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ABSTRACT

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The Long Run Impacts of Merit Aid: Evidence from California's Cal Grant

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We examine the impacts of being awarded a Cal Grant, among the most generous state merit aid programs. We exploit variation in eligibility rules using GPA and family income cutoffs that are ex ante unknown to applicants. Cal Grant eligibility increases degree completion by 2 to 5 percentage points in our reduced form estimates. Cal Grant also induces modest shifts in institution choice at the income discontinuity. At ages 28-32, Cal Grant receipt increases by three percentage points the likelihood of living in California at the income discontinuity, and raises earnings by four percentage points at the GPA discontinuity.

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Over the last twenty years, the United States has gone from being the world leader in the percentage of high school students that go on to graduate with a B.A. or other four-year college degree to ranking 19th in the world.[1] The Obama Administration, state governments, and policymakers at all levels have prioritized increasing college enrollment and completion to improve U.S. competitiveness and to reduce income inequalities.

Need- and merit-based aid are perhaps the most visible policy levers that states use to offset tuition and other costs. State aid programs have become more prominent over the past two decades, with funding increasing by 83% from 2002 to 2012 (NASSGAP, 2012). Merit-aid programs in particular have expanded from Arkansas and Georgia in the early 1990s to over twenty state programs (Domina, 2014; Doyle, 2006). Such financial aid programs have a variety of goals including decreasing the net cost of attendance, reducing "brain drain" out of state, and making salient the fact that college attendance can be low-cost or tuition free for large groups of targeted students (e.g. Dynarski 2008; Scott-Clayton 2011; Cohodes and Goodman 2014).

There is relatively little research to date that would allow financial aid programs to measure their long-run return on investment. Causal impacts of financial aid have been predominately restricted to short-term college attendance and bachelor degree completion outcomes. However recent work in other areas, such as early childhood education, suggest that a program's long-term impacts may swamp short-term gains (Chetty et al., 2011; Dynarski, Hyman, & Schanzenbach, 2013) and that educational programs may actually pay for themselves through increased future tax revenues (Bettinger et al., 2016). The ultimate returns of financial aid require policymakers to observe a more diverse set of outcomes, which would include how aid impacts labor force decisions, mobility, health, family formation, and other economically critical decisions. This requires the ability to follow students over a much longer time-frame than has previously been available.

We examine impacts from California's Cal Grant program, one of the largest and most generous state merit aid programs as measured by number of students and overall expenditure.[2] The Cal Grant system contains a number of features that make it ideal for examining financial aid's long-

[1] *OECD Education at a Glance* 2014.

[2] For example, the Cal Grant awarded over $1.6 billion in grants for the 2013-14 academic year.

term impact. Individual-level data on Cal Grant applicants exist beginning with the high school graduating cohort of 1998. These data allow us to track students for over fifteen years after they enter college. Given that the two best administrative data sources for college-going – National Student Clearinghouse and 1098-T tax forms – only become available or reliable around this time period, these data are likely to serve as the best source of aid's long-term impacts on degree completion available in the United States. In contrast to many other state aid programs, Cal Grant can be applied to tuition at any in-state public or private institution. Tuition at public institutions is completely covered, and private school tuition is subsidized between nine to ten thousand dollars per year.

The Cal Grant also presents an ideal opportunity for analysis because eligibility is based upon a series of strict cutoffs in family income and high school GPA. Crucially, in the years of our analysis the location of these cutoffs was not known to applicants ahead of time. We use the discontinuities to identify two subpopulations of students: (1) students whose family incomes lie below the income cutoff, but whose GPAs are near the minimum GPA cutoff; and (2) students who meet the minimum GPA requirement, but whose family incomes are near the income threshold. These discontinuities represent separate populations, and as we show, the heterogeneity in estimated impacts across discontinuity are informative. We estimate the impact of the Cal Grant on a variety of outcome variables using a regression discontinuity design. We improve on Kane's (2003) earlier analysis of the Cal Grant by using a larger sample, a longer follow-up period, and a broader set of outcomes than previously available. Specifically, we combine Cal Grant application and receipt data with data from the National Student Clearinghouse, administrative tax returns, and federal student loan data to estimate impacts of the Cal Grant on college enrollment and completion, student loans, earnings and employment status, and geographic mobility.

We find that Cal Grant receipt has no meaningful effect on overall college attendance, in part due to college-going rates among this population being quite high.[3] At the income discontinuity, we find shifts in the type of college a student attends: attendance at four-year private institutions increases by 5.7 percentage points, with an offsetting reduction in attendance rates at public

[3] Completing a FAFSA is a condition for Cal-Grant application. It is not surprising then that a high percentage of our sample attends college.

California universities. The Cal Grant also raises graduation rates by 4.6 percentage points at the income discontinuity. Students at the income discontinuity are also 3.1 percentage points more likely to reside in California between ages 28 and 32, on average, as a result of Cal Grant eligibility.

Near the GPA threshold we do not detect any evidence of shifting of institution type in the first year following high school graduation. However there are noticeable effects on four year college attendance three and four years after high school graduation, likely because the Cal-Grant increases persistence in college. We find that the Cal Grant significantly increases the probability of earning a Bachelor or graduate degree among this relatively lower-achieving population by over 2.6 and 2.3 percentage points, respectively, which correspond to increases of roughly 5% and 16%. Point estimates on earnings suggest that Cal Grant may raise earnings by 4.7 percentage points on average between ages 28 and 32 for those at the GPA discontinuity; however, the year-by-year estimates are quite imprecise.

Our paper furthers research on the impact of federal student aid policies, such as the American Opportunity Tax Credit, the suspended Hope Scholarship, and the Lifetime Learning Credit. Like the Cal Grant A, these federal tax incentives for higher education are targeted to middle and higher-income students and provide financial support of a similar magnitude to students who choose to use the Cal Grant towards a four-year public California institution. Understanding the impacts of programs like the Cal Grant can inform the design of these other student aid programs. In addition, our analyses inform the extent to which state-based aid programs impact the utilization of these and other sources of federal student aid, and their implications for long-run residency and earnings.

I. Prior Literature

The Human Capital model (e.g., Becker (1975)) suggests that individuals attend college when the expected benefits exceed the costs. Broadly, the goal of financial aid is to decrease the cost of college, especially among those who are liquidity-constrained. Aid can alter students' cost-benefit calculus and induce additional students to enroll and persist. Indeed, the literature has documented positive effects of financial aid on attendance, persistence, and completion (Bettinger, 2004; Bettinger, Long, Oreopoulos, & Sanbonmatsu, 2012; Dynarski, 2003;

Goldrick-Rab, Kelchen, Harris, & Benson, 2016; Hoxby & Turner, 2013; Kane, 2007; Scott-Clayton, 2011; Seftor & Turner, 2002).

State-based merit-aid programs have multiple goals. First, by setting minimum academic thresholds for eligibility, they can incentivize additional academic effort at the high school level, a key predictor of college completion. A number of authors find that well-designed incentives can increase human capital accumulation in high school, potentially reduce state expenditures (e.g. by reducing time to degree), and accelerate students' entry into the labor market by one or more years (Domina, 2014; Henry & Rubenstein, 2002; Pallais, 2009; Scott-Clayton, 2011).

Second, merit aid may directly affect college attendance and completion rates through: a) reducing liquidity constraints that prevent students from attending, b) enabling students to travel farther to better institutions, c) decreasing the need to work during college, thus allowing students to concentrate more on their studies. There is significant evidence that state aid programs, whether through merit-based, need-based, or hybrid programs, can increase college attendance rates and completion rates, though results vary by state (Castleman & Long, forthcoming; Cornwell, Mustard, & Sridhar, 2006; Dynarski, 2000, 2004, 2008; Kane, 2003; Scott-Clayton, 2011; Singell & Stone, 2002; Van Der Klaauw, 2002).[4] Merit aid may also increase human capital accumulation if it produces additional effort or alters students' use of time by, for example, reducing the hours needed to work (DesJardins, McCall, Ott, & Kim, 2010).

Finally, a third goal of state-based programs is to decrease "brain drain" by increasing the likelihood that top-performing students stay locally for college and enhancing the stock of college-educated adults within the state. Unlike other forms of aid (e.g., Pell grants), state-based merit aid prioritizes specific institutions to keep the strongest students within state, which is particularly important as the market for high-performing students becomes increasingly national (Hoxby, 2009). In doing so, states hope to experience stronger economic growth, increase their tax base (Groen, 2004)), and generate other benefits to individuals within their state (Oreopoulos & Petronijevic, 2013). Evidence on whether aid induces students to attend college in-state is

[4] Only a few of papers on financial aid use a regression discontinuity design, with other work relying on difference-in-difference estimation using large-scale nationally representative datasets (e.g., Dynarski, 2008).

mixed, with research suggesting aid reduced out-migration in Georgia, with no equivalent effect in Tennessee (Cornwell et al., 2006; Pallais, 2009). The few available studies that examine long-term workforce outcomes rely on large panel data estimates and find that merit aid increased the likelihood that students resided within state through their early 30s, though estimated effects are generally small (Fitzpatrick & Jones, 2012; Sjoquist & Winters, 2013, 2014; Zhang & Ness, 2010). However the only study that relied on student-level microdata found no effect on long-term retention within Georgia (Sjoquist & Winters, 2013).

The effects of state aid programs likely depend on program details such as minimum academic thresholds, income limits, the size of the award, or the renewal requirements while in college (Domina, 2014; Long, 2004; Sjoquist & Winters, 2014). As one example, Cal Grant provides larger tuition subsidies for private institutions than it does for public institutions; most states provide either equal or smaller tuition payments to private institutions (Domina, 2014). The heterogeneity in program design across states may partly explain the divergence in results found across previous studies.

Our study is the first to construct a causal regression discontinuity estimate of merit-aid receipt on long-term mobility and employment outcomes. An additional strength is the timeframe currently available, which includes over a dozen years of follow up data to estimate academic and workforce outcomes. This longer timeframe is crucial for studying workforce outcomes, as individual earning profiles flatten significantly for individuals in their early 30s (Chetty, Hendren, Kline, & Saez, 2014; Haider & Solon, 2006), the age at which we can now observe these students. An additional benefit of using individual-level data is that we estimate returns to aid, as measured by both college completion and administrative earnings records. We compare these returns to the monetary amount spent on each student. Our results shed light on whether merit-based aid expenditures, which have totaled billions of dollars over the last few decades, are producing their intended effects.

II. Institutional Details, Research Design and Sample Construction

A. Overview of the Cal Grant Program

The Cal Grant program is a need- and merit-based financial aid program administered by the California Student Aid Commission (CSAC). CSAC offers several awards that vary in their target populations and benefits. We focus on what is referred to as “Cal Grant A” for the high school graduating cohorts of 1998-99 through 2000-01. This award provides four years of full-time tuition assistance. Tuition at California State University (CSU) or the University of California (UC) was approximately $1,500 and $3,500, respectively, in the late 1990s. In addition, students could use Cal Grant A to attend any in-state private institution, with the award subsidizing between $9,000 and $9,700 depending on the year.[5] Students could not use Cal Grant A to attend a community college, but the award could be put on hold for up to two years for students who wished to delay four-year enrollment.[6]

Baseline eligibility for the Cal Grant requires applicants to be a California resident (either a U.S. citizen, permanent resident, or eligible non-citizen), have no defaults on federal loans, and have not previously earned a Bachelor degree. Students must have submitted the FAFSA and a GPA verification form, which was to be completed by the high school attended, by March 2nd.[7] The GPA verification form is completed by the high school and sent directly to CSAC. In addition, applicants are disqualified if their assets (excluding housing value and retirement funds) exceed some limit.[8]

The primary form of eligibility for recent high school graduates depends on a student meeting a minimum GPA requirement and being below specific income thresholds. Importantly, these eligibility rules fluctuated because of changes in annual funding during our analysis period, resulting in several plausibly exogenous discontinuities in eligibility. First, the income limits varied from year to year using cost of living increases based on the California Constitution. These limits would have been almost impossible for families to calculate and anticipate. We compare students on either side of these income thresholds. In 1998 the income limits ranged from $53,100 for family of three or fewer to $67,000 for families of six or larger, and in 2000 ranged from $59,000 to $74,100 for the same categories. Second, income-eligible applicants

[5] Subsidy amounts were $9,036, $9,420, and $9,708, for the 1998, 1999, and 2000 cohorts, respectively.
[6] California community college tuition was $11 per unit in 1999-2000, which was the lowest rate in the nation.
[7] In practice, CSAC included all applications received by March 12th, to allow for potential complications in the mail.
[8] During our sample period dependent students and independent students with dependents were disqualified if they had assets (excluding housing value) between $42,000 and $49,600 (depending on the year). Independent students without dependents (other than a spouse) were required to have assets below $20,000 and $25,110 (depending on the year).

were ranked by GPA in descending order and were offered awards until funding was exhausted. This produced a GPA cutoff for eligibility that was unknown to applicants *a priori*. The resulting GPA cutoffs were 3.15, 3.09 and 2.95 for 1998, 1999 and 2000, respectively. We compare income-eligible students who fall on either side of these GPA thresholds. Figure 1 shows how the GPA cutoff varied by year until 2001-02 when it was fixed (and publicly known) at 3.0.

For students near the GPA discontinuity, there is a second income limit – about half the size of the maximum income allowed – that is used to allow "low-income" students to compete for an alternate grant award, Cal Grant B. For some of students falling below this low-income threshold, the GPA threshold is not meaningful. Specifically, students earning above a specific number of "points" were guaranteed a Cal Grant award. Points were earned through GPA and family income, along with other demographic characteristics, and the point threshold varied from year to year.[9] As a result, very low-income students near the GPA cutoff generally earned a Cal Grant, so crossing the GPA threshold has no impact on award receipt.[10] We remove point-eligible students from our analysis so that crossing the GPA threshold shifts students from no award eligibility to being eligible for Cal Grant A. In our robustness and heterogeneity of effects analyses, we present GPA discontinuity results for these two income groups separately.

Finally, simply meeting the income or GPA requirements is a sufficient but not necessary condition for receiving the Cal Grant. In addition, a student or their family must also have sufficient "unmet financial need," which is calculated based on a student's potential expenses and expected family contributions.[11] We ignore this distinction and present reduced form results

[9] The other demographic factors were family size, parental education, and parental marital status. Students could earn up to 100 points, and the award-eligibility cutoff fell at roughly 50 to 60 points. The point values for GPA and income were assigned via a fairly convoluted process that differed than the simplistic Cal Grant A.

[10] Students with GPA near the threshold with family incomes below roughly $27,000 (for a family with two members in 2000) to $37,000 (for a family with five or more members in 2000) were generally guaranteed awards. For the sample of students who meet the points requirement, we find that crossing the GPA threshold has a precisely estimated null effect on award utilization (results available upon request). Although this point system offers the promise of an additional RD analysis, we do not study it here due to the relatively small sample size, as well as other technical details specific to how Cal Grant B was handled in those years.

[11] CSAC's "unmet need" requirement is different than what is generally reported from the FAFSA. To calculate whether a student has unmet need requires three steps. First, a student has listed up to six schools on their FAFSA, and each is assigned a Cost of Attendance. Second, CSAC subtracts a student's Expected Family Contribution from each school's Cost of Attendance to create the unmet need value. For

that include these students, due to both difficulty in calculating CSAC's unmet need and potentially endogeneity as student expenses are directly related to the types of institutions they wish to attend.

California expanded the Cal Grant program significantly in 2001-02, changing how awards were allocated (though the monetary value of the awards remained constant). Beginning in this year, the GPA threshold for Cal Grant A was set at 3.0 in perpetuity, and so could be known by applicants *a priori.* In addition, family income thresholds were more widely publicized at this time. We find evidence that applicants were likely aware of the eligibility thresholds beginning in these years.[12] Thus, we restrict our analysis to applicants prior to the 2001-02 academic year.

B. Research Design

Because the Cal Grant is allocated by a combination of academic achievement and financial need, simple comparisons of outcomes between financial aid recipients and non-recipients will likely produce biased estimates of the impact of financial aid, as family background and academic preparation are correlated with the likelihood of receiving aid, the amount of aid students receive, and the likelihood of attending and graduating from college. To estimate the causal impact of the Cal Grant on student outcomes, we exploit the GPA and income eligibility cutoffs using a regression discontinuity (RD) design, where we compare students who just qualified for a grant to similar students who were just ineligible by utilizing the Equation 1:

$$(1) \qquad Y_{it} = \beta_0 + \beta_1 * Distance_{it} + \beta_2 * CG_{it} + \beta_3 * CG_{it} * Distance_{it} + X_{it} + \varepsilon_{it}.$$

In this regression, Y_{it} is an outcome of interest (such as college enrollment or earnings) for student *i* in year *t*, CG_{it} is a variable that equals one if a student is Cal Grant eligible in year *t*, and $Distance_{it}$ is a continuous running variable that determines assignment to treatment in year *t*, centered at the year-specific eligibility cutoff. We run these regressions separately for the GPA

a student to be Cal Grant A eligible, a student must have unmet need equal to the maximum Cal Grant award amount available for that institution plus $1500, rather than simply having a positive COA-EFC.

[12] Correspondence with CSAC personnel indicates that 2002 was the first year that CSAC's "Fund Your Future Workbook" published the exact income limits. We find clear evidence of violations in the density of applicants around the income cutoff in later years, though the violation appears to be that ineligible families simply did not apply, rather than altered their income. We do not find strong evidence of violations around the GPA cutoff, but choose not to use these cutoffs at this time.

cutoff and for the income cutoff. We show a linear specification here, but $Distance_{it}$ can take a flexible functional form that includes higher-order polynomials. The vector X_i may contain baseline observable characteristics including cohort, family composition, gender, family assets, and mother and father education.[13] Thus, the parameter of interest, β_2, represents the intent-to-treat parameter or the causal effect of the offer of the Cal Grant award on our outcomes of interest. In practice, the inclusion of observable characteristics X_i is optional; their inclusion does not result in significant changes to our estimation of β_2 but improves precision for some of our outcomes, particularly for earnings. Standard errors are clustered by standardized GPA when exploiting the GPA cutoff because the assignment to treatment variable is discrete (Lee and Card 2008). We report heteroscedasticity robust standard errors for regressions using the income cutoff.

We also run the following instrumental variables (IV) regression:

$$(2) \qquad Award_{it} = \alpha_0 + \alpha_1 * Distance_{it} + \alpha_2 * CG_{it} + \alpha_3 * CG_{it} * Distance_{it} + X_{it} + \varepsilon_{it}$$
$$Y_{it} = \beta_0 + \beta_1 * Distance_{it} + \beta_2 * \widehat{Award}_{it} + \beta_3 * \widehat{Award}_{it} * Distance_{it} + X_{it} + \varepsilon_{it}$$

The first-stage regression predicts the likelihood that students utilize the Cal Grant at the margin. We then use these predicted values to estimate a Local Average Treatment Effect (LATE) for those induced to use the Cal Grant. This parameter estimates the effect for those who take up the treatment, as compared to those who were unlikely to use the treatment irrespective of their assignment.

There are several reasons why an applicant who satisfied the GPA and income eligibility requirements may not be awarded a grant. Some students may choose to not attend college or attend an out-of-state institution. Other students may be denied an award based on the unmet need requirement, which we are unable to precisely estimate. In addition, Cal Grant A cannot be used at a community college, which is a commonly attended institution for many students at the margins of GPA eligibility. Finally, students who are initially ineligible for the Cal Grant may later receive an award, generally via one of two ways. First, students initially apply for the award in 12th grade with their cumulative 10th and 11th grade GPA. If their 12th grade GPA pushes them

[13] All cutoffs include a "family size by year" fixed effect (where family size varies from two to "six or more") to account for the varying income eligibility cutoffs.

above the required margin, then can apply in the subsequent year with their new cumulative GPA. Second, CSAC began to offer an alternative "Competitive" award for older, non-traditional students who are two or more years out of high school, and some initially ineligible students may later qualify for this financially equivalent award.

In summary, we focus on two distinct cutoffs:

- *The "Income" Threshold*, which compares GPA eligible students just above and below the maximum income eligibility limits;
- *The "GPA" Threshold*, which compares income-eligible students just above and below the GPA eligibility criteria who were not eligible for Cal Grant B;

In both of these cases, students who meet the respective income or GPA requirements are eligible for Cal Grant A, provided that they satisfy the "unmet need" requirement. Students who do not meet the cutoff are not immediately eligible for any Cal Grant award.

C. Data and Sample Construction

Our sample consists of retrospective data on all students in California who were minimally eligible for the Cal Grant program, and submitted both a FAFSA and GPA verification form to CSAC during their final year of high school, which occurred between 1998 and 2000. Data on these hundreds of thousands of high school graduates who applied for the Cal Grant are provided by CSAC.

We gather outcome data from several sources. Data on college enrollment and degree completion come from the National Student Clearinghouse (NSC). The NSC data cover about 94 percent of all college enrollments and have significant degree completion records. NSC data provide information on all institutions that a student attended, dates attended, whether the student transferred, whether degrees were conferred, the types of institutions attended, the intensity of enrollment, and the length of time required for degree completion.[14]

[14] NSC data is increasingly used for tracking postsecondary outcomes, but is subject to bias due to missing data and errors in matching that rely on students' names and birthdates (Dynarski, Hemelt, & Hyman, 2015). In general we find that 1098-T tax forms provide similar estimates of college-going as NSC data.

As a supplemental source of information on college attendance, we collect information returns (Forms 1098-T) that colleges submit to the IRS to report "qualified educational expenses" in a given year. These are drawn from the population-based, administrative tax records for each student, available beginning in 1999. We match colleges on these information returns to institutions in the Integrated Postsecondary Education Data System (IPEDS) to identify the type of institution that a student attends. For each Cal Grant applicant, we also construct information on federal student aid that they have received. These data come from the National Student Loan Data System (NSLDS), a comprehensive national database of information on federal financial aid.

Labor market and mobility data are drawn from administrative, population-level U.S. federal tax filings. For each Cal Grant applicant, we construct a panel of tax returns spanning tax years 1999 through 2014, supplemented with several information returns filed with the IRS by third parties (e.g. W-2s filed by employers). Tax return data provide information on workforce outcomes, including household-level wage and non-wage earnings. We additionally collect the limited demographic information available on a tax return: marital status, number of children, and state of residence. Because tax returns provide earnings data conditional on filing a tax return, and because earnings are reported at the household level when married filing jointly, we also consider individual-level earnings data. These data come from Form W-2, the information return on wage and salary income filed by employers, and Form 1099-MISC, the information return on non-employee compensation. We compute labor income as the sum of earnings on these two tax forms. To account for outliers in these unedited data, we winsorize income variables at the 99th percentile.

In our baseline analysis, we use a 0.3 point bandwidth around the GPA eligibility cutoff, and a $10,000 bandwidth around the income eligibility cutoff, as suggested by cross-validation and Imbens and Kalyanaram (2012) optimal bandwidth techniques.[15] Table 1 shows summary statistics for the sample of 31,500 applicants who are within 0.3 points of the GPA discontinuity and 18,097 applicants who are within $10,000 of the income discontinuity. At the GPA

[15] In general the optimal bandwidth varies by both validation technique and outcome chosen (e.g., first-stage award utilization, degree completion). We err on the conservative side and use the shortest of the suggested bandwidths.

discontinuity 56 percent of applicants are female, and 86 percent are U.S. citizens. Forty-four percent attended a California public four-year institution, with an additional 9 percent initially attending some form of private college. Mean family income was $35,100 at the time of application. Twelve years after applying 86 percent of the sample is living in California. Forty-five percent are married and 37 percent have children.

Our two analytic samples are quite different from applicants in general because we focus on students near the eligibility thresholds. Students at the income discontinuity have higher incomes and high school GPA, are more likely to attend private colleges or four-year institutions, and were more likely to be employed. They were also more likely to be married but less likely to have children.[16] These differences potentially shed light on why results might vary across the two analytic samples.

D. Validation of the RD Design

Before turning to our main results, we provide evidence that the discontinuities in award eligibility can serve to produce unbiased estimates of the effects of state-based aid. The three key assumptions for the validity of an RD design are: (1) that the predicted discontinuity creates a large change in assignment to treatment as a function of the running variable; (2) any observed differences in the neighborhood of the discontinuity occur only as a result of differences in the running variables; and (3) that there is no evidence of manipulation in assignment to treatment near the discontinuity. We address each of these assumptions in turn.

Figure 2 shows that Cal Grant A utilization rates vary discretely at each eligibility cutoff. We pool our data across all years and center the running variable at zero for each year-specific threshold. The left panel of Figure 2 shows that the GPA threshold predicts close to a 40 percentage point increase in ever receiving a Cal Grant payment. Table 2 provides corresponding point estimates for Cal Grant receipt, and also shows that total CSAC payments increases by roughly $4,000 for the average student at the GPA cutoff.[17]

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[16] Results not reported.

[17] There are some students below the GPA cutoff who received Cal Grant awards. This is primarily due to three reasons: students who applied in their senior year could resubmit the following year by incorporating their 12th grade GPA; CSAC's Competitive award that became available in 2002 and was

There is a similar shift in Cal Grant utilization at the income threshold. See the right panel of Figure 2. In this and all future income-based figures, we multiply the running variable by -1 so that positive (negative) values correspond to Cal Grant eligibility (ineligibility). Table 2 shows that total payments received are significantly larger at the income threshold, at roughly $8,000 per award offer. This larger amount derives in large part from students at this threshold attend more expensive UC and private schools. IV estimates suggest that the average full payment for students who utilized the Cal Grant payments award were close to $11,000 and $19,000 at the GPA and income thresholds, respectively.

Next, we examine whether factors that are correlated with student outcomes change discontinuously at the thresholds that determine assignment to treatment. For each observable characteristic, X_{it}, we run the following regression:

(3) $X_{it} = \beta_0 + \beta_1 * Distance_{it} + \beta_2 * CG_{it} + \beta_3 * CG_{it} * Distance_{it} + \varepsilon_{it}$

In Appendix Table 1, we present estimates for β_2, which captures the difference in a covariate between those just above and just below the eligibility threshold. These results provide evidence of continuity across the thresholds. Importantly, we find that GPA is smooth at the income discontinuity, and vice versa, suggesting there is no systematic sorting of eligible students. We find no imbalance in the likelihood of being female, a U.S. citizen, or having married parents at the threshold. Appendix Figure A1 provides corresponding graphical evidence.

Finally, if students were able to manipulate assignment to treatment, then observable or unobservable characteristics of applicants may differ around the cutoff. In principle, there is limited scope for manipulation because it would have been difficult, if not impossible, to know the eligibility cutoffs *a priori*. Nevertheless, we provide evidence that there is no manipulation in the years of our analysis. Directly examining manipulation for the GPA threshold is difficult for two reasons. First, the McCrary test, which relies on non-parametric estimation, is problematic for discrete distributions (McCrary, 2008). Second, Cal Grant applicants who are high school seniors utilize their unadjusted 10th and 11th grade GPA, leading to a "lumpy" distribution.

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applicable for students more than one year removed from high school; we were able to eliminate some but not all point-eligible students at the "low-income" GPA threshold. In all cases we keep only the earliest Cal Grant application for each student, so thresholds are exogenous.

Appendix Figure A2 shows the exact distributions for GPA in each year. Although the number of applicants bunches at specific GPA points, especially at 3.0, this lumping is equivalent across the three years, with little observational evidence that students are sorting differentially with respect to the cutoff. An overlay of the three years shows that distributions are similar, even though the GPA thresholds changed markedly between years. Estimates that remove excessive heaps, such as those found at GPA values of 3.0, produce similar results and are provided in later Appendix tables. To check against the possibility of manipulation around the income cutoff, we examine the density of observations around the income threshold using the McCrary test (McCrary, 2008). Appendix Figure A3 shows that the distributions are smooth with no evidence of manipulation around income thresholds in the pre-expansion years.[18]

III. Results

In this section, we present results in two broad outcome categories: (1) college attendance and attainment, and (2) longer-run earnings and mobility outcomes. We examine effects at the GPA and income discontinuities separately. Importantly, the effects of Cal Grant eligibility (equation 1), and of Cal Grant utilization (equation 2) are identified using somewhat different groups of students depending on which discontinuity is being utilized. The students at the margin of the GPA cutoff are, on average, entering college with weaker academic preparation.

A. College Attendance and Completion

Table 2 presents results from estimating equation (1) on our educational attendance outcomes. We report reduced form impacts using linear slopes with rectangular kernels. Because college attendance outcomes using NSC data and 1098-T data produce similar results, we present NSC-based results in Appendix Table 2. Results using alternate functional forms over longer bandwidths or by removing heaps produce similar results, and are shown in Appendix Table 3.

The first two rows of Table 2 show results on degree attainment, with corresponding graphical results presented in Figure 3. We report both the reduced-form and instrumental variable results. At the GPA threshold, reduced-form estimates show that the likelihood that students achieved a

[18] The McCrary test at the income cutoff provides an estimate 0.0033 with a standard error of 0.0365 (t-stat=0.09) for the NSC sample and 0.0194 with a standard error of 0.0382 (t-stat=0.51) for the Treasury sample.

bachelor degree increased by 2.6 percentage points. The implied IV results suggest a 7.1 percentage point increase in college degree completion. We also consider effects on graduate degree completion. Using the GPA discontinuity we find that Cal Grant eligibility raises graduate degree completion by 2.3 percentage points. Although we do not show results here, the increased graduate degree completion at the GPA margin also occurs almost exclusively within California colleges.

At the income threshold, we find larger results on bachelor degree completion, with reduced form and IV estimates showing a 4.6 and 10.7 percentage point increase, respectively. In Appendix Table 4, we disaggregate these results by students who earned above and below a 3.5 high school GPA, as this cutoff predominately divides students into those who switched from community college to a private four-year (below 3.5 GPA) and those who switched from UC to a private four-year (above 3.5 GPA). Although we find positive completion effects for both groups, the magnitude on Bachelor degree completion for the low-GPA group is twice as large as the magnitude for the high-GPA group. In contrast to the GPA threshold, we find no significant effects on graduate degree completion, perhaps as these academically prepared students are significantly more likely in baseline to earn a graduate degree. Appendix Figure A4 shows year-by-year results on bachelor and graduate degree completion at the GPA and income thresholds. The pattern of results suggests that the Cal Grant impact is primarily on ever completing a degree, rather than simply reducing time-to-degree.

Table 2 indicates that Cal Grant eligibility had no meaningful impact on whether a student ever attended a post-secondary institution or a four-year public or private institution at the GPA margin (column 2 rows 3, 5, and 6).[19] The immediate college-going rate of this population is well above 70 percent (not shown) and the eventual rate is over 90 percent. For students around the GPA discontinuity, we also find that Cal Grant eligibility had no meaningful impact on the college sector attended.

The null result on attending a four year institution only holds in the first year or two following high school graduation. Appendix Figure A5 takes the GPA discontinuity and plots the estimated effects of Cal Grant eligibility by years since graduation. At four years post high

[19] We present estimates for one year after application because this is the first year for which we have 1098-T data for all cohorts.

school graduation, Cal Grant eligibility raises the likelihood of being in a four year university by about 3 percentage points and the effect is statistically significant. The most natural interpretation of these results (plus the bachelor degree attainment results) is that Cal Grant promotes college persistence.[20] In results not reported here, we find that Cal Grant eligible students accumulate about 0.02 additional years of total enrollment in four-year institutions each year, such that eligible students have about 0.08 extra years of education after four years (0.2 years in the IV estimate). As there are no initial enrollment impacts, these results suggest that enrolled students are less likely to drop out at each point along the way towards college completion.

At the income threshold, we find that the Cal Grant impacts college choice (Table 2 columns 5-6, rows 3-6). Cal Grant eligibility leads to a statistically significant 5.7 percentage point increase in private school attendance (row 6), and results are presented graphically in Figure 4. In Appendix Figure A6 we plot the effects of Cal Grant eligibility on private school choice against years since high school graduation. We see that the effect on private school choice is five to six percentage points and remains relatively constant from years one through four after high school graduation.

B. Long Run Earnings and Mobility

Table 3 presents a series of estimates on Cal Grant eligibility's impacts on whether the individual filed a tax return, log (labor income), log (adjusted gross income), and living in California (based on filing address). In all cases, we run stacked regressions for 10 through 14 years after the student applied for a Cal Grant, when most applicants would be between 28 and 32 years old. Standard errors in these specifications are clustered by household. Appendix Figure A7 shows year-by-year point estimates of the likelihood of filing a return at the GPA and income thresholds. In all cases the effects on filing a return are statistically insignificant, with the largest values approximately 1 percentage point.

Earnings estimates are noisy. At the GPA discontinuity, we find that Cal Grant eligibility raises labor income by roughly 4.7 percent and this effect is statistically significant at the 5 percent level. At the income discontinuity, we find positive impacts of 3.1 percentage points on in-state

[20] Cal Grant could cause students to a) persist within their initial college, b) transfer from two year to four year institutions or even c) make transfers within the four year sector that lead to persistence.

residency. Both results are presented graphically in Figure 5. Appendix Table A5 shows that wage results are relatively equal between students from high- and low- income families, but that residency results appear largest for low GPA students.

We examine the wage effects at the GPA threshold for each year post-application, and there is additional evidence suggesting impacts on earnings (Figure 6). The point estimates for years 8-14 are all positive and trending upward. Years 11-12 have statistically significant 0.05-0.06 effects on log(labor income).

We do not see hints of positive earnings effects around the income discontinuity. In particular the estimated effects on log (adjusted gross income) and log(labor income) averaged over years 10 through 14 are both near zero. Appendix Figure A8 plots these effects year by year. The estimated effects for "log labor income" remain near zero for most years. The lack of earnings effects at the income discontinuity is consistent with the fact that students at the income discontinuity are being induced into attending moderately selective or not selective four year privates away from four year publics. We did not a priori expect that switching to these privates would create large earnings effects.

In the fourth row of Table 3 we examine impacts of Cal Grant eligibility on mobility. At the income discontinuity we see a three percentage point increase in the likelihood of remaining in California, with year-by-year results plotted in Figure 7. This is particularly relevant as these students are the highest earners in the Cal Grant sample, and so might provide California the greatest return in increased revenues. At the GPA discontinuity we do not find any impact from Cal Grant A on remaining within California 10-14 years after award receipt; year-by-year results are plotted in Appendix Figure A9. Although this may be evidence against merit aid impacting out-migration, it also suggests that the additional graduates produced by the award are likely to remain within the state.

C. Cost-Benefit Discussion

Although economists recognize the need to lower college costs for liquidity constrained students, there is debate over whether aid is best allocated through formulaic merit- or need-based programs. Proponents of merit-aid programs suggest that aid is more effective when targeted towards students who have the necessary preparation to complete college. But this also suggests that the majority of merit payments may be subsidies to families who would have been willing to pay for college even in the absence of the program. Poorly designed programs might also have a negative educational impact on individuals, leading students to strategically reduced course loads or shift out of demanding STEM fields, possibly increasing time to degree or lowering completion rates (Cohodes & Goodman, 2014; Cornwell, Lee, & Mustard, 2005; Scott-Clayton, 2011; Sjoquist & Winters, 2015).

To the extent that aid subsidizes students to enroll in lower-quality institutions, states might not experience the gains in educated labor force or tax base as expected (Peltzman, 1973), though contextual factors such as the specific renewal requirements and the availability of competitive institutions play a role in the effectiveness of the program (e.g., Scott-Clayton (2011)). Finally, even if merit aid increases college enrollment and completion it may not necessarily lead to a stronger labor force, as recent work suggests that college may induce migration above and beyond where students initially attend (Malamud & Wozniak, 2012; Wozniak, 2010). Nonetheless, Dynarski (2008) provides one of the only cost-benefit analyses of state-based programs, and finds that they are socially efficient even if one assumes a low rate of return to schooling.

In order to provide a cost-benefit analysis for the Cal Grant program, we must first estimate the total cost of the program for the marginal student. Using data on total payments for each individual, the RD specification indicates that the marginal student received total payments across all years of $4,062 at the GPA discontinuity and $8,184 at the income discontinuity. This is substantially lower than the potential cost of roughly $36,000 per student, which would be the case if all individuals received the full four years of private subsidy. The net costs are lower because not everyone above the threshold qualifies for the award, many do not attend more expensive private schools or choose to not use it, and some students leave college without using all four years of payments.

Our reduced form point estimate is that the Cal Grant A eligibility raises bachelor degree receipt by two to five percentage points. Consider the strong assumption that the only impact of the program is to raise three of each one hundred students from “some college” to college completion, thus ignoring any graduate degree or other unobserved effects. The expenditure is equivalent to spending from $135,000 (i.e., $4062/0.03, in the case of the GPA discontinuity) to

$164,000 per additional B.A., (i.e., $8184/.05, at the income discontinuity). Moving an adult from some college to a bachelor's degree might raise earnings by an annuity of $20,000 for forty years for a net present value of around $360,000 at a 5% interest rate.

This back of the envelope suggests that Cal Grant's increased graduation rates could easily "pay" for the program if we think of program costs as being more than offset by the increased earnings. This is obviously a highly simplistic analysis because Cal Grant is really a transfer just as the increased earnings could be a transfer from one worker to another as opposed to a societal gain. Additionally, we do not have precise estimates of the actual earnings gains of the Cal Grant recipients.

A more realistic analysis would take into account the fact that Cal Grant may impact earnings through a whole variety of mechanisms including choice of institution, locational decisions, marital status, and student loan take up, among others. The challenge is that our earnings estimates are both large and noisy and encompass both positive and negative estimates. This makes it essentially impossible to ask whether the estimated earnings effects exceed the known costs. At the GPA discontinuity, our estimated 6 percentage point increase in earnings is large relative to the $4,000 cost.

Importantly the Cal Grant is largely a transfer from tax payers to students and their families. In other words the Cal Grant is not a pure deadweight loss but rather a transfer which may or may not have a deadweight loss. So even if the earnings gains for the average student are smaller than the costs of administering the program, the program could still be welfare enhancing.

Cal-Grant may be less cost effective than low cost interventions which have been shown to induce students to attend college. These programs likely induce at least some of those additional college attendees to graduate. Dynarski et al. (2013) calculate the cost per additional college enrollee for a variety of interventions. The HR Block experiment (Bettinger et al., 2012) costs only $1100 per additional student enrolled. The Hoxby and Turner (2013) intervention costs $6 per student and creates better student-university matches and which should lead to increased graduation rates for those students. In contrast, Head Start costs $133,000 per additional student enrolled while the STAR experiment cost about $400,000 per additional enrollee.

IV. Conclusion

State sponsored merit- and need-based aid constitutes one of the most important and fastest growing sources of student assistance for postsecondary education. The income and GPA discontinuities for Cal Grant eligibility produce sharp changes in grant receipt. Cal Grant eligibility produces no changes in overall college attendance but importantly does raise Bachelor degree and graduate school attainment. Cal grant eligibility raises BA attainment by two to five percentage points. The effect of actual Cal Grant receipt on BA attainment is 7 to 10 percentage points.

We find evidence of some impacts on the types of colleges attended and degree completion, although these vary by the subpopulation examined. For students near the income threshold, we detect shifts into private institutions and away from public four-year colleges in California. The IV results suggest that Cal Grant receipt, which averages about $8,000 per student, increases private school attendance by approximately 13 percentage points, which is nearly a doubling relative to the control mean.

In contrast, we find no evidence of shifting in the type of college attended among students near the GPA eligibility cutoff. We instead find that the Cal Grant has indirect effects on these students' higher education, inducing students with typically low overall graduate degree completion rates to complete graduate school by an additional two percentage points, or an increase of roughly 15 percent. These findings show that financial aid can have a causal impact on additional human capital investment, particularly for lower-skilled students, perhaps through reducing debt that might prevent a student from temporarily exiting the workforce to pursue their graduate education. Another key insight is the long timeframe required to estimate these results, lending support to the importance of a life-cycle approach to estimating the returns to aid. Year-by-year analysis suggest that the graduate degree effect is precisely zero for the first six years after completing high school before gradually increasing, becoming statistically significant seven years after entering college.

However, we cannot say with precision how the changes in institution type and Bachelor's degree attainment translate into effects on lifetime earnings. Using the GPA discontinuity, we find that Cal Grant eligibility raises earnings by 4 percentage points during the late 20s and early

30s (10-14 years after application). But our standard errors also incorporate much smaller earnings gains. Given our two to five percentage point increase in BA attainment, a 4 percentage point increase in earnings would imply a very large return to BA receipt if that were the main channel for the earnings effect. However it is quite possible that Cal Grant eligibility impacts earnings through many channels including inducing students to attend graduate school and shifting which institutions are attended. More data and longer follow up periods will be needed to truly understand earnings impacts.

Interestingly, we find that during these later years after Cal Grant receipt, awardees at the GPA discontinuity appear no more likely to live in California. Awardees at the income discontinuity are 3 percentage points more likely to live in California. This particular state merit-aid program shows mixed evidence on reducing outmigration of talented workers from California.

All of these effects may be particular to the institutional context of California. California is a geographically large and diverse economy making outmigration already less likely than migration from smaller states. More importantly, Cal Grant is offered on top of a highly subsidized and broad reaching public university and community college system. Equally important is that our inferences are restricted to a particular set of Cal Grant applicants: a set of students who have taken the time to file a FAFSA form and a Cal Grant application, and virtually all participate in college at some point following high school. Our estimates are also restricted to students at the eligibility cutoffs, whereas the largest effects on attendance and persistence might be concentrated on very low-income students, who are least likely to attend college. Overall our results suggest that the United States' largest merit aid program does not boost initial college enrollment but has meaningful impacts on persistence and graduation and may have large earnings effects.

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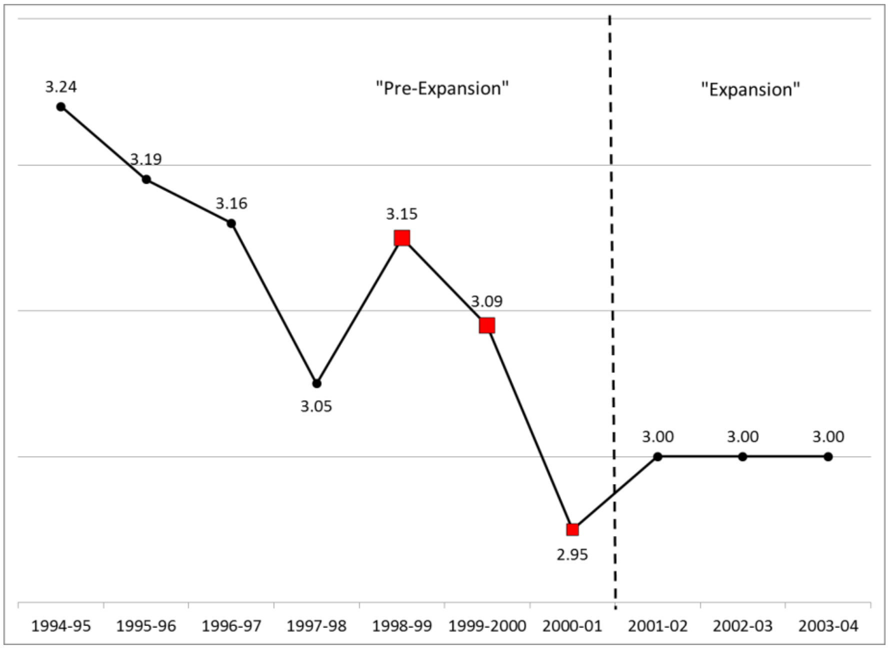

FIGURE 1. GPA CUTOFFS OVER TIME

Notes: This figure depicts the year-specific GPA thresholds for eligibility for Cal Grant A. Red squares indicate the years that are included in our analysis.

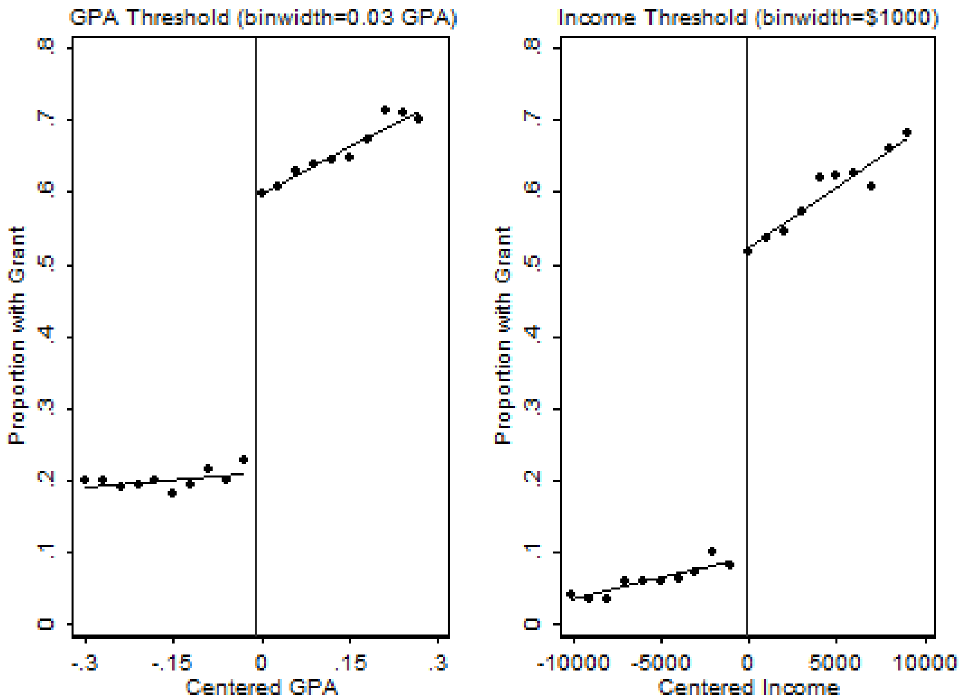

FIGURE 2. CAL GRANT UTILIZATION

Notes: This figure depicts the proportion of students who "Ever Received a Cal Grant payment." The left panel bins students by GPA relative to the year-specific eligibility threshold, pooled across years. The right panel bins students by $1,000 relative to the year-specific eligibility threshold, pooled across years. Income is reversed so that values above the cutoff represent lower family incomes.

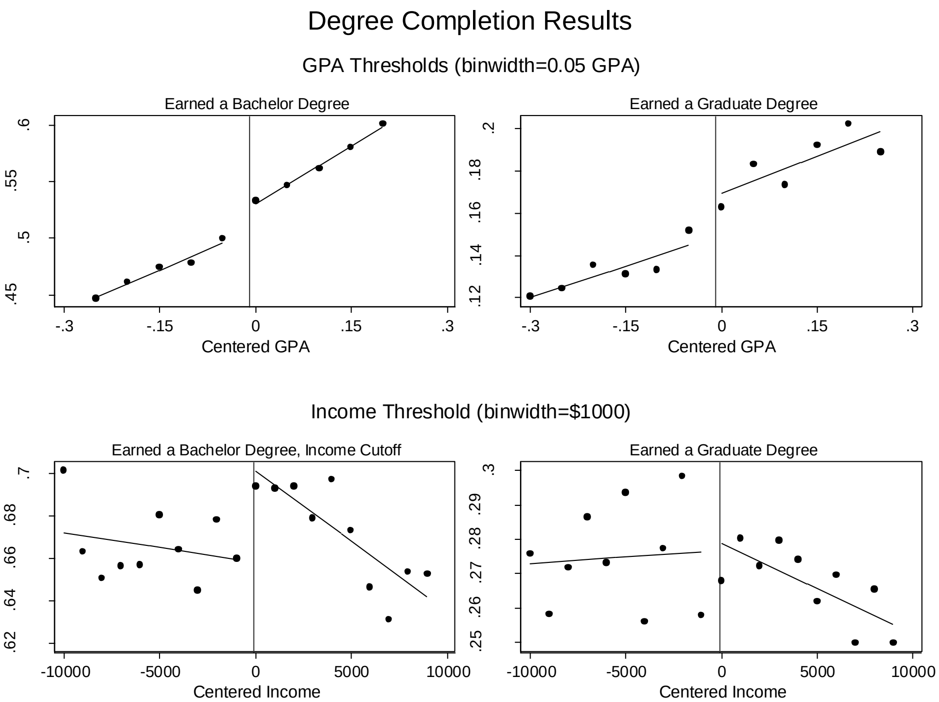

FIGURE 3. POSTSECONDARY ATTAINMENT

Notes. This figure depicts the proportion of students who earned a Bachelor's degree or a graduate degree, based on National Student Clearinghouse data. The top panel bins students by 0.05 GPA points relative to the year-specific eligibility threshold, pooled across years. The top left panel shortens the bandwidths slightly to sharpen the focus on impacts at the threshold. The bottom panel bins students by $1,000 relative to the year-specific eligibility threshold, pooled across years. Income is reversed so that values above the cutoff represent lower family incomes.

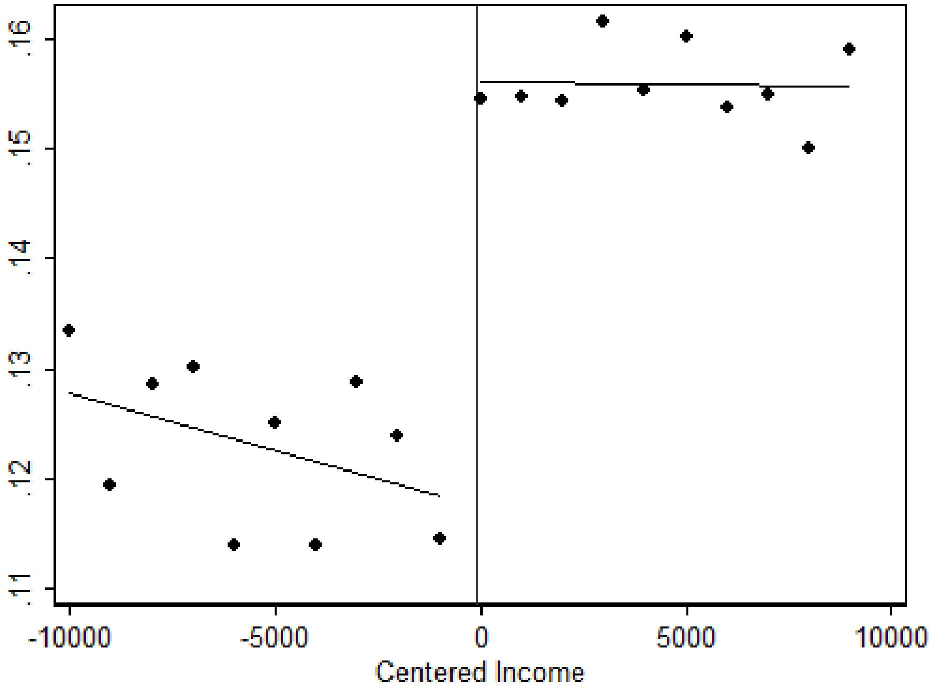

FIGURE 4. ATTENDS PRIVATE INSTITUTION, INCOME THRESHOLD

Notes: This figure depicts the proportion of students around the income threshold who attended a private institution at any point between 1 and 4 years since their Cal Grant application, pooled over cohorts. College attendance is based off of Form 1098-T, and institution types are derived using IPEDs data. Income is reversed so that values above the cutoff represent lower family incomes. Students are binned by $1,000 relative to the year-specific income threshold.

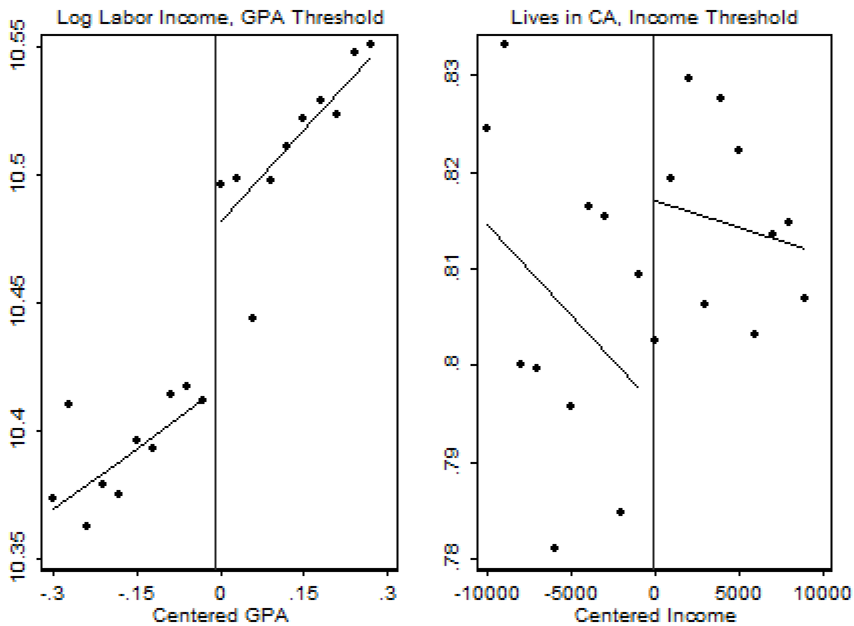

FIGURE 5. SELECT LONGER-RUN OUTCOMES, 10-14 YEARS AFTER APPLICATION

Notes: This figure depicts select tax return-based outcomes, averaged over 10-14 years after Cal Grant application and pooled over cohorts. The left panel bins students by 0.03 GPA points relative to the year-specific eligibility threshold; the right panel bins students by $1,000 relative to the year-specific eligibility threshold. Income is reversed so that values above the cutoff represent lower family incomes.

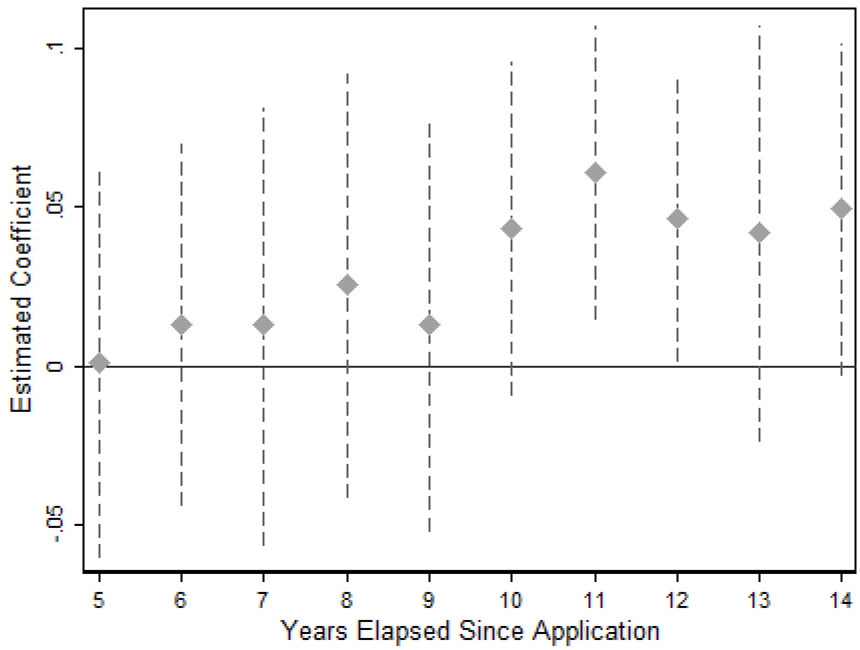

FIGURE 6. LOG LABOR INCOME, GPA THRESHOLD

Notes: This figure depicts the evolution of the effect of Cal Grant eligibility on log labor income since the year of application. The diamonds represent coefficients from our regression discontinuity specification for a specific year relative to time of application, and the dashed lines represent 95% confidence intervals. The regressions include students within 0.3 GPA points of the GPA threshold. The regressions include the student's age, a dummy for parental college attainment, a dummy for U.S. citizenship, a dummy for parents being married, family size by year fixed effects, and zip code fixed effects. Standard errors are clustered by the running variable.

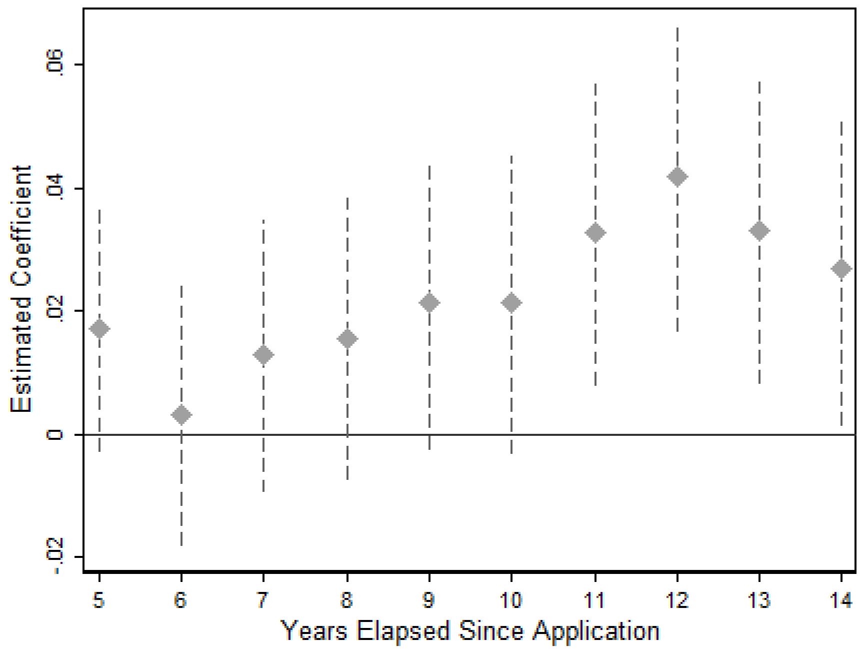

FIGURE 7. RESIDENCY RESULTS, INCOME THRESHOLD

Notes: This figure depicts the evolution of the effect of Cal Grant eligibility on California residence since the year of application. The diamonds represent coefficients from our regression discontinuity specification for a specific year relative to time of application, and the dashed lines represent 95% confidence intervals. The regressions include students within $10,000 of the income threshold. The regressions include the student's age, a dummy for parental college attainment, a dummy for U.S. citizenship, a dummy for parents being married, family size by year fixed effects, and zip code fixed effects. Standard errors are heteroscedasticity robust.

Table 1: Summary Statistics

	GPA Threshold		Income Threshold	
	Mean	Std. Dev.	Mean	Std. Dev.
Demographics				
Age	18.54	2.33	18.24	1.18
Female	0.56	0.50	0.58	0.49
Citizen	0.86	0.34	0.94	0.24
Parents married	0.44	0.50	0.53	0.50
Dependent	0.97	0.16	1.00	0.07
GPA	3.08	0.18	3.55	0.28
Family income	35,103	14,490	60,492	7,971
Year 1 after Application				
Attends school	0.83	0.37	0.93	0.25
School in CA	0.74	0.44	0.84	0.37
Two-year public	0.22	0.41	0.15	0.35
Four-year public	0.44	0.50	0.54	0.50
CSU	0.29	0.45	0.23	0.42
UC	0.15	0.36	0.32	0.47
Private school	0.09	0.28	0.15	0.36
Years 1-4 after Application				
Attends school	0.95	0.22	0.99	0.12
School in CA	0.88	0.32	0.92	0.27
Two-year public	0.38	0.49	0.24	0.43
Four-year public	0.58	0.49	0.66	0.47
CSU	0.40	0.49	0.32	0.47
UC	0.19	0.39	0.37	0.48
Private school	0.14	0.35	0.21	0.41
Year 12 after Application				
Files a tax return	0.93	0.26	0.95	0.22
Log wage income	37,369	30,377	45,584	34,309
AGI	63,734	85,427	79,058	142,248
Married	0.45	0.50	0.49	0.50
Has kids	0.37	0.48	0.31	0.46
Lives in California	0.86	0.35	0.81	0.39

Note: This table provides means and standard deviations for all students at the GPA and income thresholds. The GPA subsample includes students within 0.3 of the GPA threshold, and the income subsample include students within $10,000 of the income threshold. The demographic and college attendance variables are available for all applicants: 31,500 observations at the GPA threshold and 18,097 observations at the income threshold. The indicator for filing a tax return and wage income (based off of W-2s) are also available for all applicants. The tax-return based variables are only available for tax filers: 29,250 observations at the GPA threshold and 17,252 observations at the income threshold.

Table 2. Educational Outcomes

	GPA Threshold			Income Threshold		
	Control Mean	Reduced Form	IV	Control Mean	Reduced Form	IV
College Completion (NSC)						
Bachelor Degree	48.5%	0.026***	0.071***	66.0%	0.046***	0.107***
		(0.009)	(0.025)		(0.014)	(0.032)
Graduate Degree	14.4%	0.023**	0.061***	25.8%	0.002	0.005
		(0.009)	(0.023)		(0.013)	(0.030)
College Attendance (1098-T)						
Attend	93.9%	0.004	0.011	98.8%	-0.001	-0.002
		(0.005)	(0.013)		(0.003)	(0.008)
California Community College	40.0%	-0.009	-0.023	25.3%	-0.035***	-0.083***
		(0.010)	(0.027)		(0.013)	(0.030)
California Four-Year Public	57.2%	-0.002	-0.005	71.1%	-0.048***	-0.114***
		(0.013)	(0.034)		(0.014)	(0.033)
California Private	12.3%	0.005	0.012	17.5%	0.057***	0.135***
		(0.006)	(0.014)		(0.012)	(0.028)
Student Loans						
Loan Amount	$16,188	146.736	1,152.94	$23,962	1,911.09	4,196.03
		(906.566)	(2,206.624)		(1,373.117)	(3,050.697)
Log Student Loans	9.6	-0.005	0.042	9.9	0.045	0.079
		(0.042)	(0.082)		(0.044)	(0.079)
First-stage						
Ever Received a Cal Grant Payment, NSC	20.2%	0.370***	--	8.6%	0.427***	--
		(0.012)			(0.011)	
Total Cal Grant Aid Received, NSC	$1,750	4061.826***	--	$1,076	8184.713***	--
		(167.460)			(280.897)	
Ever Received a Cal Grant Payment, 1098-T	20.2%	0.386***	--	8.6%	0.420**	--
		(0.010)			(0.012)	
Total Cal Grant Aid Received, 1098-T	$1,716	4306.551***	--	$1,000	8128.888**	--
		(170.801)			(286.066)	

Notes. * p<0.1, ** p<0.05, *** p<0.01. This table presents estimates of the coefficient on Cal Grant eligibility from Equation (1). Bandwidths are 0.3 GPA and $10,000 at the GPA and income thresholds, respectively. In specifications using NSC data, there are 31,836 and 18,588 observations at the GPA and income thresholds, respectively. In specifications using the 1098-T data, there are 31,500 and 18,097 observations at the GPA and income threshold, respectively. In the log student loan specification, there are 19,039 and 12,767 observations at hte GPA and income threshold, respectively. All regressions include year-by-family size fixed effects to control for year-specific income eligibility thresholds. Standard errors clustered by GPA for GPA threshold regressions and are heteroskedasticity-robust in Income threshold regressions. IV outcomes utilizes whether a student ever received a Cal Grant payment as the first-stage. Reduced form control value means are all students within 0.05 GPA (for GPA thresholds) or within $1000 (for Income thresholds).

Table 3: Longer-Run Income and Demographic Outcomes, 10-14 Years after Application

	GPA Threshold			Income Threshold		
	N	Control Mean	Reduced Form	N	Control Mean	Reduced Form
Filed a Tax Return	157,500	0.93	0.003	90,485	0.96	-0.007
			(0.005)			(0.005)
Log labor income	138,932	10.43	0.047**	81,651	10.72	-0.022
			(0.019)			(0.025)
Log AGI	144,369	10.75	0.01	84,999	10.99	-0.017
			(0.018)			(0.024)
Lives in CA	146,027	0.87	-0.004	85,991	0.81	0.031***
			(0.007)			(0.011)

Notes: * p<0.1, ** p<0.05, *** p<0.01. All regressions include student's age, a dummy for parental college attainment, a dummy for U.S. citizenship status, a dummy for parents being married, year-by-family size fixed effects, zip code fixed effects, and tax year and cohort fixed effects. GPA regressions include students within 0.3 of the GPA threshold, and income regressions include students within $10,000 of the income threshold. Standard errors are clustered by household. Reduced form control value means are all students within 0.05 GPA (for GPA thresholds) or within $1000 (for income thresholds).

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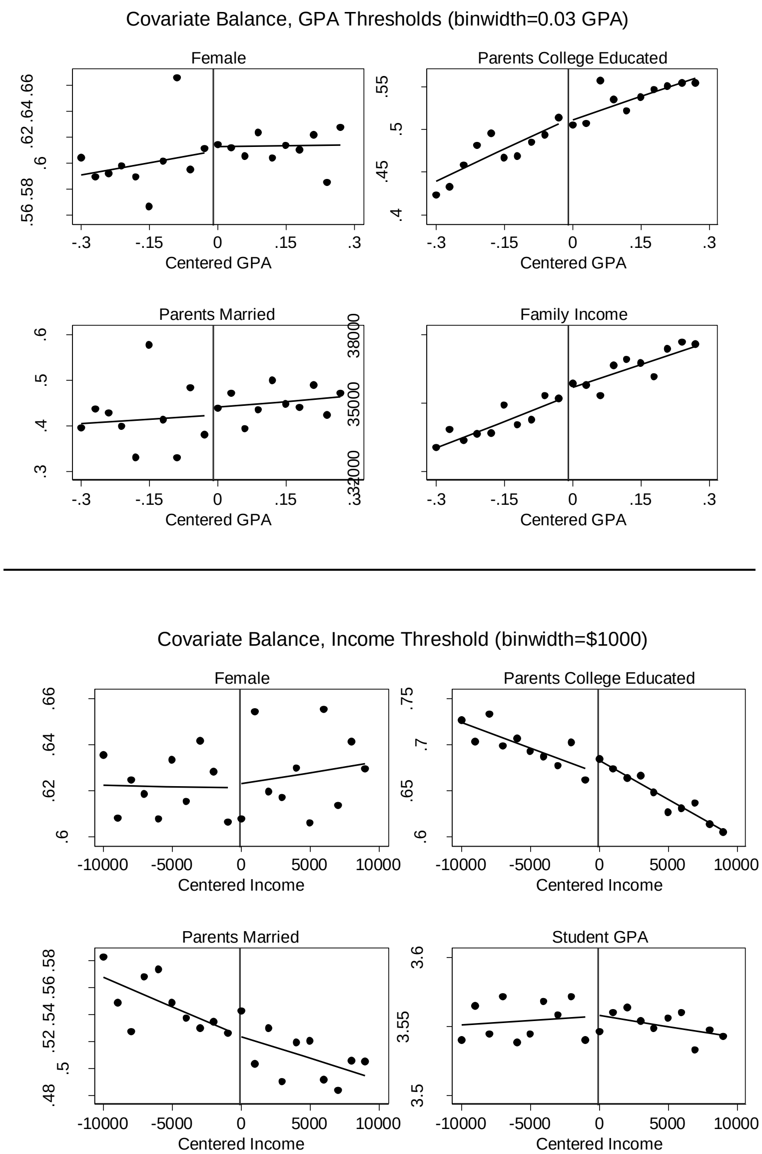

FIGURE A1. COVARIATE BALANCE

Notes: This figure depicts demographic characteristics at the relevant thresholds, pooled over cohorts. The top panel bins students by 0.03 GPA points relative to the year-specific eligibility threshold; the bottom panel bins students by $1,000 relative to the year-specific eligibility threshold. Income is reversed so that values above the cutoff represent lower family incomes.

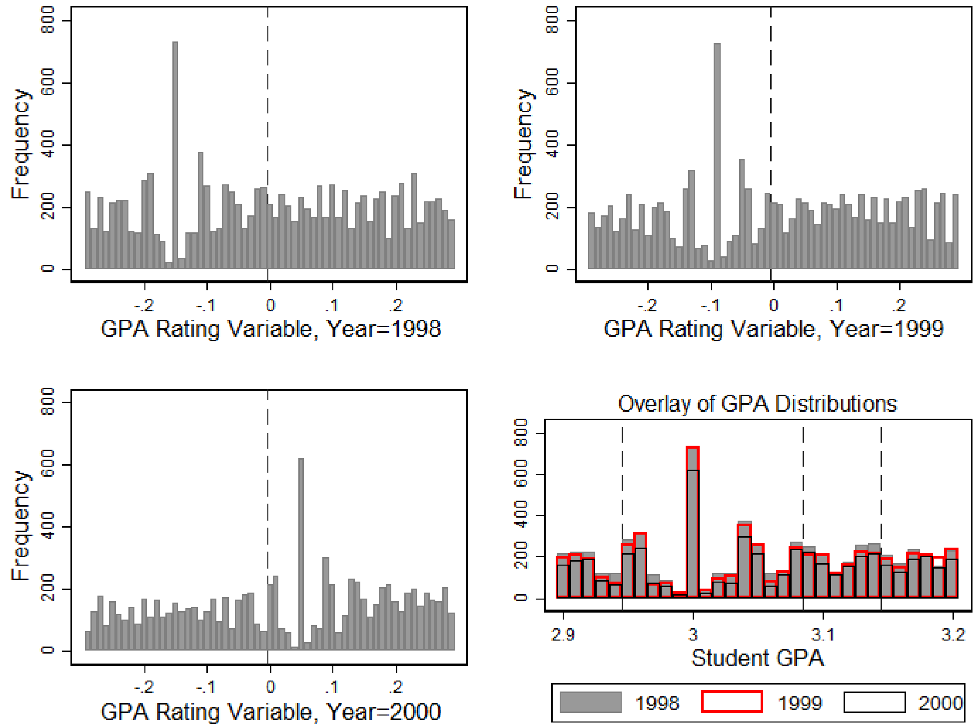

FIGURE A2. HISTOGRAMS OF GPA DISTRIBUTION

Notes: This figure depicts the distribution of students across the GPA distribution relative to the GPA threshold for each cohort separately, and then overlaid on top of one another in the bottom right panel.

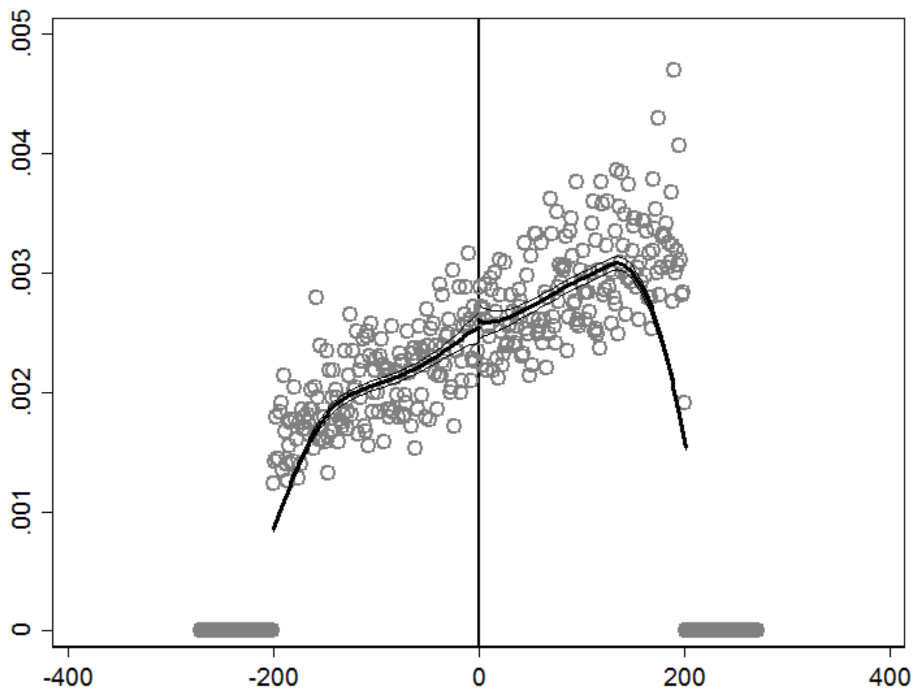

FIGURE A3. MCCRARY TEST OF APPLICANT DENSITY AT INCOME THRESHOLD, TAX DATA

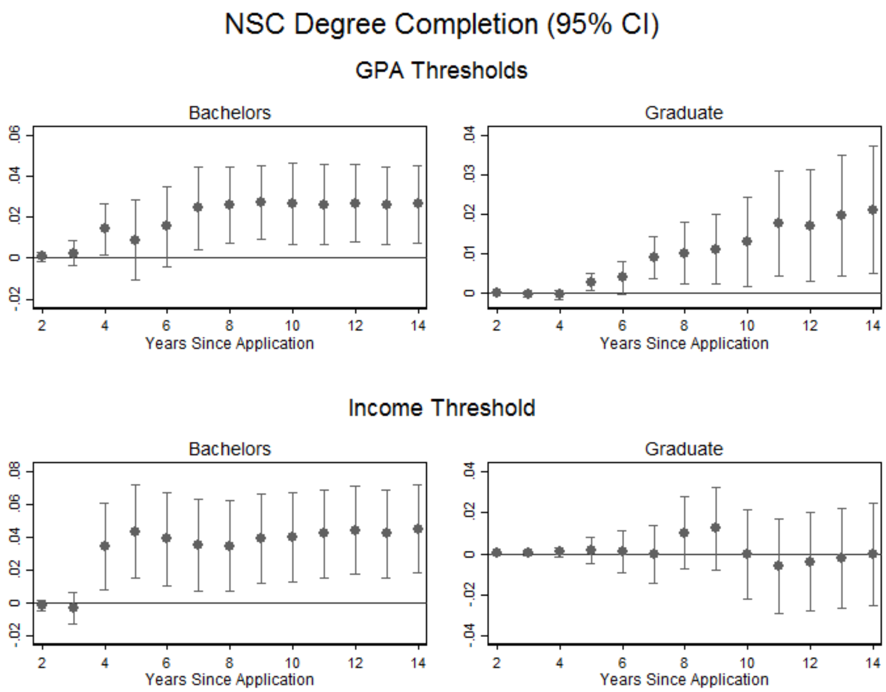

FIGURE A4. EDUCATIONAL ATTAINMENT OVER TIME

Notes: This figure depicts the evolution of the effect of Cal Grant eligibility on degree completion since the year of application. The circles represent coefficients from our regression discontinuity specification for a specific year relative to time of application, and the dashed lines represent 95% confidence intervals.

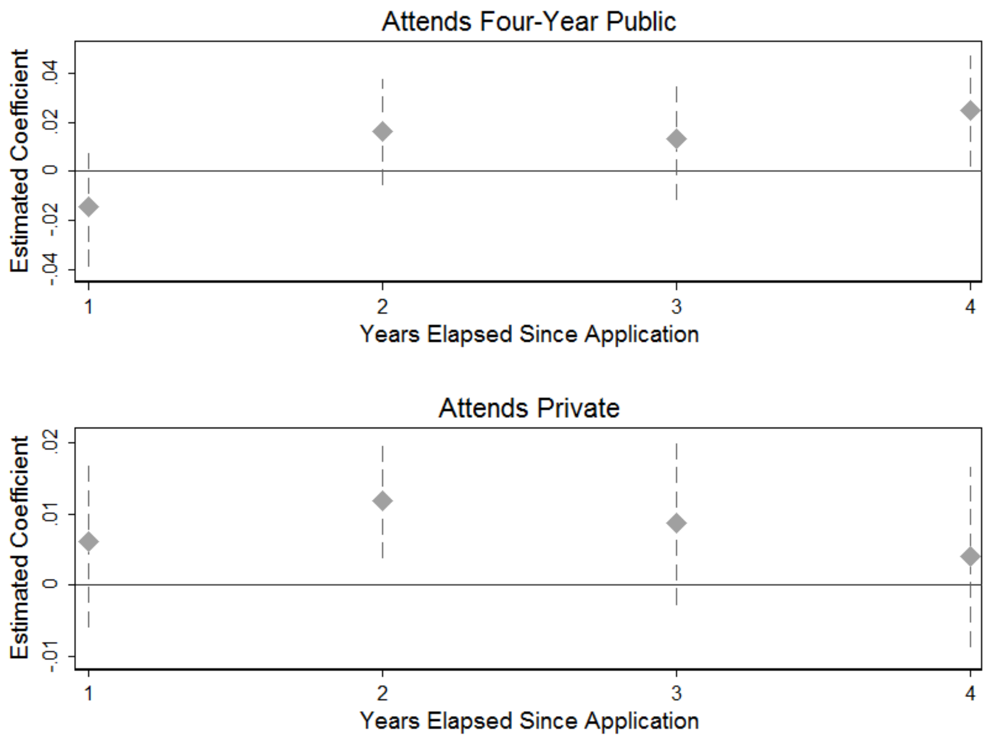

FIGURE A5. EDUCATIONAL ATTENDANCE OVER TIME, GPA THRESHOLD

Notes: This figure depicts the evolution of the effect of Cal Grant eligibility on type of institution attended since the year of application at the GPA threshold. The diamonds represent coefficients from our regression discontinuity specification for a specific year relative to time of application, and the dashed lines represent 95% confidence intervals.

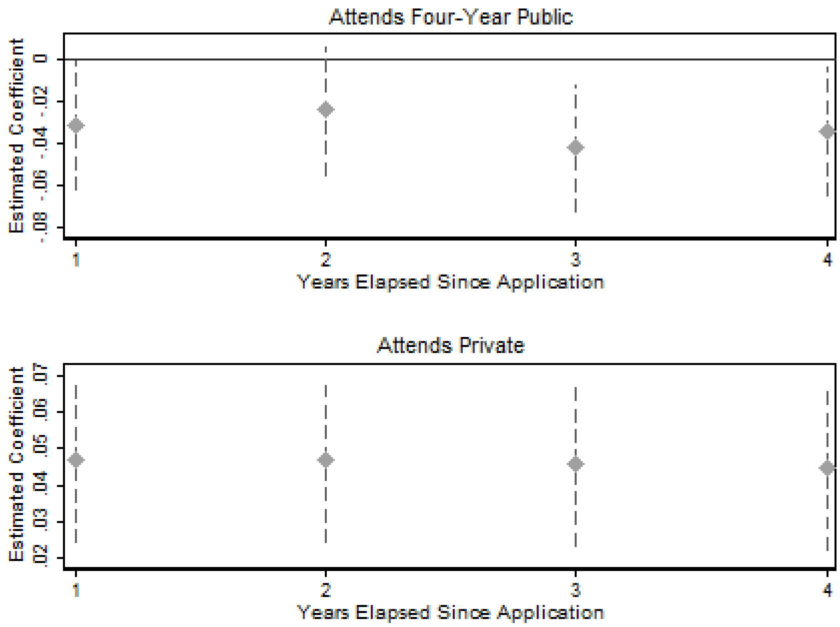

FIGURE A6. EDUCATIONAL ATTENDANCE OVER TIME, INCOME THRESHOLD

Notes: This figure depicts the evolution of the effect of Cal Grant eligibility on type of institution attended since the year of application at the income threshold. The diamonds represent coefficients from our regression discontinuity specification for a specific year relative to time of application, and the dashed lines represent 95% confidence intervals.

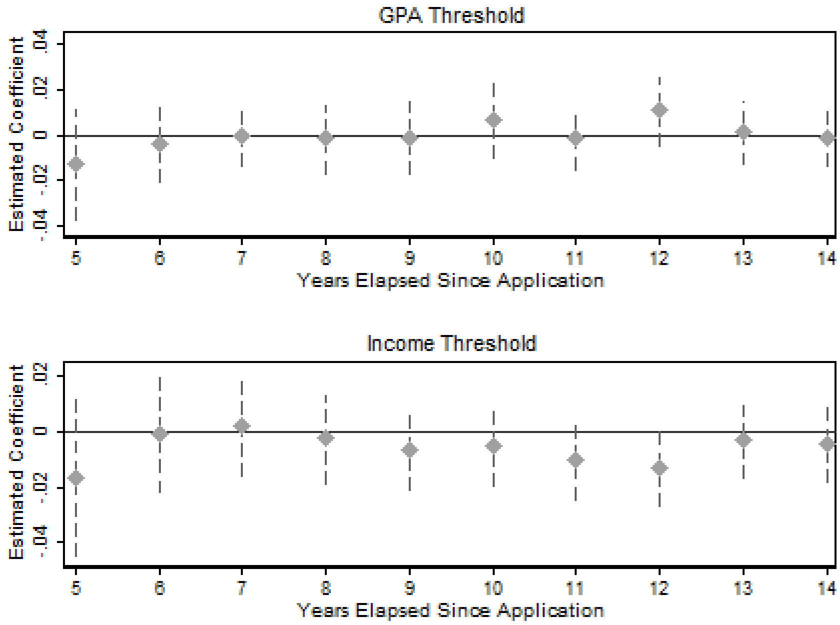

FIGURE A7. TAX FILING OVER TIME

Notes: This figure depicts the evolution of the effect of Cal Grant eligibility on the probability of filing a tax return since the year of application. The diamonds represent coefficients from our regression discontinuity specification for a specific year relative to time of application, and the dashed lines represent 95% confidence intervals. The top panel includes students within 0.3 GPA points of the GPA threshold, and the bottom panel includes students within $10,000 of the income threshold. The regressions include the student's age, a dummy for parental college attainment, a dummy for U.S. citizenship, a dummy for parents being married, family size by year fixed effects, and zip code fixed effects. Standard errors in the top panel are clustered by the running variable, and standard errors in the bottom panel are heteroscedasticity robust.

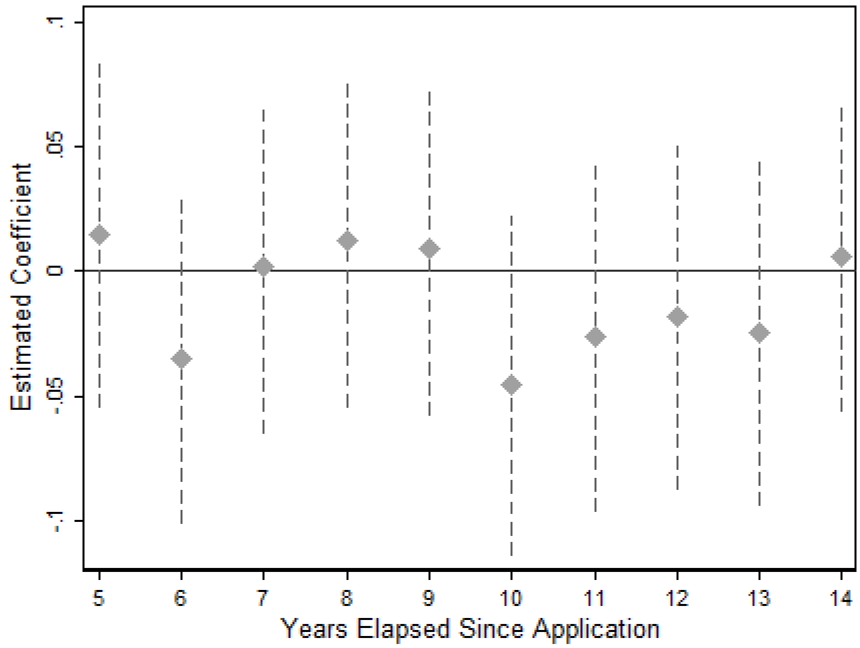

FIGURE A8. LOG LABOR INCOME OVER TIME, INCOME THRESHOLD

Notes: This figure depicts the evolution of the effect of Cal Grant eligibility on log labor income since the year of application. The diamonds represent coefficients from our regression discontinuity specification for a specific year relative to time of application, and the dashed lines represent 95% confidence intervals. The regressions include students within $10,000 of the income threshold. The regressions include the student's age, a dummy for parental college attainment, a dummy for U.S. citizenship, a dummy for parents being married, family size by year fixed effects, and zip code fixed effects. Standard errors are heteroscedasticity robust.

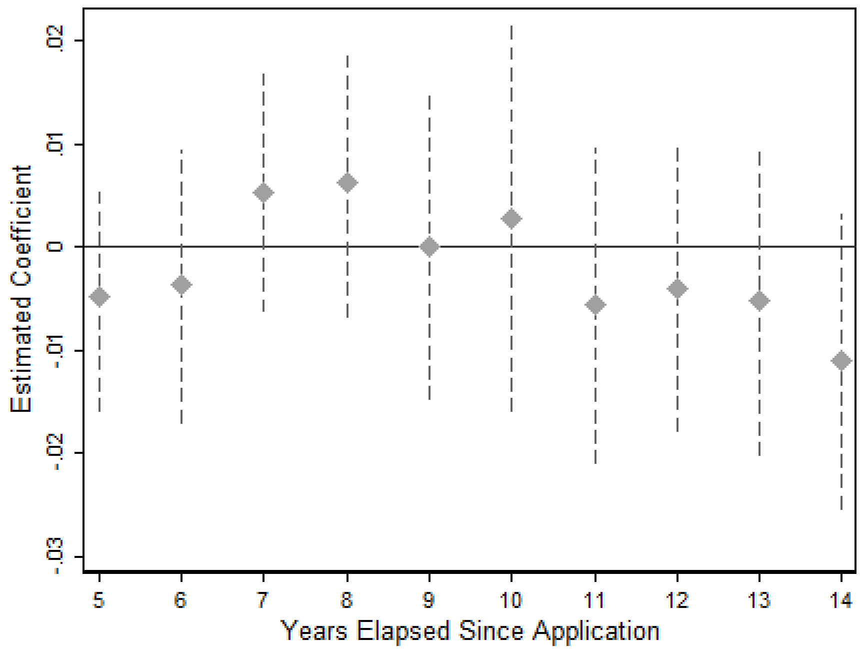

FIGURE A9. RESIDENCY RESULTS OVER TIME, GPA THRESHOLD

Notes: This figure depicts the evolution of the effect of Cal Grant eligibility on the probability of living in California (based on filing address). The diamonds represent coefficients from our regression discontinuity specification for a specific year relative to time of application, and the dashed lines represent 95% confidence intervals. The regression includes students within 0.3 GPA points of the GPA threshold. The regressions include the student's age, a dummy for parental college attainment, a dummy for U.S. citizenship, a dummy for parents being married, family size by year fixed effects, and zip code fixed effects. Standard errors are clustered by the running variable.

Appendix Table 1: Smoothness of Covariates

	Covariates							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Student GPA	Family Income	Age	Female*	Parent college educated	Citizen	Parents married	Family size
GPA Threshold								
Tax data		102.334	0.057	-0.005	0.001	0.004	-0.001	0.003
		(192.189)	(0.072)	(0.013)	(0.010)	(0.007)	(0.009)	(0.025)
NSC data		-49.157	-0.009	0.006	0.000	0.002	-0.000	-0.013
		(173.000)	(0.014)	(0.011)	(0.009)	(0.011)	(0.014)	(0.024)
Income Threshold								
Tax data	0.003		-0.026	0.014	0.018	0.009	-0.003	-0.023
	(0.008)		(0.033)	(0.017)	(0.014)	(0.007)	(0.008)	(0.032)
NSC data	0.002		0.015	0.002	0.017	0.008	-0.009	-0.014
	(0.008)		(0.016)	(0.015)	(0.014)	(0.009)	(0.011)	(0.032)

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. All regressions include year-by-family size fixed effects, except when family size is the outcome. GPA regressions include students within 0.3 of the GPA threshold (31,500 observations), and income regressions include students within $10,000 of the income threshold (18,097 observations). Standard errors are clustered by GPA for GPA threshold regressions and are heteroskedasticity-robust in income threshold regressions. Regressions using female as the outcome variable only include the 1999 and 2000 cohorts because of missing data problems with the 1998 cohort (sample sizes are 20,377 and 12,398 for the GPA threshold and income threshold, respectively).

Appendix Table 2. Educational Outcomes, National Student Clearinghouse data

	GPA Threshold			Income Threshold		
	Control Mean	Reduced Form	IV	Control Mean	Reduced Form	IV
College Completion						
Bachelor Degree	48.5%	0.026***	0.071***	66.0%	0.046***	0.107***
		(0.009)	(0.025)		(0.014)	(0.032)
Graduate Degree	14.4%	0.023**	0.061***	25.8%	0.002	0.005
		(0.009)	(0.023)		(0.013)	(0.030)
College Attendance						
Attend	86.2%	0.000	0.001	90.5%	0.018**	0.042**
		(0.007)	(0.020)		(0.008)	(0.020)
California Community College	23.5%	-0.005	-0.014	12.0%	-0.020**	-0.048**
		(0.010)	(0.026)		(0.009)	(0.021)
California Four-Year Public	40.0%	0.004	0.011	51.3%	-0.006	-0.013
		(0.011)	(0.030)		(0.015)	(0.034)
California Private	8.3%	0.008	0.022	14.0%	0.046***	0.109***
		(0.005)	(0.015)		(0.011)	(0.024)
First-stage						
Ever Received a Cal Grant Payment	20.2%	0.370***	--	8.6%	0.427***	--
		(0.012)			(0.011)	
Total Cal Grant Aid Received	$1,750	4061.826***	--	$1,076	8184.713***	--
		(167.460)			(280.897)	

Notes. * p<0.1, ** p<0.05, *** p<0.01. This table presents estimates of the coefficient on Cal Grant eligibility from Equation (1). Bandwidths are 0.3 GPA and $10,000 at the GPA and income thresholds, respectively. These specifications use NSC data, and there are 31,836 and 18,588 observations at the GPA and income thresholds, respectively. All regressions include year-by-family size fixed effects to control for year-specific income eligibility thresholds. Standard errors clustered by GPA for GPA threshold regressions and are heteroscedasticity-robust in Income threshold regressions. IV outcomes utilizes whether a student ever received a Cal Grant payment as the first-stage. Reduced form control value means are all students within 0.05 GPA (for GPA thresholds) or within $1000 (for Income thresholds).

Appendix Table 3. Robustness of Educational Attainment Results, National Student Clearinghouse data

Functional Form	Linear	Linear	Linear	Quad	Quad	Quad	Linear	Linear	Linear	Quad	Quad	Quad	Linear	Linear	Linear	Quad	Quad	Quad
Covariates	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Removed Heaps	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
GPA Thresholds																		
Bandwidth	0.60	0.60	0.60	0.60	0.60	0.60	0.45	0.45	0.45	0.45	0.45	0.45	0.30	0.30	0.30	0.30	0.30	0.30
Bachelor Degree	0.024***	0.016**	0.019**	0.020**	0.016	0.019	0.022***	0.016*	0.020**	0.023*	0.014	0.014	0.026***	0.017	0.020*	0.020	0.010	0.009
	(0.007)	(0.008)	(0.008)	(0.010)	(0.012)	(0.012)	(0.008)	(0.009)	(0.010)	(0.012)	(0.014)	(0.014)	(0.009)	(0.011)	(0.012)	(0.016)	(0.017)	(0.018)
Graduate Degree	0.011*	0.009	0.008	0.014	0.014	0.013	0.008	0.006	0.005	0.024**	0.023**	0.022**	0.023**	0.021**	0.021**	0.010	0.006	0.006
	(0.006)	(0.006)	(0.006)	(0.010)	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)	(0.011)	(0.010)	(0.010)	(0.009)	(0.008)	(0.009)	(0.012)	(0.013)	(0.013)
N	59785	59783	53280	59785	59783	53280	47590	47590	41982	47590	47590	41982	31836	31836	28451	31836	31836	28451
Income Threshold																		
Bandwidth	$25,000	$25,000	$25,000	$25,000	$25,000	$25,000	$17,500	$17,500	$17,500	$17,500	$17,500	$17,500	$10,000	$10,000	$10,000	$10,000	$10,000	$10,000
Bachelor Degree	0.026***	0.027***	0.031***	0.042***	0.043***	0.046***	0.031***	0.033***	0.035***	0.052***	0.051***	0.055***	0.046***	0.048***	0.051***	0.034*	0.035*	0.035
	(0.009)	(0.009)	(0.009)	(0.013)	(0.013)	(0.014)	(0.010)	(0.011)	(0.011)	(0.015)	(0.016)	(0.017)	(0.014)	(0.014)	(0.015)	(0.020)	(0.022)	(0.022)
Graduate Degree	0.004	0.006	0.006	0.003	0.004	0.005	0.004	0.006	0.006	0.005	0.003	0.006	0.002	0.000	0.004	0.012	0.007	0.010
	(0.008)	(0.008)	(0.009)	(0.012)	(0.013)	(0.013)	(0.010)	(0.010)	(0.011)	(0.015)	(0.015)	(0.016)	(0.013)	(0.014)	(0.014)	(0.019)	(0.020)	(0.021)
N	46043	46042	42613	46043	46042	42613	32584	32583	30180	32584	32583	30180	18588	18588	17233	18588	18588	17233

Notes. * p<0.1, ** p<0.05, *** p<0.01. All regressions include year-by-family size fixed effects to control for year-specific income eligiblity thresholds. Standard errors clustered by GPA for GPA threshold regressions and are heteroskedasticity-robust in Income threshold regressions. Covariates include zip code fixed effects and student age, parental education, parental marital status, and citizen status. Non-heaped regressions remove all observations that report income that is a multiple of $1,000 (at the income threshold) or is a multiple of 0.33 or 0.25 (at the GPA threshold), respectively.

Appendix Table 4: Educational Outcomes, Heterogeneous Impacts

	(1)	(2)	(3)	(4)	(5)
	Two-Year Public	Four-Year Public	Private	Bachelor	Graduate
GPA Threshold					
Middle-income	0.001	-0.007	0.007	0.031*	0.015
	(0.012)	(0.016)	(0.007)	(0.016)	(0.012)
Control Mean	42.5%	56.4%	12.8%	48.4%	14.4%
N	17,719	17,719	17,719	17874	17874
Low-income	-0.02	0.006	-0.001	0.021	0.032**
	(0.020)	(0.021)	(0.012)	(0.014)	(0.012)
Control Mean	36.8%	58.3%	11.5%	48.6%	14.4%
N	13,781	13,781	13,781	13962	13962
Income Threshold					
GPA>=3.5	-0.031**	-0.053***	0.068***	0.030*	-0.005
	(0.015)	(0.018)	(0.016)	(0.017)	(0.018)
Control Mean	17.9%	70.5%	20.3%	71.5%	29.5%
N	10,380	10,380	10,380	10631	10631
GPA<3.5	-0.035	-0.041*	0.040**	0.065***	0.011
	(0.021)	(0.021)	(0.017)	(0.022)	(0.018)
Control Mean	34.0%	71.9%	14.2%	59.5%	21.3%
N	7,717	7,717	7,717	7957	7957

Notes: * p<0.1, ** p<0.05, *** p<0.01. All regressions include year-by-family size fixed effects. GPA regressions include students within 0.3 of the GPA threshold, and income regressions include students within $10,000 of the income threshold. Standard errors are clustered by GPA for GPA threshold regressions and are heteroskedasticity-robust in income threshold regressions. Reduced form control value means are all students within 0.05 GPA (for GPA thresholds) or within $1000 (for income thresholds).

Appendix Table 5: Longer-Run Income and Demographic Outcomes, Tax Returns 10-14 Years after Application

	(1)	(2)	(3)	(4)
	Filed a Tax Return	Log labor income	Log AGI	Lives in California
GPA Threshold				
Middle-income	0.011*	0.052*	0.030	-0.002
	(0.006)	(0.027)	(0.020)	(0.009)
Control Mean	93.4%	10.46	10.76	86.6%
N	88,595	79,090	81,865	82,759
Low-income	-0.007	0.04	-0.011	-0.007
	(0.009)	(0.027)	(0.024)	(0.010)
Control Mean	91.6%	10.40	10.74	87.5%
N	68,901	59,842	62,504	63,268
Income Threshold				
GPA>=3.5	-0.011***	-0.016	-0.016	0.014*
	(0.004)	(0.019)	(0.018)	(0.007)
Control Mean	97.2%	10.76	11.06	78.6%
N	51,900	46,857	49,021	49,620
GPA<3.5	0.004	-0.021	-0.005	0.053***
	(0.005)	(0.024)	(0.020)	(0.008)
Control Mean	94.2%	10.67	10.91	83.8%
N	38,585	34,794	35,978	36,371

Notes: * p<0.1, ** p<0.05, *** p<0.01. All regressions include year-by-family size fixed effects, cohort fixed effects and tax year fixed effects. GPA regressions include students within 0.3 of the GPA threshold, and income regressions include students within $10,000 of the income threshold. Standard errors are clustered by GPA for GPA threshold regressions and are heteroskedasticity-robust in income threshold regressions. Reduced form control value means are all students within 0.05 GPA (for GPA thresholds) or within $1000 (for income thresholds).