	[-.14, .40]	[-.14, .37]	[-.08, .30]	[-.13, .33]	[-.12, .32]	[-.07, .32]
6-year completion rate						
Conventional	.08	.07	.09	.09	.08	.14
	(.10)	(.09)	(.09)	(.08)	(.08)	(.10)
Robust	.07	.07	.10	.06	.07	.14
	(.14)	(.13)	(.09)	(.12)	(.11)	(.10)
CI	[-.20, .33]	[-.18, .32]	[-.08, .28]	[-.17, .29]	[-.15, .29]	[-.05, .33]
cumulative GPA						
Conventional	.06	.09	.10	.10	.10	.14
	(.17)	(.16)	(.16)	(.15)	(.15)	(.18)
Robust	.02	.01	.11	.06	.07	.15
	(.21)	(.21)	(.17)	(.20)	(.19)	(.18)
CI	[-.39, .44]	[-.39, .42]	[-.22, .44]	[-.32, .45]	[-.31, .45]	[-.21, .50]

Notes: This table replicates the results from Table 4 using different bandwidths. Columns 1 and 2 use bandwidths \$2,000 and \$1,000 smaller than the optimal, respectively. Column 3 shows the results with the optimal bandwidth, while Columns 4 and 5 use bandwidths \$1,000 and \$2,000 larger. Column 6 tests the sensitivity of the results to the functional form of the relationship between the outcomes of interest and the EFC by including a quadratic term of the EFC and its interaction with the quadratic term.
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

Table B2: Discontinuity at the Income Threshold in Persistence and Completion Among Pell Recipients with a GPA Above 2.0

	Persistence			Graduation		
	Second	Third	Fourth	4 years	5 years	6 years
	(1)	(2)	(3)	(4)	(5)	(6)
Conventional	-.03	-.08	-.15*	-.06	-.13	-.13
	(.05)	(.07)	(.08)	(.09)	(.10)	(.10)
Robust	-.03	-.09	-.17*	-.06	-.14	-.14
	(.06)	(.07)	(.08)	(.10)	(.11)	(.11)
CI	[-.14, .08]	[-.23, .06]	[-.33, .00]	[-.25, .13]	[-.35, .07]	[-.35, .07]

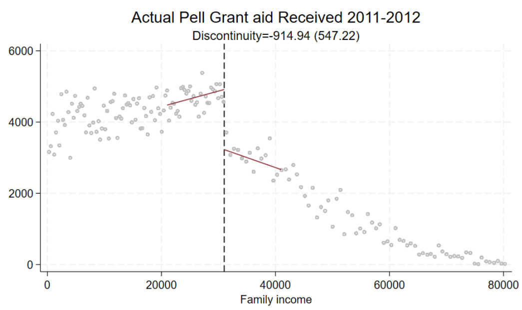
Notes: This table shows the discontinuity at the income threshold in persistence and completion rates among Pell Grant recipients with a GPA above 2.0. All models control for age, gender, enrollment status, tuition and fees in 2011-2012, total institutional aid in 2011-2012 (including institutional grants), total Stafford loans borrowed, parental receipt of federal benefits in 2011-2012, and parental education level. All analyses use BPS sampling weights. The sample size is rounded to the nearest 10.

* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level

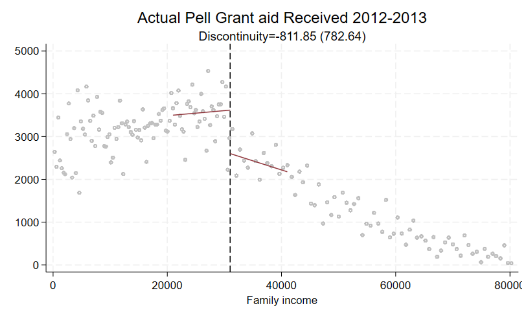
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

Figure B1: Discontinuity in Actual Pell Grant

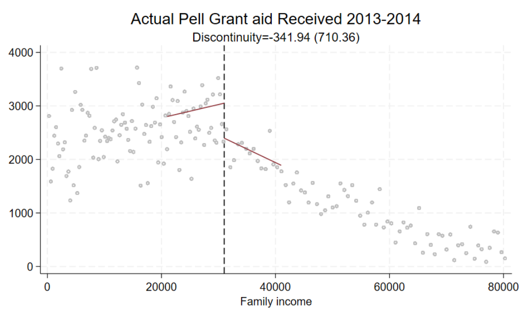
(a) Actual Pell, 2011-2012



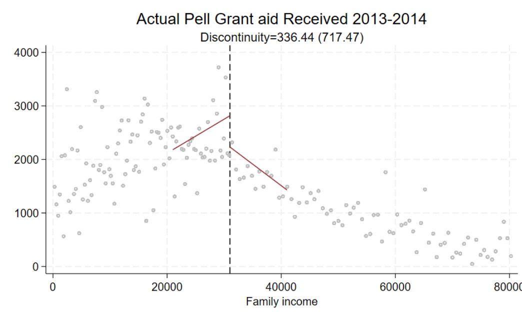
(b) Actual Pell, 2012-2013



(c) Actual Pell, 2013-2014



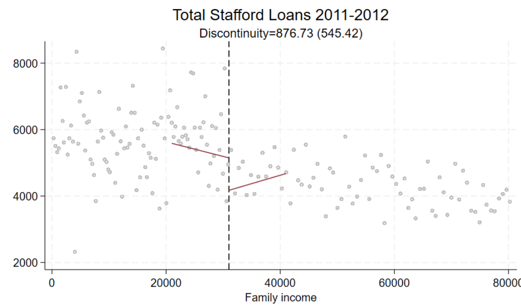
(d) Actual Pell, 2014-2015



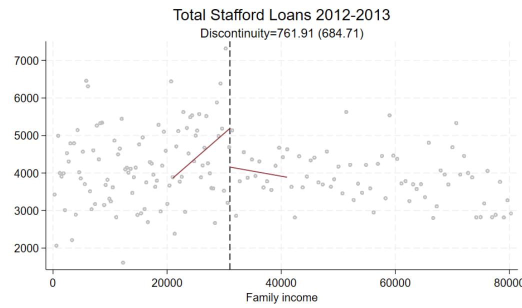
Notes: These figures display the actual Pell Grant received by first-time undergraduate students who entered college in the 2011-2012 academic year, and students who were either dependent and independent students with dependents. A dashed line represents the automatic-zero (AZ) income threshold, set at $31,000 for the 2011-2012 academic year. The Pell-eligible amount may not be equal to the actual Pell Grant received by students, as the final amount considers other factors beyond the EFC, such as the cost of attendance, enrollment intensity, and whether students were enrolled for a full academic year. Each figure shows bias-corrected RD estimates from a local linear regression of each outcome variable on AGI, noted at the top of each figure, with the standard error shown in parentheses. Solid red lines indicate estimates from local linear regression, and light rose dotted lines represent the robust biased-corrected (RBC) confidence intervals. In the first year (2011-2012), students just below the income threshold received an additional $915 in Pell Grant than those just above the threshold. This gap reduced to $812 in the second year (2012-2013) and became insignificant, further decreasing to $342 and $336 in the third and fourth years, respectively. This reduced gap can be partially explained by a decreased share of students enrolled as full-time students and by students who transferred to 2-year institutions.
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

Figure B2: Discontinuity in Other Grants

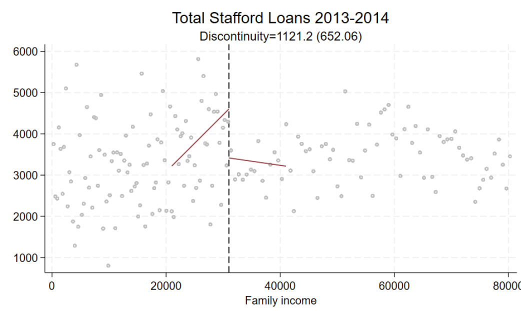
(a) Stafford Loan, 2011-2012



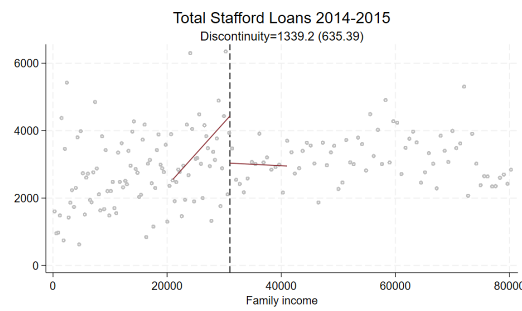
(b) Stafford Loan, 2012-2013



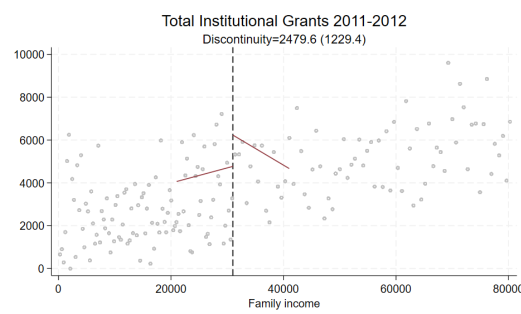
(c) Stafford Loan, 2013-2014



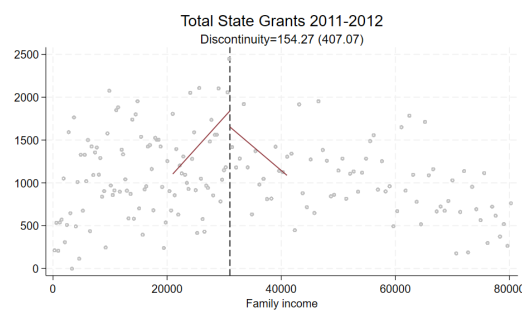
(d) Stafford Loan, 2014-2015



(e) Total Inst Grants, 2013-2014

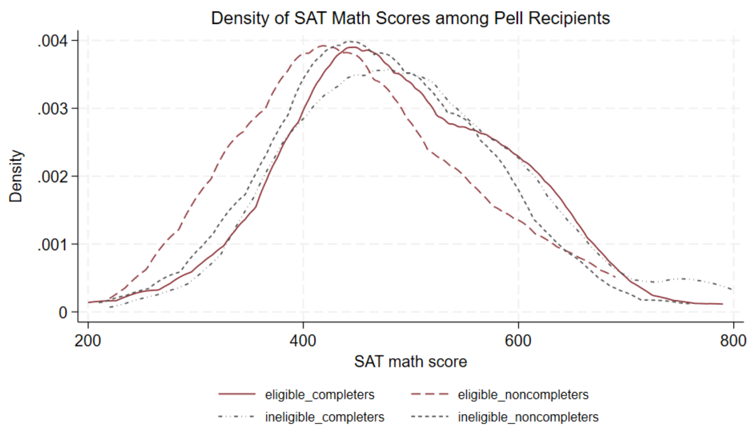


(f) Total State Grants, 2014-2015



Notes: These figures illustrate the discontinuities in Stafford Loans from the first to the fourth years, as well as the discontinuities in total institutional grants and total state grants during the first year. Each figure shows bias-corrected RD estimates from a local linear regression of each outcome variable on AGI, noted at the top of each figure, with the standard error shown in parentheses. Solid red lines indicate estimates from local linear regression, and light rose dotted lines represent the robust biased-corrected (RBC) confidence intervals. In the first year (2011-2012), students just below the income threshold borrowed $877 more in Stafford loans, including both subsidized and unsubsidized, than those just above the threshold. This gap narrowed to $762 in the second year (2012-2013) but increased to $1,121 and $1,339 in the third and fourth years, respectively. Additionally, students above the threshold received about $2,480 more in institutional grants in their first year.
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

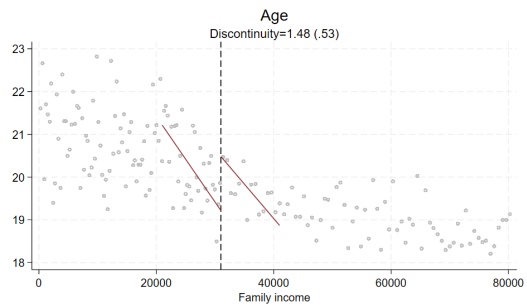
Figure B3: Density of SAT Math Scores Among Pell Recipients



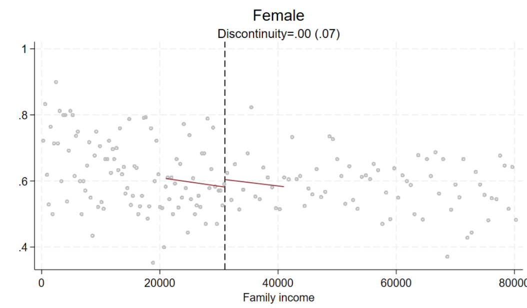
Notes: This figure shows the density of SAT math scores within the analyzed sample. The results of the Kolmogorov-Smirnov test show that among students below the income threshold, those who did not persist in college had significantly lower SAT math scores compared with those who did, with this difference being significant at the 1 percent level. Similar findings were observed among students above the income threshold; those who did not persist in college had lower SAT math scores, with the gap being significant at the 5 percent level.
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

Figure B4: Discontinuity in Students' Observable Demographic Characteristics

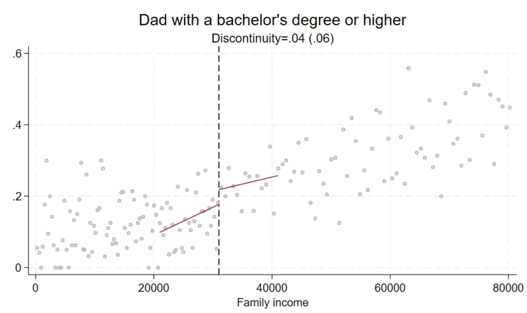
(a) Age



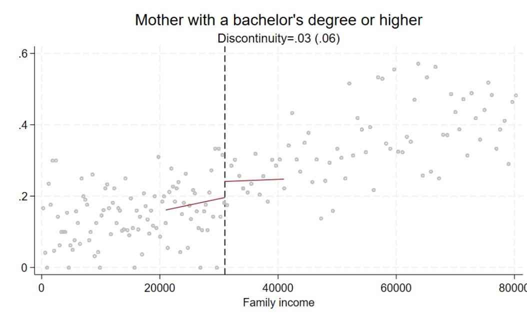
(b) Female



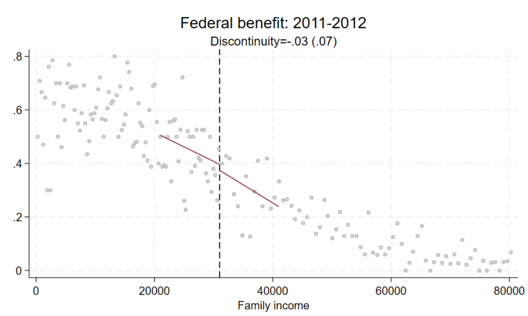
(c) Dad bachelor's degree



(d) Mom bachelor's degree



(e) Federal benefits

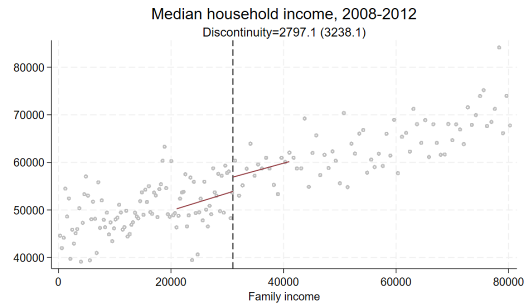


Notes: These figures show the discontinuities in students' observable demographic characteristics at the AZ income threshold. Each figure shows bias-corrected RD estimates from a local linear regression of each outcome variable on AGI, noted at the top of each figure, with the standard error shown in parentheses. Solid red lines indicate estimates from local linear regression.

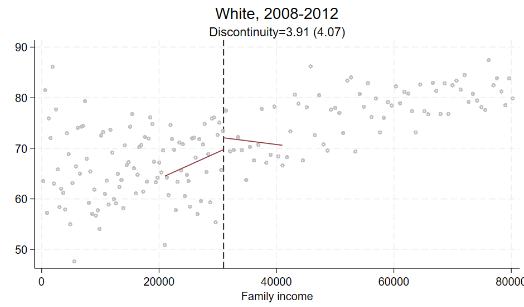
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

Figure B5: Discontinuity in Students' Census Tract Information, 2008-2012

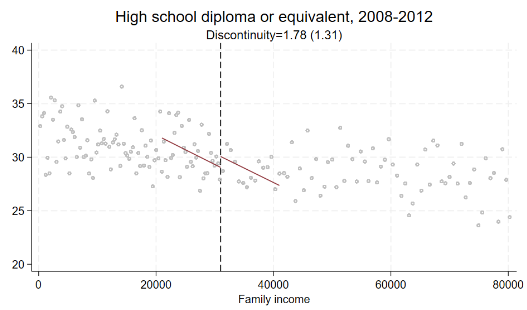
(a) Median household income



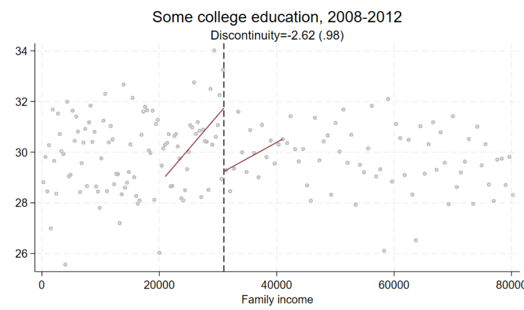
(b) White population



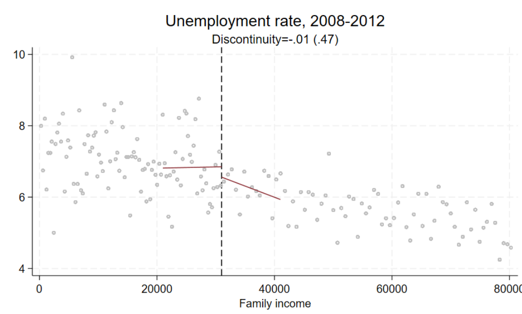
(c) High school diploma or equivalent



(d) Some college education

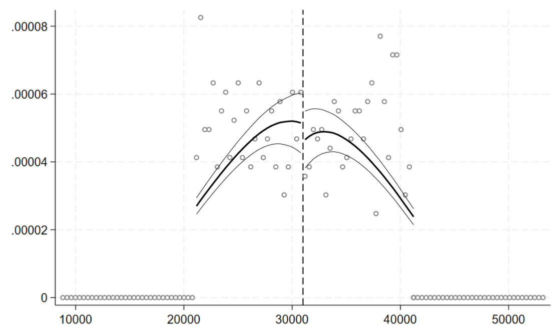


(e) Unemployment rate



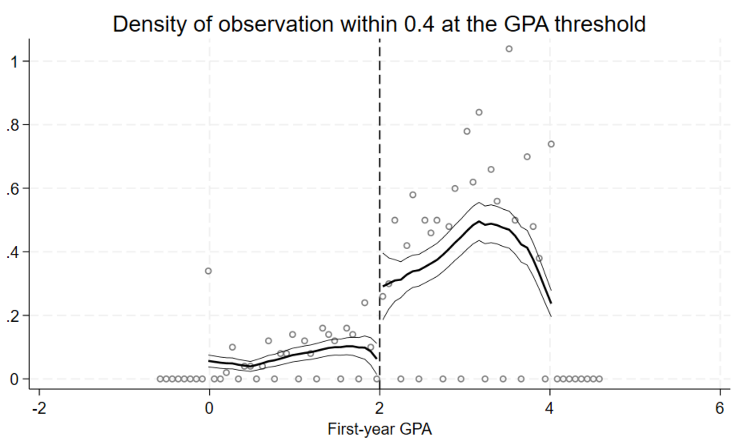
Notes: These figures show the discontinuities in students' census tract information for the period 2008-2012 at the AZ income threshold. Each figure shows bias-corrected RD estimates from a local linear regression of each outcome variable on AGI, noted at the top of each figure, with the standard error shown in parentheses. Solid red lines indicate estimates from local linear regression. The 'Median household income' figure shows the median household income within students' census tracts from 2008-2012. The 'White' figure indicates the percentage of the tract population that was white during this period. The 'High school diploma or equivalent' figure shows the percentage of the population over age 25 within the students' census tracts who held a high school diploma or equivalent. Similarly, the 'Some college education' figure shows the percentage of the population over age 25 with some college education. Finally, the 'Unemployment rate' figure represents the percentage of the population over the age of 16 within the students' census tracts who were unemployed.
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

Figure B6: Density of observations withing ± 10,000 at the AZ threshold



Notes: This figure shows the density of observations on family income within approximately ±$ 10,000 around the AZ income threshold for the analyzed sample. Using the density test introduced by McCrary (2008), the analysis reveals a discontinuity estimate of -0.11, with a standard error of 0.14.
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study

Figure B7: Density of observations within ± 0.4 at the GPA Threshold



Notes: This figure shows the density of observations within ± 0.4 at the 2.0 GPA threshold for the analyzed sample. Using the density test introduced by McCrary (2008), the analysis reveals a discontinuity estimate of 2.52, with a standard error of 0.87.
Source: 2012/2017 Beginning Postsecondary Students Longitudinal Study