Cost Uncertainty, Financial Aid, and the Enrollment Choices of Low-Income Students*

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November 2023

Abstract

Research shows that college costs and financial aid affect students' choices and outcomes, but less attention has been paid to the role of uncertainty in total degree (four-year college) costs. This study offers new evidence on the importance of financial aid and degree cost certainty for students' decisions about where to attend college. Leveraging a unique tuition promise at a public flagship, where eligibility is determined by household adjusted gross income (AGI), I study how the upfront commitment of grants to cover four years of tuition for middle- and lower-income residents affects the decision to enroll conditional on an admissions offer. I use a regression discontinuity design that exploits the cutoff in AGI and a differences-in-differences design to isolate the effects of the four-year tuition guarantee. I find that in its first year, the program meaningfully increases grant aid and enrollment among middle-income students. In addition, results indicate that the promise component of the program increases enrollment yield of low-income students, suggesting that they value the certainty provided by the advance commitment of full tuition coverage.

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*Preliminary draft: please contact the author before citing.

†Department of Economics, University of Wisconsin-Madison (email: marifian@wisc.edu). I am very grateful to Jeff Smith, Chris Taber, Corina Mommaerts, Matt Wiswall, Jonathan Becker, Sharada Dharmasankar, Kathy Michelmore, Stephanie Owen, Sandra Spirovska, and Tatiana Velasco for fruitful conversations and insightful comments. This project would not be possible without the enthusiastic support of Eric Grodsky and Nicholas Hillman and my partners in the UW-Madison Division of Enrollment Management, especially Helen Faith, Derek Kindle, Audrey Peek, André Phillips, Terry Ruzicka, Cori Splain, and Bonniejean Zitske. I thank Joshua Bach-Hanson, Sami Boynton, Greer Davis, John Dreger, Renee Koerner, Shane Maloney, Viviana Rodriguez, and Karla Weber for helpful discussions and for sharing their expertise on admissions and financial aid processes and administrative data at UW-Madison. I also thank SSTAR Lab colleagues, conference participants at the 2022 AEFP Annual Meeting, and seminar participants in the Economics Department and the ITP Seminar at UW-Madison for providing helpful feedback on earlier presentations. This project was reviewed by the UW-Madison IRB under application 2021-0354. The research reported here was supported by the Institute of Education Sciences, U.S. Department of Education, through Award #R305B150003 to the University of Wisconsin-Madison. The opinions expressed are those of the author and do not represent views of the Department of Education or the University of Wisconsin-Madison. All errors are mine.

1 Introduction

In recent years, concern about the effects of rapidly rising tuition on college access and economic mobility has led a number of states to offer *tuition promises*, a financial aid program that guarantees a minimum tuition award for students who meet certain eligibility criteria, typically a residency requirement and means test. Tuition promises are unique among financial aid policies because institutions make a transparent and advance commitment about the level of tuition coverage eligible students will receive if they enroll. This guarantee offers prospective students increased certainty in the estimated out-of-pocket (OOP) cost of a degree.

Increasing certainty in degree costs may affect student choices at different stages in the college process. Prior research suggests that greater certainty may increase low-income students' applications to selective colleges (Dynarski et al., 2021), which may help to shrink persistent socioeconomic gaps in college-going (Hoxby and Avery, 2013b; Hoxby and Turner, 2013, 2015). Degree cost uncertainty also may affect choices at the enrollment stage, with economically disadvantaged students likely to have greater uncertainty about future income streams and ability to pay in later years. This cost uncertainty may dissuade students from accepting admissions offers at more selective schools, which typically have higher published tuition, even if they offer more generous financial aid. Even at the enrollment stage, increasing certainty about college costs may shrink socioeconomic gaps in selectivity among high-achieving students (Hoxby and Avery, 2013a) and lower academic mismatch (Dillon and Smith, 2017). Despite the potential for promise programs to increase access for academically talented students from modest means, most statewide promise programs only cover tuition at community colleges, with few states offering a promise for selective public colleges.[1] Disadvantaged students who are academically prepared to thrive at a more selective public college, such as the state flagship, do not receive tuition benefits for these institutions under community college promise programs.[2]

The aim of this paper is to study whether the increased cost certainty offered by a tuition promise affects the probability that high-achieving, low-income students attend the state flagship. I take advantage of the 2018 introduction of Bucky's Tuition Promise (BTP) at the University of Wisconsin-Madison, a last-dollar financial aid program that guarantees

[1]These are New York, Wisconsin, and Michigan.

[2]State flagship universities typically receive the most generous funding and resources and provide the highest quality public education in a state. These attributes make them well-positioned to reduce the aforementioned gaps and improve the college quality and match of academically talented students from modest means.

all eligible incoming freshman students four years of grant aid to cover full tuition and fees.[3] In the program's first year, new students qualified for BTP if they were Wisconsin residents with a household adjusted gross income below $56,000.[4] BTP incorporates both a certainty treatment and a grant aid treatment, so the policy can affect enrollment choices through different channels.

In the first part of the paper, I use a regression discontinuity (RD) design to examine how BTP eligibility affects grant aid, total aid, and the enrollment decisions of first-year admitted resident students with incomes just below the state median. My empirical strategy exploits the abrupt change in program eligibility at the $56,000 household AGI cutoff. Because the income threshold is at the state median, the RD allows me to study the impacts of increased grant aid and cost certainty on middle-income students, whose greater financial means often exclude them from more generous need-based financial aid benefits, such as the federal Pell grant. To obtain estimates for a broader income group that includes high-need students, I complement the RD design by estimating effects using a difference-in-differences (DID) design. In the second part of the paper, I examine the effect of the certainty treatment on enrollment choices.

I find that in the first year of the tuition promise, among Pell-ineligible students, students eligible for BTP are offered nearly $8,000 more in grant aid (relative to their BTP-ineligible counterparts), while among Pell-eligible students, on the other hand, BTP-eligibility confers no such benefit, owing to the fact that these students already receive generous offers that exceed the cost of tuition and fees. I estimate that the program increases the conditional probability of enrolling by 7 percentage points.

To analyze the certainty channel, I take advantage of the last-dollar nature of the promise. I first identify students who received only the certainty treatment in fall 2018, i.e., students who received gift aid from non-BTP sources that exceeded tuition and fees, so no BTP grant aid was awarded. I do the same for the fall 2017 cohort: that is, I identify students who, had the BTP policy been in place, would have received only the certainty treatment. With this sample of students, I estimate effects of certainty on enrollment using a DID model that compares the change in enrollment from 2017 to 2018 for "certainty-only" BTP-eligible students to that of BTP-ineligible students with slightly higher household AGI. I find that the certainty-only admits still respond to the BTP offer, increasing their probability of accepting an admissions offer by approximately 10.7 percentage points.

[3]Eligible transfer students are guaranteed two years of tuition and fee coverage. Students who have obtained a prior bachelor's degree are not eligible.

[4]The key eligibility requirements are income and residency, but applicants must file a FAFSA for income eligibility determination.

This paper contributes to several related strands in the literature. A number of papers explore the causal relationship between college costs and college attainment (see Dynarski et al., 2022, for a review). One possible explanation for the income gap in college-going is that college costs are perceived differently across socioeconomic status. A nascent literature in the behavioral economics of education has drawn attention to behavioral biases as potential factors that prevent academically talented students with modest means from applying to or attending more selective and higher quality institutions.[5] An alternative explanation is that disadvantaged students may be more risk averse or more uncertain about the aid for which they will qualify in subsequent years (or both). In this case, even when disadvantaged students receive a generous first-year financial aid package to a selective institution with a high sticker price, uncertainty about aid coverage in subsequent years may lead them to forgo that option in favor of a less selective institution offering less aid but a more predictable four-year cost. Any of these barriers can lead to academic under-matching and create earnings disparities between college graduates from different socioeconomic backgrounds, undermining the potential for college to serve as a vehicle for social mobility. My paper adds to the research evidence by documenting student responses to a policy that offers increased grant aid and reduced uncertainty in degree costs.

My research also contributes to a well-developed evidence base regarding the effects of financial aid on application and enrollment decisions, especially among low-income students (see, e.g. Dynarski, 2003). Several influential studies use regression discontinuity designs to study the effects of financial aid, with this paper closely related to the pioneering RD study by van der Klaauw (2002), who also examines how financial aid affects admitted students' enrollment decisions; recent papers by Denning et al. (2019) and Eng and Matsudaira (2021) leverage discontinuities in Pell grant eligibility to examine how financial aid impacts college-going and earnings outcomes of low-income students.

My paper complements these studies in several ways. Unlike van der Klaauw (2002), which examines financial aid at an elite private school on the East Coast in the late 1980s, I study how financial aid affects admitted students' decision to enroll in a selective Midwestern public university in recent years. In the Pell context, the amount of grant aid offered is a step-wise increasing function of Expected Family Contribution (EFC); in contrast, students eligible for BTP are guaranteed the same minimum level of coverage (grants covering tuition

[5] Examples of these behavioral biases include incorrect beliefs by students and families (e.g., the perception that more selective colleges are not affordable), over-weighting of present costs relative to future benefits, and aversion to student loan debt. See Lavecchia et al. (2016) for a review. Other non-behavioral factors such as modest Pell grant maximums and borrowing constraints may also dissuade low-income students from choosing to accept enrollment offers from more selective institutions.

and fees) regardless of their household income or ability to pay, so BTP students likely receive different coverage of their financial need. I also consider a different population than those typically considered in the RD Pell literature, where the effective sample is limited to students whose EFC falls around thresholds for Pell eligibility and benefit generosity. In particular, my RD design allows me to estimate impacts for students with more moderate incomes, some of whom are not Pell-eligible, and thus would not be "treated" in any of the Pell contexts. These students may experience different degrees of uncertainty about cost and ability to pay than their Pell counterparts and likely receive less generous financial aid offers, so their enrollment responses may differ from those estimated in the Pell literature.

My project also is closely related to recent work by Dynarski et al. (2021), who use an information experiment in Michigan to study the effect of guaranteeing expected aid offers before students apply to college. In their setting, in advance of applying, prospective students are offered the same grant aid that they would qualify for in expectation if admitted.[6] Our institutional contexts differ in several important dimensions. First, the program at the University of Michigan, the "High Achieving Involved Leader," or HAIL Scholarship, is not a tuition promise policy. Because the University of Michigan guarantees to meet a student's financial need, the HAIL treatment is about information and salience; students do not receive a different financial aid offer under the HAIL treatment. In contrast, UW-Madison does not guarantee to meet a student's financial need, so BTP-eligible students can (and do) see a meaningful change in their grant aid and total aid levels. Second, for the initial cohort studied here, the BTP announcement and implementation occurs after students applied to UW-Madison, which allows me to isolate the effect of BTP on the conditional enrollment choice, a different margin than is explored when treatments occur prior to the college application process (as in the HAIL context). My paper complements their study by examining a different type of treatment and a different response margin.

My paper also extends the literature on the effect of tuition promises on application, enrollment, and persistence (Andrews et al., 2010; Dynarski et al., 2021). I build upon these papers by generating credible estimates of the enrollment effects of tuition promises offered by a selective public institution. Given that low-income students account for a small share of undergraduate enrollees in many state flagships (Mugglestone et al., 2019), are more likely to academically under-match (Dillon and Smith, 2017), and attend less selective colleges

[6] In a follow-up to Dynarski et al. (2021), Burland et al. (2023) extend the experiment to include an informational arm about a different "free tuition" program at the University of Michigan, called the "Go-Blue Guarantee" (GBG). The GBG differs in meaningful ways from the BTP and HAIL programs, and in particular, removes the guarantee/certainty component because it can be revoked if a student's financial situation changes.

than their affluent peers (even among high achievers) (Hoxby and Turner, 2013), offering a tuition promise at the flagship could help address income-based disparities in the college-going behavior of high-achieving students. My estimates provide support for this hypothesis. More generally, my work contributes to the broader literature examining how financial aid affects students' enrollment decisions (e.g., Avery and Hoxby, 2013; Avery and Kane, 2004; Bettinger et al., 2012)

The paper proceeds as follows. Section 2 describes the institutional context and details the program features and implementation of Bucky's Tuition Promise. In Section 3 I describe the data and sample construction and provide summary statistics and descriptive evidence of the analysis sample. Section 4 describes the research design and estimation approach. I discuss the regression discontinuity results in Section 5 and present the certainty analysis in Section 6. I conclude in Section 7.

2 Setting

The University of Wisconsin-Madison is a public research university and the state's flagship institution, enrolling 31,650 undergraduates in Fall 2020. Undergraduate admissions received 45,941 applications for the Fall 2020 freshman class and accepted 57.2 percent of applicants[7], with 27.8 percent of admitted students matriculating. Of the 7,306 students in the Fall 2020 freshman class, 3,802 (52 percent) were in-state students.[8] Freshman at UW-Madison represented approximately 5.8 percent of all Wisconsin high school graduates in 2019, up from 4.9 percent in 2010.

UW-Madison is one of thirteen public universities in the University of Wisconsin System. Table 7 in the Appendix shows published resident tuition and fees for the thirteen UW System schools in the 2018-2019 academic year, the first year of Bucky's Tuition Promise.[9] UW-Madison charges the most at $10,616, followed by UW-Milwaukee at $9,638, 9 percent less than UW-Madison. UW-Stout charges the lowest resident tuition and fees at $5,824, 45 percent less than UW-Madison, but on average, the other twelve UW-System schools charge

[7]In Fall 2020, 73 percent of resident applicants were admitted, compared to 53.8 percent of nonresident applicants.

[8]The University of Wisconsin Board of Regents previously limited the share of out-of-state undergraduates at UW-Madison to 27.5 percent. In December 2015, the Board changed the enrollment policy in two ways: First, it removed the cap on the undergraduate out-of-state enrollment. Second, it created a requirement that the UW-Madison fall freshman class include at least 3,600 students from Wisconsin, which exceeded the average number of Wisconsin high school graduates enrolled at UW-Madison in the prior ten years.

[9]The tuition and fees described throughout the paper are baseline academic year (2-semester) rates for resident undergraduates. Some majors, such as engineering and business, charge additional tuition. Published tuition and fees do not account for any financial aid students receive.

approximately 24 percent less than the flagship.

Although published tuition and fees at UW-Madison are considerably higher than those at Wisconsin's other public four-year universities, attending the state flagship appears to be a relatively "good deal" in Wisconsin compared to neighboring states, as the sticker price at UW-Madison is substantially lower than that of its out-of-state public rivals. In 2018-2019, tuition and fees were $15,094 at the University of Illinois Urbana-Champaign (+42 percent relative to UW-Madison), $14,760 at the University of Minnesota Twin Cities (+39 percent), and $15,262 at the University of Michigan Ann Arbor (+44 percent). The exception is the University of Iowa, which charged $9,492 in 2018-2019, 11 percent less than UW-Madison.

UW-Madison's sticker price also is relatively low compared to the larger population of public flagships. In 2021, UW-Madison had the seventeenth lowest in-state tuition and fees of the 50 public flagship universities (Ma and Pender, 2021), which was 11.5 percent less ($1,405) than the average flagship.[10] In addition to charging a lower sticker price than most other state flagship universities, UW-Madison ranks among the ten most affordable flagships for low-income dependent students (Mugglestone et al., 2019).

Despite its favorable costs, in recent years UW-Madison has lagged behind its peers in enrollment of low-income students. As of the 2016-2017 academic year (two years before the introduction of BTP), just 11 percent of UW-Madison students received federal Pell grants.[11] This share is less than half the national average (30 percent) at very selective 4-year colleges, and lower than the shares at all neighboring state flagships—Michigan (15 percent), Minnesota (19 percent), Illinois (22 percent), and Iowa (23 percent); in fact, in terms of Pell enrollment share, UW-Madison ranks behind every flagship except the University of Virginia and Pennsylvania State University (Mugglestone et al., 2019).

2.1 UW-Madison Financial Aid and Bucky's Tuition Promise

During the period studied, UW-Madison uses a programs-based model of allocating financial aid to students with financial need. These named financial aid programs target different types of students, including Pell-eligible, first-generation college, public assistance recipient, and transfer students. For each program, UW-Madison identifies students who meet the eligibility criteria. Students who do not qualify for one of the named programs are grouped based on

[10] Author's calculations using data from Ma and Pender (2021), retrieved from `https://research.collegeboard.org/xlsx/trends-college-pricing-excel-data-2021-0.xlsx`.

[11] Federal Pell grants are awarded to students from families whose Free Application for Federal Student Aid (FAFSA) demonstrates a low ability to pay for college. In academic year 2018-2019, these students would have an expected family contribution (EFC) under $5,486; that year, the maximum annual Pell Grant award was $6,095.

their need, with higher-need students prioritized for aid allocation. UW-Madison does not guarantee to meet students' financial need[12], but the admissions process is need-blind.

Research evidence suggests that misconceptions about affordability and uncertainty about overall costs may deter high-achieving, low-income students from applying to or enrolling in the state flagship, despite the fact that the flagship is often the cheapest option among in-state, public 4-year colleges for students with high financial need (Dynarski et al., 2021). Given the low Pell enrollment share at UW-Madison—even with its relatively low sticker price—such misconceptions and uncertainty about college costs are likely present in Wisconsin.

Indeed, anecdotal evidence suggests that concern about the salience of these barriers among less affluent Wisconsin families led to the creation of Bucky's Tuition Promise, a means-tested undergraduate financial aid program designed to increase access and affordability for new resident students from low- and moderate- income households.[13] UW-Madison Chancellor Rebecca Blank unveiled BTP at a board meeting of the Regents of the University of Wisconsin System on February 8, 2018. Beginning with the Fall 2018 cohort, incoming freshman students who qualify for BTP are guaranteed grants to cover full tuition and fees for four years.[14] BTP is a last dollar award that is funded with private gifts and other institutional resources; at the time of the announcement, the University expected to spend $825,000 annually per class on BTP (above the aid that eligible students would receive otherwise), or $3.3 million dollars per year once the program included four cohorts (Erickson, 2018).

BTP was designed to have simple and transparent eligibility criteria, which is unsurprising given the University's concerns about the roles of incorrect beliefs and uncertainty about total costs.[15] A student must submit the Free Application for Federal Student Aid

[12] A student's financial need is computed as the cost of attendance (COA) minus the EFC, the latter of which is determined by the FAFSA.

[13] In public communications about Bucky's Tuition Promise, UW-Madison leadership explicitly noted these concerns as part of the motivation for the program. For instance, then-Chancellor Rebecca Blank highlighted families' uncertainty about costs ("Many low- and middle-income families in Wisconsin are simply uncertain whether they can afford to send their child to UW–Madison") and the impact of families' perceptions about costs on application choices ("We know there's a perception that UW–Madison is financially out of reach for some of our Wisconsin families, and we know this keeps some high school students in our state from applying here") in her announcement of BTP at the Board of Regents meeting (Erickson, 2018).

[14] Incoming transfer students receive two years of coverage. At the time of the announcement, resident tuition and fees were $10,533 (for the 2017-2018 academic year).

[15] When BTP was revealed, then-Director of the Office of Student Financial Aid Derek Kindle said, "Bucky's Tuition Promise will provide parents with clarity around cost much earlier in the college-selection process...For the first time ever, we are saying to these Wisconsin families, in the clearest and most concise way possible, that if your student applies here and is accepted, we will cover the cost of tuition and fees — plain and simple" (Erickson, 2018).

(FAFSA) to be considered for any need-based financial aid at UW-Madison, but she need not apply directly for BTP: If an admitted student is eligible for BTP, she automatically is a BTP recipient.

To be eligible for BTP, a student must satisfy four criteria. First, only new students (freshman and transfer) may receive BTP; that is, the policy is not retroactive, so students who began their studies at UW-Madison prior to Fall 2018 are not covered. Second, the student must be pursuing her first bachelor's degree. Third, the student must be a Wisconsin resident. Lastly, the student's household adjusted gross income (HH AGI) as reported on the FAFSA[16] must fall below a threshold approximately equal to the state median; in 2018, the household AGI cutoff to qualify for BTP was $56,000.[17] UW-Madison does not employ an asset test for BTP, nor does it require students to re-certify that they meet the income threshold in subsequent years.[18] Thus, the only criterion used for means testing is the household AGI reported in the student's first-year financial aid application.

Bucky's Tuition Promise guarantees eligible students a minimum level of grant coverage; students may receive financial aid offers (including grant aid) that exceed the cost of tuition and fees, which will depend primarily on financial need.

2.1.1 BTP Treatments and Mechanisms

BTP aid is applied as a last-dollar grant: In a given financial aid year, the financial aid office first allocates all other sources of aid (whether Pell grants, student loans, work study, outside scholarships, etc.), and then the BTP tuition and fees guarantee is applied to the student's award package. This means that a BTP recipient is only awarded "BTP dollars" (in a given year) if the amount of grant aid she receives from other sources does not cover the full cost of tuition and fees. Regardless of whether a BTP student is awarded any BTP dollars in her first year (or subsequent years), she never loses the "promise": She is guaranteed grant coverage of tuition and fees for four years.

Because UW-Madison does not guarantee to meet a student's full financial need, the introduction of BTP *could* increase the dollar value of a student's first-year financial aid offer (relative to what she would receive absent BTP). BTP can affect a student's first-year

[16]Students filling out the FAFSA for Fall 2018 provide household demographic, income, and asset information from their 2016 federal income tax returns. Household adjusted gross income is the total of student and parent AGI for dependent students, and student and spousal AGI for independent students.

[17]The household AGI threshold increased to $60,000 for students entering in Fall 2019, but this decision was not announced until February 2019, after the freshman applications deadline for Fall 2019. Consequently, students applying for Fall 2019 enrollment were under the impression that the AGI cutoff was $56,000.

[18]Even though students remain eligible for Bucky's Tuition Promise if their household income exceeds the AGI cutoff in subsequent years, they still must resubmit the FAFSA to receive the award.

financial aid package in two ways. First, BTP may increase the amount of grant aid a student is offered without changing the total amount of her financial aid award, that is, change only the aid package's composition. This type of treatment is unlikely, but it is most likely to occur for students who are awarded federal work-study. Work-study funds are limited, so BTP recipients who would have been offered work study under non-treatment may not be offered such funds under treatment, as the university may prioritize offering these funds to other students.

The second and more likely way that BTP may impact a student's *first-year* financial aid package is by increasing both her grant aid and total aid offer. Importantly, this can include changing the aid package's size and/or its composition. Students that receive BTP dollars under treatment are likely to have been offered federal student loans in the absence of the program, which they may still receive even when they are awarded BTP dollars. Thus, it is likely that receipt of BTP dollars increases students' total aid packages.

Each of these types of dollar-value treatments may affect admitted students' enrollment decisions. In the first case, BTP grant aid may partially or fully crowd out an eligible student's out-of-pocket costs, work-study contributions, or (though less likely) educational loans. All of these channels are expected to (weakly) increase the conditional probability of enrollment: Lowering out-of-pocket costs reduces the student's present financial burden; replacing work study with grants frees up time to study; and reducing borrowing may be attractive to students and families with debt aversion. In the second case, a larger total aid package reduces the student's overall cost of attendance, which will increase the utility of enrolling at UW-Madison; larger aid packages may also increase the probability of enrollment if students face borrowing constraints, which is likely among low-income students.[19]

For some BTP recipients, especially high-need students, BTP may have no impact on the first-year financial aid package. Some low-EFC resident students are offered financial aid packages that meet their full need[20], while others without full need coverage may still

[19] The estimated cost of attendance at UW-Madison in 2018-2019 was $26,026 for non-commuter residents, so these students could expect to incur approximately $15,400 in living and related expenses in the first year alone. Students who are awarded one of a limited number of work-study positions may be able to offset up to one-third of these expenses. Annual federal student loan limits for dependent undergraduates are $5,500 in the first year, $6,500 in the second year, and $7,500 in the third year and beyond, so it is likely that student loans will only cover 35 to 50 percent of additional (non-tuition) costs of attendance. Federal Direct PLUS loans are available to parents to borrow up to the cost of attendance minus other aid, but credit checks are conducted, and parents with adverse credit histories may be unable to secure the loan. Some students may be able to obtain private student loans, but these often require minimum credit scores or co-signers; low-income students may not have family members who would be willing or approved to co-sign the loan. Thus, borrowing constraints may prevent low-income students from enrolling at UW-Madison even if their tuition and fees are covered by BTP.

[20] For example, FASTrack, short for "Financial Aid Security Track," is a UW-Madison undergraduate finan-

receive grants in excess of tuition and fees. It is therefore unlikely that BTP would affect these students' enrollment decisions through improved first-year financial aid packages.

Nevertheless, the BTP offer may still impact expected degree costs and uncertainty about ability to pay total degree costs through the tuition pledge component. This treatment channel may affect enrollment decisions for all eligible students, although possibly to different degrees depending on their expected aid coverage in the absence of BTP.[21]

To see this, first consider—in a world without BTP—the sources of uncertainty that lower-income admitted students face when deciding whether to attend UW-Madison. Some students may be unsure about their family's ability to contribute to the cost of attendance in subsequent years (perhaps due to job or income instability, illness or dependent care, unexpected expenses, increased housing costs, etc.). In addition, most students likely face some uncertainty about their expected family contribution (which can be difficult to predict) and aid coverage (which is awarded at the University's discretion and is not guaranteed to meet financial need) in subsequent years. Moreover, all admitted students face uncertainty about published tuition and fees beyond the first year, as these charges are not published prior to the academic year[22] and may deviate from historical trends due to unexpected political and economic factors.[23] Thus, even with their admissions and financial aid offers in hand, students deciding where to enroll may be uncertain about several revenue and/or expense components in their college budget for later years and must form expectations about these costs and revenue sources.

Now consider how the presence of BTP changes these sources of uncertainty. BTP provides guaranteed coverage of tuition and fees for four years, so both the expected value and the variance of 4-year tuition and fee costs should collapse to zero for BTP recipients. Given that tuition and fees are independent of living expenses, the variance in total out-of-pocket degree costs for BTP recipients will only depend on living expenses.

cial aid program for incoming resident students from low-income households that receive public assistance. The program commits to meeting a student's financial need for four consecutive years (two for incoming transfer students) using a combination of grants, scholarships, and work-study. Because the program has limited space, eligible students are not guaranteed a spot.

[21]Students selected into FASTrack receive a 4-year commitment that their need will be met, but this pledge does not guarantee full coverage of tuition and fees (although they likely would be covered). In an extreme case, a FASTrack student's EFC could increase enough in a subsequent year that FASTrack does not cover full tuition and fees, while BTP would.

[22]The Board of Regents of the University of Wisconsin System sets tuition rates at UW-Madison, typically in July or August before the start of the new academic year.

[23]Consider, for example, the Great Recession: While some institutions froze tuition and fees, in other instances, state budget shortfalls led to increases in tuition and fees.

3 Data and Descriptive Statistics

3.1 Data

My analyses use individual-level administrative data from the Student Information System (SIS) at UW-Madison. I use records and data elements sourced from the Office of Admissions and Recruitment, the Office of Student Financial Aid, and the Registrar's Office. I obtain records of all undergraduate first-year and transfer applicants for matriculation starting in Fall 2016 through Spring 2019. I then restrict the sample to admitted students who satisfy requirements for Wisconsin residency and who completed a FAFSA.

For academic year 2018-2019, 43,130 students applied for undergraduate admission, 9,984 of which were Wisconsin residents (23 percent). Among applicants, 23,016 received offers of admissions, 6,469 of which were Wisconsin residents (28 percent of admits); of these admitted students, 5,238 (81 percent) submitted a FAFSA. Table 1 shows annual FAFSA submission rates by resident admits.

I make several additional restrictions to the sample. First, I include only first year applicants (i.e., transfer applicants are excluded) because the transfer application deadline was after the BTP announcement. Second, I exclude observations with household AGI below zero.[24] Third, I exclude students who submitted applications after the admissions application deadline (typically February 1 for first years) for the fall term admissions cycle or before the fall admissions cycle opened (August 1). Fourth, it is important that I only include students whose application decisions could not be affected by BTP so that I can isolate the impacts of the financial aid offers on the conditional enrollment decision. Therefore, I exclude all students who submitted their admissions application on or after the public announcement of BTP (February 8, 2018). For this reason, I do not use data from the 2019-2020 academic year.[25] For some descriptive analyses, I also use data for the 2017-2018 school year, and I impose the same sample restrictions outlined in this paragraph.

Implementing my research design requires a variable indicating a student's BTP eligibility. I construct this variable for my baseline sample by combining information on the student's residency, prior degree information, and household AGI. Wisconsin residents who are pursuing their first bachelor's degree and whose household AGI on the FAFSA is at or below $56,000 are coded as BTP eligible. Figure 13 panel (a) plots the constructed indicator for BTP eligibility (treatment assignment) against binned values of the running variable, household AGI; as expected, the probability of being eligible for BTP drops abruptly from

[24]These families are typically very wealthy. Results are qualitatively unchanged if they are included.

[25]That is, for the RD analyses, I only use applicants for the 2018-2019 school year.

one to zero as household AGI crosses \$56,000. Panel (b) plots treatment receipt; only a few students appear to be non-compliers (i.e., coded as eligible with income above \$56,000, or coded as ineligible with income below). It is possible that these students ultimately were assigned to the appropriate student group after the data I use were extracted from the SIS, or they may represent professional judgments by financial aid staff. Regardless, given the small amount of non-compliance, it is reasonable to think of treatment assignment and treatment receipt as coinciding, but in discussing results I phrase effects in terms of eligibility since the estimands are intent-to-treat.

I use a rich set of demographic/pre-treatment covariates. These include sex, number of family members (in household), number of household family members in college, expected family contribution, assessed financial need, Pell eligibility indicator, auto-zero EFC indicator, first-generation indicator, financial independence indicator, household and student assets, household and student taxes paid, student AGI, auto-zero EFC indicator, ACT score, SAT score, UW-Madison targeted minority indicator, eligibility for the FASTrack financial aid program[26], indicator if the mother completed college (and if missing), flags for the urbanicity of the most recent school attended (suburban, rural). I also use several zip code-level controls from the American Community Survey, which include population, mean house value, and mean household income.

3.2 Descriptive Statistics

This section documents descriptive statistics for the analysis sample. Table 1 shows FAFSA submission by in-state admitted students for years 2016-2019. This rate is increasing over time, with 83 percent of in-state admitted students submitting a FAFSA in 2018.

Table 2 reports the mean, median, 25th, and 75th percentiles of the distributions for household AGI, household assets, household taxes paid, and EFC; Table 3 reports means, medians, and standard deviations for the same variables stratified by BTP eligibility.

As shown in Table 2, the average resident admit has a mean household AGI of \$98,000 and assets of \$127,000. Interestingly, the median resident applicant has slightly higher income

[26]Incoming Wisconsin first years and transfer students are eligible for FASTrack if their family receives public assistance, including Medicaid or Supplemental Security Income (SSI), Supplemental Nutrition Assistance Program (SNAP), Free or Reduced Price School Lunch, Temporary Assistance for Needy Families (TANF), or Special Supplemental Nutrition Program for Women, Infants, & Children (WIC). Students that are homeless or a ward of the court are also considered. Badger Promise is a resident-based financial aid program for Wisconsin transfer students who are first-generation, that is, neither parent holds a bachelor's degree. In 2019, BTP+ is introduced for residents, which expands BTP by guaranteeing to meet full need for Pell-eligible incoming resident students with a combination of grants, scholarships, and work-study.

at \$102,000 but substantially lower assets at \$26,000.[27] Note that this median income is 82 percent higher than the state median.

Table 3 shows that BTP-eligible students have much lower financial resources than the mean resident admit. The median household AGI is approximately \$32,600 and the mean is \$31,300, with a standard deviation of \$16,700. The median assets for BTP-eligible students are just shy of \$5,000, and the median EFC is only \$460. These statistics show that the BTP eligible admits are a high need population and do not have the resources to pay for the cost of attendance at UW-Madison. In contrast, the median BTP-ineligible household has household assets of \$37,000 and an EFC of \$19,660; in other words, the median BTP-ineligible student's expected family contribution is nearly double the cost tuition and fees. The average EFC among the BTP-eligible sample is approximately equal to the cost of attendance.

Table 1: FAFSA Submission by In-State Admitted Students

	WI Admits	w/ FAFSA	Share w/ FAFSA
2016-17	5,395	3,880	0.72
2017-18	5,519	4,455	0.81
2018-19	5,261	4,345	0.83
2019-20	5,438	4,548	0.84
Total	21,613	17,228	0.80

Table 2: FAFSA Summary Statistics for Fall 2018 Resident Admits

	Mean	Median	25th	75th
Household AGI	97,698	102,343	65,000	132,446
Househod Assets	127,087	26,119	4,717	117,500
Household Taxes	8,612	7,311	2,506	13,882
EFC	21,256	15,568	6,291	28,142
Observations	3,035			

Notes: Table 2 shows summary statistics in dollars for Fall 2018 in-state first-year applicants who received offers of admission to UW-Madison and who completed a FAFSA. Household AGI, assets, and taxes are reported on the 2018-2019 FAFSA using 2016 tax return data. A student's Expected Family Contribution (EFC) is determined by the U.S. Department of Education using information provided in the FAFSA.

[27] In fact, mean assets exceed the 75th percentile, indicating that the household asset distribution has a few large values that skew the mean upward.

Table 3: FAFSA Summary Statistics for Fall 2018 Resident Admits, by BTP Eligibility

	BTP Eligible			BTP Ineligible		
	Median	Mean	SD	Median	Mean	SD
Household AGI	32,606	31,331	(16,724)	114,868	114,495	(31,680)
Househod Assets	4,890	66,051	(222,101)	37,124	142,535	(353,514)
Household Taxes	0	796	(1,422)	9,323	10,590	(6,586)
EFC	458	3,147	(9,521)	19,660	25,839	(31,621)
Observations	613			2,422		

Notes: See Table 2 notes.

In Table 4 I document the mean and median household AGI, household assets, and EFC of resident admit students by AGI eligibility for 2017 (prior to BTP) and 2018 (the first year of BTP). The key takeaway from the table is that household AGI is essentially unchanged between 2017 and 2018 for both BTP-eligible and BTP-ineligible students. Similarly, EFC is nearly identical between the two years, indicating that the introduction of BTP does not correspond with a change in families' ability to pay for college.

In Table 5 I restrict my attention to the sample of BTP-eligible students. As above, I report the mean and median household AGI, household assets, and EFC for 2017 and 2018, this time by Pell-eligibility. As expected, income, assets, and EFC are substantially different between Pell-eligible and Pell-ineligible students. However, there appears to be little change in household AGI between 2017 and 2018 for both Pell-eligible and Pell-ineligible students.

Table 4: Summary Statistics for Resident Admits

	2018		2017	
	AGI Eligible	Not Eligible	AGI Eligible	Not Eligible
HH AGI				
	31,414	113,241	31,094	115,683
	34,944	112,965	33,172	115,737
HH Assets				
	37,599	65,349	28,181	65,917
	6,000	27,300	3,402	26,862
EFC				
	2,439	20,189	2,120	20,162
	419	18,202	444	17,904
Obs.	339	1,555	433	1,671

Notes: Table 4 shows summary statistics (mean and median, in 2016 USD) of financial variables, separately by BTP AGI eligibility, for in-state first-year applicants for Fall 2017 and 2018 who received offers of admission to UW-Madison, who completed a FAFSA, and whose household AGI (as reported on the FAFSA) was at or below $175,000. The FAFSA for Fall 2018 (2017) enrollment uses tax return data filed in 2017 (2016) for the 2016 (2015) tax year.

Table 5: Summary Statistics for BTP Eligible Students by Pell Status

	2018		2017	
	Pell Eligible	Not Pell Eligible	Pell Eligible	Not Pell Eligible
HH AGI				
	29,033	45,501	29,140	46,765
	30,668	47,644	30,675	48,440
HH Assets				
	22,574	126,521	18,256	107,790
	4,090	99,300	2,316	75,966
EFC				
	1,023	10,820	1,009	11,033
	8	7,921	100	7,388
Obs.	290	49	385	48

Notes: Table 5 shows summary statistics (mean and median, in 2016 USD) of financial variables, separately by Pell eligibility, for in-state first-year applicants for Fall 2017 and 2018 who received offers of admission to UW-Madison, completed a FAFSA, and have household AGI that qualify them for BTP. The FAFSA for Fall 2018 (2017) enrollment uses tax return data filed in 2017 (2016) for the 2016 (2015) tax year.

For academic year 2018-2019, BTP was the only new financial aid policy. Because of this, and the fact that most Pell-eligible resident students were offered generous aid packages in 2017, the amount of grant and total aid offered before and after BTP should be similar for high-need students. Figure 1 shows that this is the case: From 2017 to 2018, most BTP-eligible students with EFC between $0 and $5,486 (which qualifies them for federal Pell grants) are offered financial aid packages with similar total aid (panel (b)) and similar or only slightly higher grant aid (panel (a)). Regardless of their household income, Pell-eligible students' full tuition and fees are (on average) covered by grant aid, as shown by the fact that all binned scatter points are above the horizontal dashed line, which delineates the cost of in-state tuition and fees. Total aid packages are typically within $5,000 of the total cost of attendance (COA), which in 2018 is approximately $26,344 for non-commuter resident students.[28]

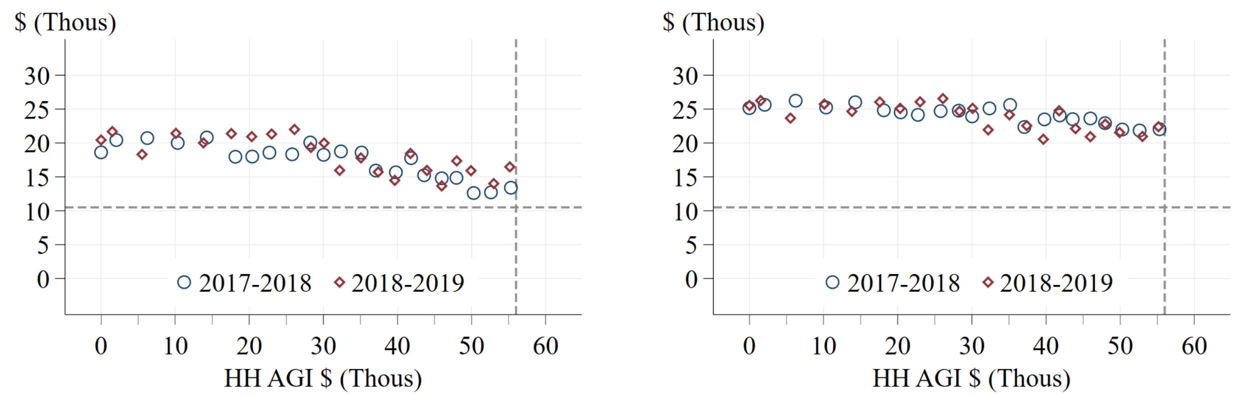
In contrast, as Figure 2 suggests, for Pell-ineligible students with higher incomes and moderate EFCs (between approximately $5,500 and $9,000), the grant and total aid offered under BTP often is substantially higher than that offered in the state of the world without BTP. For instance, as panel (a) of Figure 2 shows, most students received approximately $2,500 in grant aid prior to BTP, but in 2018, those offers typically doubled.[29] This feature of

[28]Tuition, and thus, cost of attendance, is slightly higher for some degree programs, like Engineering (COA=$29,194 in 2018) and Business (COA=$27,366 in 2018).

[29]For BTP-eligible students, grant offers below the $10,896 guaranteed by BTP may reflect measurement error, as the data are collected at a single point in time and do not necessarily reflect updated offers.

the institutional setting implies that, for students who just satisfy the BTP AGI requirement but who are not Pell-eligible, the BTP treatment includes both the tuition guarantee and a (likely generous) increase in grant aid. For this reason, I will focus on the results for this sub-sample of students.

Figure 1: Grant and Total Aid Offers for Pell-Eligible and BTP-Eligible Admits, by Year



(a) Ave. Grant Aid

(b) Ave. Total Aid

Notes: Panels (a) and (b) in Figure 1 show binned scatter plots of average grant and total aid offers, respectively, before and after BTP for admitted first-year resident students who were Pell- and BTP-eligible. The sample includes admitted resident students in AY 2017-2018 and AY 2018-2019 who applied for financial aid and satisfy Pell and BTP eligibility criteria: Pell-eligible students have EFC at or below $5,486 and BTP-eligible students have household AGI at or below $56,000. The horizontal line delineates the level of grant aid coverage (tuition and fees, approximately $10,896) that would be provided under BTP. The vertical line shows the $56,000 household AGI eligibility cutoff used for BTP in 2018.

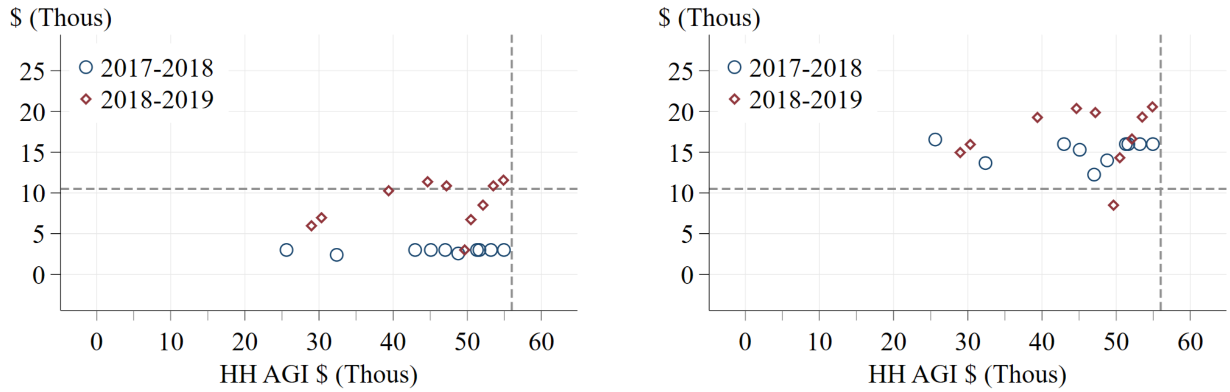
4 Empirical Approach

In this section I describe my empirical strategy for identifying the effects of BTP on financial aid and on admitted resident students' decision whether to enroll at the state flagship. In particular, the strict cutoff in household AGI lends itself to using a regression discontinuity design to examine the effects of financial aid on middle-income students.

4.1 The Effects of Financial Aid on Enrollment

Following the pioneering work of van der Klaauw (2002), I leverage the abrupt discontinuity in treatment eligibility at the AGI threshold to identify and estimate the impact of BTP eligibility on the conditional probability of enrollment, i.e., that a resident applicant with household income near the state median accepts an enrollment offer from UW-Madison. Denote this parameter τ_{BTP}. Let $i = 1, ..., n$ index individuals. Household adjusted gross

Figure 2: Grant and Total Aid Offers for Pell-Ineligible and BTP-Eligible Admits with Moderate EFC, by Year



(a) Ave. Grant Aid

(b) Ave. Total Aid

Notes: Panels (a) and (b) in Figure 2 show binned scatter plots of grant and total aid offers, respectively, before and after BTP for admitted resident students who were BTP-eligible and Pell-ineligible. The sample includes admitted resident students in AY 2017-2018 and AY 2018-2019 who applied for financial aid, satisfied BTP eligibility criteria, and had an EFC above $5,486 and below $9,000. The horizontal line delineates the level of grant aid coverage (tuition and fees, approximately $10,896) that would be provided under BTP. The vertical line shows the $56,000 household AGI eligibility cutoff used in for BTP 2018.

income is the assignment or running variable (or "score") and is denoted by X_i, while c denotes the eligibility cutoff in X_i, which is $56,000 in the first year of BTP. Let $D_i \in \{0, 1\}$ denote the treatment assignment rule, a deterministic function of X_i which exhibits a discontinuity at the cutoff:

$$D_i := \mathbf{1}\{X_i \leq c\} = \begin{cases} 1 \text{ if } X_i \leq c, \\ 0 \text{ if } X_i > c \end{cases}$$

with $D_i = 1$ indicating assignment to treatment, i.e., BTP eligibility. I model the relationship between BTP eligibility and the enrollment decision of resident applicants, conditional on admission to UW-Madison, using the following linear regression:

$$Y_i = \tau_{BTP} D_i + f(X_i) + \alpha W_i + \varepsilon_i, \quad (1)$$

where Y_i is a binary indicator of enrollment at UW-Madison, $f(X_i)$ is a flexible function of household AGI, W_i is a vector of observable student characteristics[30], and ε_i is an unobserved error.

[30] I conduct analyses with and without covariates, although I prefer the specification with covariates to absorb any additional bias, allow a wider bandwidth, and improve precision of estimated effects.

Under the assumption that $E[\varepsilon|X]$ is continuous at $X = c$, (Hahn et al., 2001; van der Klaauw, 2002), τ_{BTP} is identified:

$$\tau_{BTP} := \lim_{x \uparrow c} E[Y_i|X_i = x] - \lim_{x \downarrow c} E[Y_i|X_i = x]. \quad (2)$$

Without additional assumptions, τ_{BTP} is the Intent-to-Treat estimand (ITT), capturing the impact of BTP eligibility on the conditional probability of enrollment Y for students with household AGI around the cutoff. When treatment receipt (denote as $T_i \in \{0, 1\}$) coincides with treatment assignment, i.e., $T_i = D_i$ for each i, then τ_{BTP} also captures the average treatment effect (ATE) for observations with scores near the cutoff.

4.2 Channels

Estimates of τ_{BTP} capture the overall impact of the promise program on the conditional enrollment decision for median-income resident admits. However, as discussed in Section 2.1.1, Bucky's Tuition Promise is a multi-dimensional treatment, so several channels may contribute to the overall effect τ_{BTP}. Using the same model, I also conduct a second set of analyses to shed light on BTP's effects on financial aid dollars. While such effects are not necessary for BTP to affect the enrollment decision (because increased certainty may drive the effects), it is useful to know if enrollment effects from the grant aid channel are even possible, and for whom. As before, these analyses leverage the discontinuity in BTP treatment assignment to estimate effects on the amount of gift/grant aid offered and the total size of the financial aid package (henceforth "grant aid" and "total aid"). Let τ_G and τ_A denote the treatment effects on grant aid and total aid, respectively.

4.3 Estimation and Choice of Tuning Parameters

The RD analyses above identify the causal parameters of interest: τ_{BTP}, τ_G, and τ_A. I use local polynomial methods to estimate τ_{BTP}, which involves fitting Y_i on a low-order (e.g., order 0 or 1) polynomial expansion of X_i, separately by an observation's treatment status.[31] Since τ_{BTP} is identified under an assumption of continuity in the error at the cutoff, only observations near the cutoff are used in estimation, where "near" is determined by the econometrician's choice of two tuning parameters: the kernel function $K(\cdot)$ and the bandwidth h.[32]

[31] See Cattaneo and Titiunik (2022) for a recent view of modern RD methods.

[32] Either a single bandwidth, h or separate bandwidths below and above the cutoff (h_- and h_+, respectively), can be used.

Specifically, I separately estimate local polynomial regressions for treatment (BTP eligible) and control (BTP ineligible) observations (respectively):

$$\hat{\beta}_{-} = \underset{b_0,\ldots,b_p}{\operatorname{argmin}} \sum_{i=1} 1\{X_i \leq c\} [Y_i - b_0 - b_1(X_i - c) - \ldots - b_p(X_i - c)^p]^2 K\left(\frac{X_i - c}{h_-}\right) \tag{3}$$

$$\hat{\beta}_{+} = \underset{b_0,\ldots,b_p}{\operatorname{argmin}} \sum_{i=1} 1\{X_i > c\} [Y_i - b_0 - b_1(X_i - c) - \ldots - b_p(X_i - c)^p]^2 K\left(\frac{X_i - c}{h_+}\right). \tag{4}$$

Then, the sharp RD estimate $\hat{\tau}_{srd(h)}$ is computed as

$$\hat{\tau}_{srd(h)} = \hat{\beta}_{+} - \hat{\beta}_{-}. \tag{5}$$

Although I estimate both degree 0 and degree 1 local polynomial regressions, my preferred specification is a local linear regression (polynomial order $p = 1$), following Hahn et al. (2001) and Porter (2003). The bandwidth choice, which determines the range of observations used in estimation[33], is the key parameter for RD implementation (Calonico et al., 2020), as local polynomial estimates are highly sensitive to this choice; I use objective (data-driven) procedures that select the bandwidth that minimizes the mean-squared error (MSE) for the RD treatment effect estimator, which was first developed for the local linear regression RD point estimator in Imbens and Kalyanaraman (2012) (henceforth IK). I implement the second-generation bandwidth selection procedures developed in Calonico et al. (2014, 2019), which incorporate several extensions to the IK bandwidths, including pre-treatment covariate adjustment and different optimal bandwidths for the left and right of the cutoff[34], and which offer improved finite sample properties. An alternative data-driven bandwidth selection procedure chooses coverage error rate (CER)-optimal bandwidths, which are superior to the MSE optimal bandwidth when the objective is to construct robust bias-corrected confidence intervals with minimal coverage error (Calonico et al., 2020).[35] My preferred specification selects MSE optimal bandwidths separately above (h_+) and below (h_-) the cutoff and weights observations using a triangular kernel.[36] I conduct robustness analyses using alternative choices of tuning paramters, including uniform (rectangular) and Epanechnikov kernels and CER-optimal bandwidths.

[33]Observations outside the bandwidths are given zero weight, and thus are not used in estimation.

[34]See Cattaneo and Vazquez-Bare (2016) for a general discussion bandwidth choices in RD designs.

[35]Constructing a CER-optimal interval estimator is a different objective than constructing the optimal point estimator, but they are complementary.

[36]The triangular kernel applies the greatest weight to observations with scores nearest the cutoff, and the weight declines linearly in distance to the cutoff.

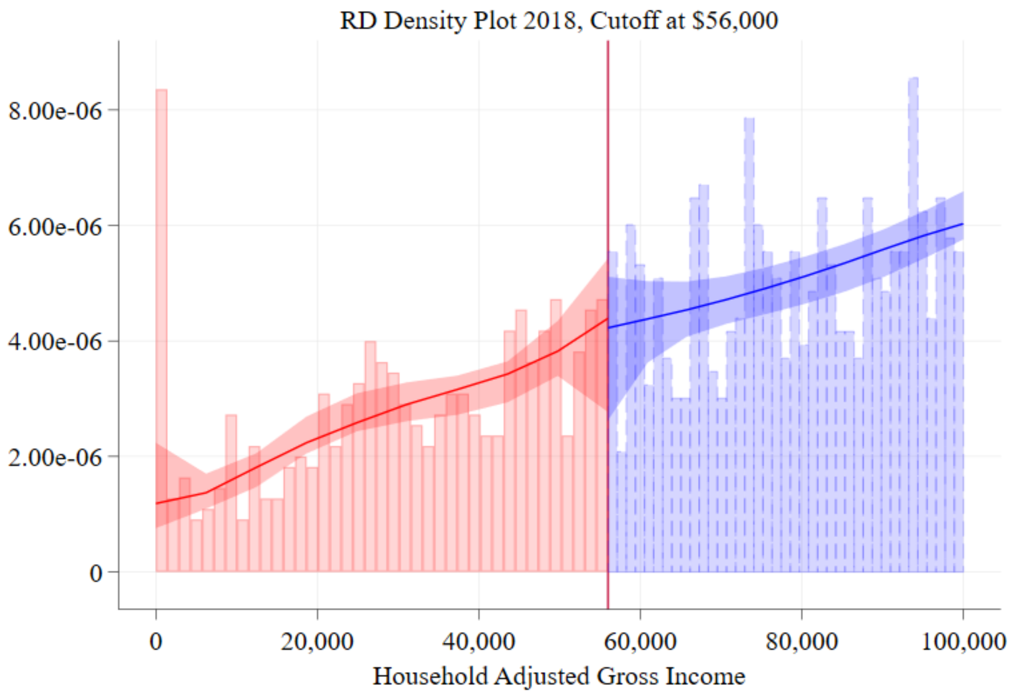
4.4 Validating the RD Design

The key identifying assumption in the sharp RD design is that the unobserved factors ε_i that affect the outcome Y_i and are correlated with the score X_i are continuous at the threshold $X_i = x_c$ (Hahn et al., 2001). In my context, this assumption means that dependent (independent) students and their parents (spouses) are unable to perfectly control their household AGI to meet the income criteria for BTP.

In the first year of the policy, it would be very difficult, if not impossible, for students and their families to precisely manipulate their household AGI so that it falls at or below the $56,000 threshold. There are several reasons for this. First, BTP was announced February 8, 2018 and immediately implemented for the financial aid packaging of new students admitted for Fall 2018 enrollment, so there was no anticipatory period (between the announcement of the program and its adoption) during which families could adjust their behavior. Second, 93 percent of Wisconsin first-year admits who ultimately enrolled at UW-Madison had already submitted their FAFSA before BTP was revealed publicly (their priority deadline for financial aid at UW-Madison was December 1, 2017). Third, even for the students who submitted the FAFSA after BTP was announced, precisely manipulating their treatment assignment would require that they be able to retroactively adjust the household AGI reported on the FAFSA. Because the 2018-2019 FAFSA uses student and parental/spousal financial data reported on 2016 tax returns, employment decisions and tax reporting choices would have been made long before BTP was announced. To ensure BTP income eligibility, families would have to go through the costly effort of filing amended 2016 tax returns, and, when doing so, be *able* to make the necessary claims and deductions (given their reported earnings) on their tax returns to end up with a household AGI at or below $56,000. Such behavior, while possible, is likely to be rare.

I complement this institutional reasoning with several empirical tests of the RD design. While the identifying assumption is fundamentally untestable, I look for manipulation of treatment assignment by testing for a discontinuity in the density of the running variable around the cutoff (McCrary, 2008). Figure 3 plots a histogram of household AGI and its density, which is estimated separately above and below the cutoff (95 percent confidence intervals are indicated by the shaded area). Visual inspection shows that household AGI evolves smoothly and confidence intervals are practically aligned at the $56,000 cutoff, both of which are inconsistent with manipulation. I confirm this conclusion by performing the statistical test described in Cattaneo et al. (2018), which fails to reject the null of continuity in the density at the cutoff (with a p-value of 0.805).

Figure 3: Plot of Manipulation Test of the RD Running Variable



Notes: Figure 3 plots a test of discontinuity in the density of units at the known cutoff (household AGI $56,000) in order to assess manipulation (self-selection or nonrandom sorting) of students into BTP eligibility. This approach is commonly used as a falsification test of the RD design. The test follows the results in McCrary (2008), Cattaneo et al. (2018), and Calonico et al. (2018) and the references therein.

5 Results

5.1 Graphical Analysis

I begin with a graphical analysis to examine how grant aid and enrollment evolve with the running variable, household AGI. I construct figures that provide two ways of visualizing the relationship between AGI and the respective variables of interest. First, each figure displays a binned scatter plot of the average value of the variable at binned values of household AGI, which shows the variation in the data while being less noisy (and more informative) than a plot of the raw data. Second, the figures plot global polynomial regressions, estimated separately above and below the BTP eligibility cutoff, which reveal the underlying relationships in the two subsamples. Unless specified otherwise, the sample used for these graphs includes first-year resident applicants for Fall 2018 who were admitted and who filed a FAFSA.[37]

I first examine how BTP eligibility affects grant aid for students with AGIs around the cutoff. Recall that BTP is a last-dollar award, meaning that it increases grant aid to cover full tuition and fees for students' whose grant aid from all other resources falls short. Therefore, one way BTP eligibility may affect enrollment is by increasing a student's first-year grant aid offer. Interestingly, the absence of an effect on grant aid would suggest that the main channel through which BTP could affect enrollment is increased certainty in degree costs. Thus, studying how BTP impacts grant aid is important for understanding potential mechanisms at play.

Figure 11 plots admitted students' grant aid offers at binned values of household AGI using evenly-spaced mimicking-variance bin selection. This measure of grant aid includes, federal and state grants and institutional grant/gift aid, but it excludes private gift aid, which refers to scholarships that a student obtains from sources outside UW-Madison. Panel (a) shows the relationship in 2018, the first year of BTP; for comparison, I plot the data for 2017 in panel (b). The sample is restricted to household AGIs between \$0 and \$170,000.

Panel (a) suggests that BTP eligibility has a positive effect on the amount of grant aid awarded to incoming resident students with median household income. The estimated polynomials are discontinuous at the cutoff, with boundary values of \$12,991 to the left and \$9,138 to the right, corresponding to a difference in grant aid of \$3,853. The binned scatter plot implies a similar conclusion. As the BTP eligibility threshold is crossed, the points exhibit a downward shift. Moreover, as with the polynomials, the two bins straddling the cutoff exhibit a discontinuity: Admitted students with AGI in the bin $[\$54,727, \$56,000]$ are offered \$13,549 in grant aid on average ($n = 23$), while the average grant award for those with AGIs in the bin $[\$56,000, \$57,5921]$ is \$10,419 ($n = 25$). In summary, the raw data suggest that BTP eligibility increases the grant aid offer by approximately \$2,714 to \$3,853 for admitted students with household AGI around \$56,000.

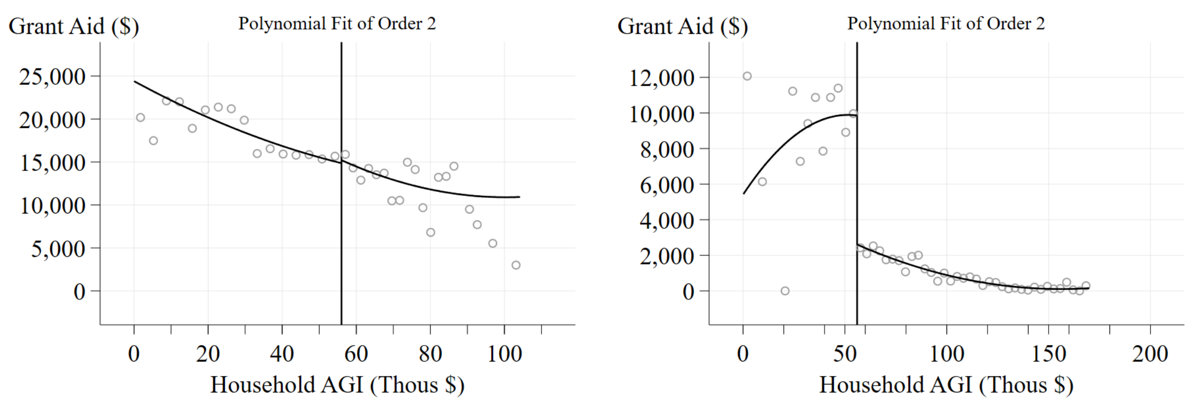
It also is worth noting how 2018 contrasts with 2017 (pre BTP). Panel (b) shows that for 2017, estimated grant aid is approximately the same for students just above and below the threshold. The polynomial boundary values are estimated to be \$8,263 and \$8,605. The binned data tell a similar story, with average grant aid values of \$10,911 ($n = 19$) in bin $[\$54,982, \$56,000]$ and \$9,645 ($n = 22$) in bin $[\$56,000, \$57,708]$. In addition, comparing panels (a) and (b) around the cutoff reveals that higher income BTP-eligible students received

[37] For most of the graphical analyses, I restrict the support of household AGI to range from \$0 to \$150,000. On occasion, to allow for closer visual inspection of the data around the cutoff, I further restrict the upper end of the support to \$120,000. I note instances where the sample restriction changes the qualitative conclusions that can be drawn from the figure.

24 percent larger grant aid offers in 2018 compared to 2017 ($13,549 versus $10,911), while gift aid offers for ineligible students just above the cutoff were 8 percent higher in 2018 ($10,418 versus $9,645). Together, the two panels in Figure 11 provide strong visual evidence that BTP eligibility increases the grant aid dollars offered to admitted resident students with family incomes near the eligibility threshold.

In Section 2.1.1, I hypothesize that BTP would have little effect on the grant aid offers of Pell-eligible resident admits, who already received generous grant aid offers prior to the introduction of BTP.[38] Importantly, even when only considering grant aid offers in 2018, this hypothesis is confirmed by investigating grant aid offers around the threshold separately for Pell-eligible and Pell-ineligible students. Figure 4 plots the same relationships as Figure 11 (a), except that Figure 4 divides the sample by Pell eligibility. Figure 4 reveals that BTP's effects on grant aid are negligible for Pell-eligible students near the cutoff. Pell resident admits with household AGI in the bin just below the cutoff [$52,705, $56,000] receive average grant aid offers of $15,920 ($n = 40$), 51 percent more than the amount guaranteed by BTP. For Pell-eligible students who just barely miss the BTP AGI threshold, the average grant offer is $16,273 ($n = 18$)—slightly more than what the BTP-eligible students receive.

Figure 4: BTP Eligibility and Grant Aid in 2018, by Pell Eligibility



(a) Pell-Eligible (b) Pell-Ineligible

Notes: Figure 4 shows how BTP eligibility affects grant aid offers separately for Pell and non-Pell students. The overall relationship is shown using global polynomial regression, while underlying variation in the data is portrayed using a data-driven binned scatter plot. The global polynomial is of order 2 and is estimated separately above and below the cutoff. Quantile-spaced bins are selected using a mimicking variance method with spacings estimators. Figures are produced using the *rdplot* command described in Calonico et al. (2017). See Calonico et al. (2015) for technical details.

[38]This fact is reflected in Figure 1 in Section 3.2, which compares aid offers in 2017 and 2018 for students eligible both for BTP and federal Pell grants.

On the other hand, when the sample is restricted to Pell-ineligible students, differences in grant aid offers around the AGI threshold are very pronounced. Figure 4 (b) shows a large change in average grant aid through the BTP cutoff for Pell-ineligible students. The discontinuity at \$56,000 in panel (b) reflects a drop in average grant aid from \$10,050 for students just below the cutoff (bin [\$52,015, \$56,000], $n = 21$) to \$2,529 for students just above (bin [\$56,000, \$57,423], $n = 17$). Given these findings, I also conduct a separate analysis of heterogeneous impacts of BTP on enrollment by Pell-eligibility status. Furthermore, the results suggest that any BTP enrollment impacts operating through the grant aid channel would be limited to Pell-ineligible students, and any enrollment effects on Pell-eligible students would be due to the increased certainty of degree costs from the tuition promise aspect of the BTP treatment.

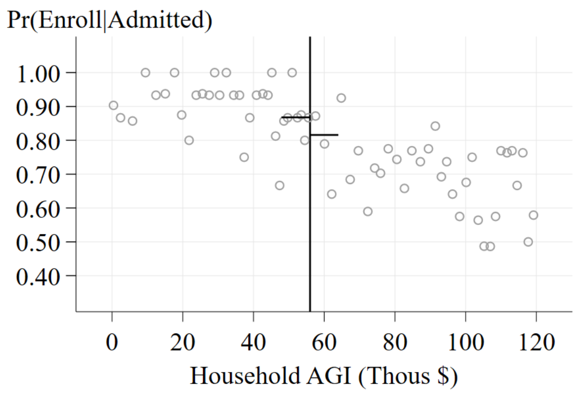
Next, I examine the graphical evidence of a discontinuity in enrollment around the BTP eligibility cutoff. Figure 5 shows polynomial regressions (of different orders) and binned scatter plots (with different bin selection procedures) of the probability of enrolling at UW-Madison, conditional on being a resident applicant who received a first-year offer of admission for Fall 2018 and who submitted a FAFSA. In each of the panels, the polynomial fits suggest the presence of a discontinuity at the AGI eligibility cutoff.[39] Because the findings from Figure 4 suggest that treatment intensity (for BTP grant dollars) is heterogeneous by Pell-eligibility, enrollment responses also may differ by Pell status, which is not controlled for in any of these figures, as each is produced using unconditional (i.e., unadjusted by other covariates) binned means. Figure 6 shows the probability of enrollment at binned values of household AGI using separate samples for Pell-ineligible and Pell-eligible admits. The discontinuity is pronounced for Pell-ineligible students, who are more likely to accept the enrollment offer just below the AGI cutoff. In contrast, a discontinuity for the Pell-eligible is not detectable.

5.2 Regression Results

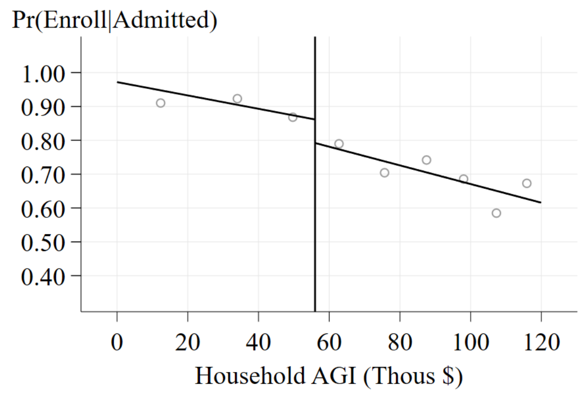
Having established graphical evidence of the effects of BTP eligibility, I now describe results from the RD regression analyses. Figure 7 shows kernel regression coefficient estimates (and 95 percent confidence intervals) of Equation (5) with polynomial order degree 0 (panel (a)) and 1 (panel (b)), a triangular kernel, and MSE-optimal bandwidths selected separately for

[39]The binned data suggest some curvature to the global relationship between AGI and enrollment probability, although the mimicking-variance (MV) approach shown in panels (a) and (c) indicates that the underlying data are somewhat noisy. A clearer pattern emerges from the IMSE-optimal bins, but at the expense of making it difficult to discern the presence of a discontinuity.

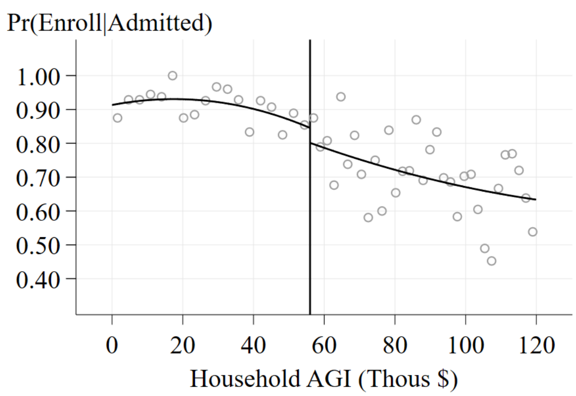
Figure 5: BTP Eligibility and Enrollment in 2018



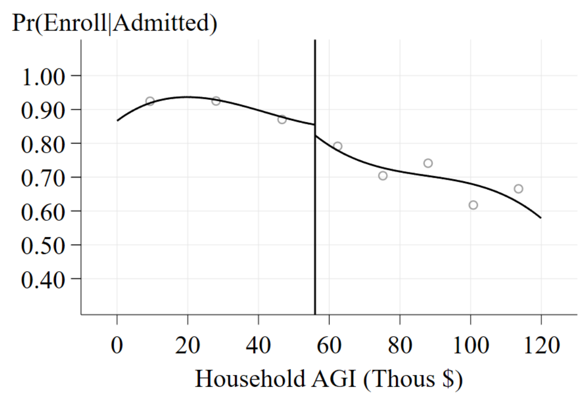
(a) QS-MV, Poly. Order 0



(b) QS-IMSE, Poly. Order 1



(c) ES-MV, Poly. Order 2



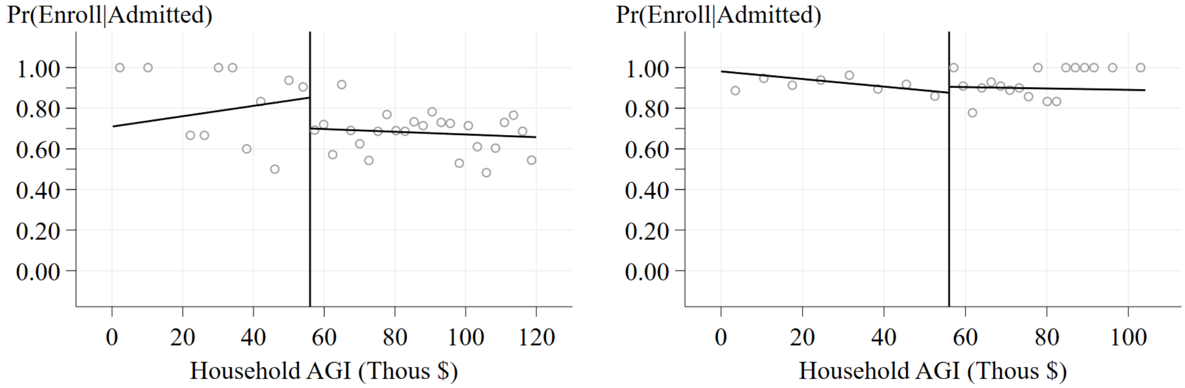
(d) ES-IMSE, Poly. Order 3

Notes: Figure 5 provides two ways of visualizing how enrollment changes with household AGI. The overall relationship is shown using global polynomial regressions (estimated separately above and below the cutoff), while underlying variation in the data is portrayed using a data-driven binned scatter plot. Each panel indicates the order of the global polynomial estimated and the type of regression-based binning procedure used: evenly-spaced (ES) or quantile (QS) partitions and mimicking variance (MV) or integrated mean square error-optimal (IMSE) criterion. Figures are produced using the *rdplot* command described in Calonico et al. (2017). See Calonico et al. (2015) for technical details.

the left and right of the cutoff. Each panel contains estimates for three samples—the full analysis sample, only Pell-ineligible students, and the Pell-eligible sample.

For the full sample, both kernel and local linear regression estimates show that BTP eligibility increases grant aid and total aid for individuals near the AGI cutoff. Point estimates indicate that students eligible for BTP receive grant aid offers \$3,600 larger than students who just miss the income threshold, and total aid is \$3,100 higher. These results are statistically significant ($p < 0.001$) and qualitatively unchanged for estimation using other kernel weights (i.e., Epanechnikov or rectangular) and/or coverage error rate (CER)-optimal

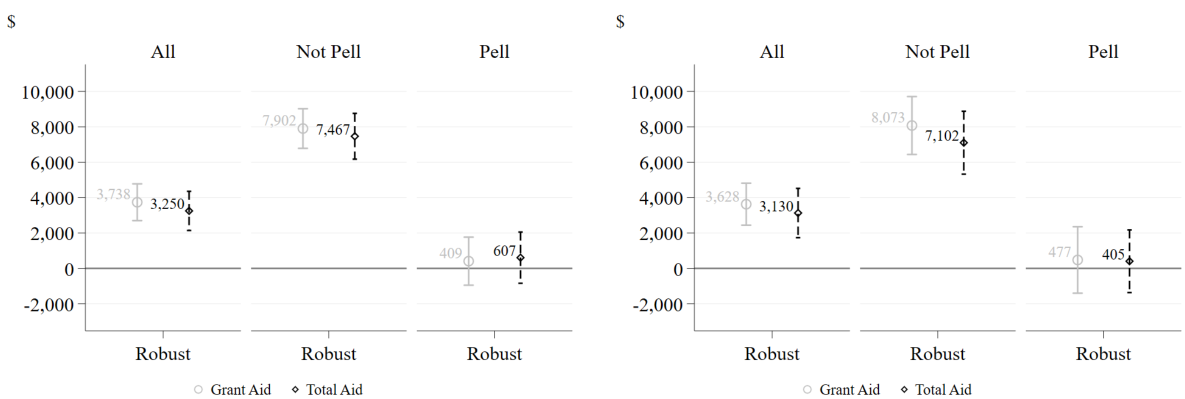
Figure 6: BTP Eligibility and Enrollment in 2018, by Pell Eligibility



(a) ES-MV, Pell-Ineligible (b) ES-MV, Pell-Eligible

Notes: Figure 6 provides two ways of visualizing how enrollment changes with household AGI for Pell-ineligible and Pell-Eligible students. The overall relationship is shown using global linear regressions (estimated separately above and below the cutoff), while underlying variation in the data is portrayed using a data-driven binned scatter plot. The regression-based binning procedure uses evenly-spaced (ES) partitions and a mimicking variance (MV) criterion. Figures are produced using the *rdplot* command described in Calonico et al. (2017). See Calonico et al. (2015) for technical details.

Figure 7: RD Estimates of Effects on Aid Measures



(a) Kernel Regression Estimates (b) Local Linear Regression Estimates

Notes: Figure 7 plots coefficient estimates of the effect of BTP eligibility on grant aid and total aid offers. Panels (a) and (b) show estimates from kernel estimation and local linear regression, respectively. Separate bandwidths above and below the $56,000 eligibility threshold are selected to be MSE-optimal (Calonico et al., 2015). Observations are weighted using a triangular kernel.

bandwidths.

Effects are even more pronounced when the sample is restricted to Pell-ineligible students: Those whose household AGI just qualifies them for BTP receive almost $8,000 more in grants than their counterparts just above the income cutoff, and their aid packages are at least \$7,000 more generous. These results show that BTP eligibility has a meaningful impact on the financial aid of middle-income students who do not qualify for federal Pell grants. This sample of students received both the promise treatment and the dollar value treatment, so each may affect enrollment decisions.

By contrast, for Pell-eligible students, BTP eligibility appears to provide little to no benefit in terms of grant and total aid. I estimate that grant aid is \$409 to \$477 higher for median-income Pell and BTP-eligible students than it is for Pell-eligible students who just miss the BTP income cutoff. Similarly, total aid packages are estimated to be \$405 to \$607 larger for students just below the cutoff. For both outcomes, results are statistically indistinguishable from zero and the confidence intervals include negative values. These findings indicate that the dollar treatment of BTP was of limited relevance for higher need students whose eligibility for federal Pell grants left them with generous grant and total aid coverage from other UW-Madison need-based financial aid programs. Accordingly, any effects of BTP eligibility for Pell-eligible students are likely to operate primarily through the tuition promise channel.

I now examine the effect of tuition promise eligibility on the decision to enroll at UW-Madison, conditional on receiving an admissions offer. Figure 8 shows point estimates and 95 percent confidence intervals of τ_{BTP} from local linear regression estimation of Equation (1) using a triangular kernel. The estimates are shown for two samples (all first-year residents and Pell-ineligible students), with and without covariates, and for both MSE- and CER-optimal bandwidth selection (estimated separately above and below the cutoff).

Among first-year resident admits, RD estimation without covariates suggests that BTP eligibility increases the probability of enrolling at UW-Madison by 7 to 8 percentage points. RD local linear regression coefficient estimates of the effect of crossing the AGI threshold (i.e., losing BTP eligibility) are -0.0714 (SE = 0.06463) and -0.0793 (SE = 0.0718) when using MSE- and CER- bandwidths, respectively. The CER-optimal bandwidths are \$11,847 (n = 180) to the left and \$33,485 (n = 610) to the right of the cutoff. The MSE-optimal bandwidths are substantially wider—\$17,891 (n = 246) to the left and \$50,572 ($n = 1,003$) to the right of the cutoff—a consequence of the fact that this bandwidth selection procedure tries to optimally trade off bias and variance. Regardless of the bandwidth selection method, the point estimates are estimated imprecisely, with standard errors of same order of magnitude as the coefficients, and estimated confidence intervals include zero in both cases.

When covariates are included in the model, estimated effects of BTP eligibility on enrollment with covariates are similar in magnitude to the estimates without covariates. The effect of just missing BTP eligibility using the CER-optimal bandwidth is essentially unchanged at -0.0716 (SE = 0.06841), although the standard error is slightly smaller (yet still imprecise). The CER-optimal bandwidth below the cutoff is a bit narrower with the covariates (\$10,876, $n = 166$) but is wider above the cutoff (\$35,699, $n = 641$), allowing the use of more observations. The point estimate using the MSE-optimal bandwidth is slightly lower at -0.0538 (SE = 0.06292), and the bandwidths are slightly wider both to the left (\$16,414, $n = 231$) and right (\$53,878, $n = 1,069$) of the cutoff

In contrast, when the sample is restricted to Pell-ineligible students, the estimated effects of tuition promise eligibility are large in magnitude. In the specification without covariates, coefficients using MSE and CER-optimal bandwidths are estimated to be -0.2915 (SE = 0.1226,) and -0.275 (SE = 0.139) percentage points, respectively, and both are statistically significant at the 5 percent levels (p-value= 0.017 and 0.048, respectively). The CER-optimal bandwidth below the cutoff (\$11,115, $n = 48$) is similar to that for the full sample, but the bandwidth above the cutoff is much larger at \$62,314 ($n = 1,143$). The MSE-optimal bandwidths are \$16,619 to the left ($n = 57$) and \$93,172 ($n = 1,842$) to the right of the cutoff.

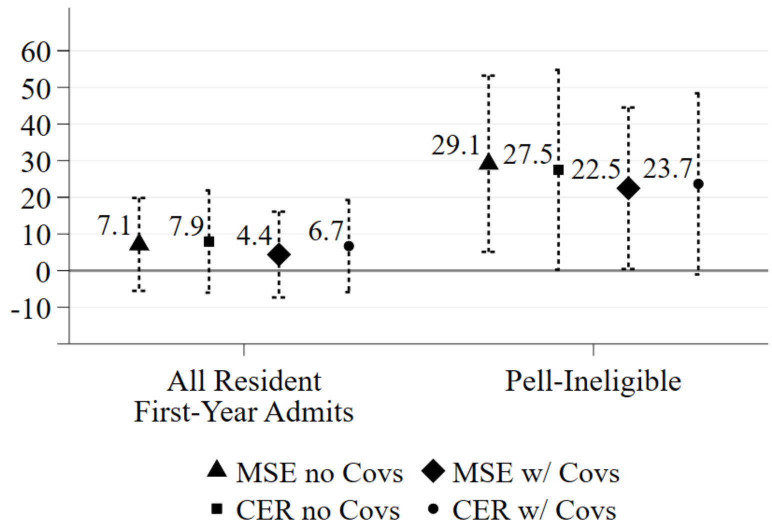
When covariates are included, the estimated enrollment effects for Pell-ineligible students decline slightly but remain large. The coefficient estimate is -0.2246 (SE = 0.1124) using the MSE-optimal bandwidth, which is slightly wider to the left of the cutoff (\$18,167, although it only includes one more observation than the specification without covariates) but narrower to the right of the cutoff (\$70,966, $n = 1,368$). This effect is significant at the 5 percent level. The magnitude of the CER coefficient estimate is one percentage point larger than the MSE-estimate (-0.2367, SE = 0.1261) and significant at the 10 percent level using 51 observations to the left (from a bandwidth of \$12,157) and 763 observations to the right of the cutoff (bandwidth=\$47,487).

Robustness estimates using alternative choices of the tuning parameters (kernel/degree 0 polynomial regressions, Epanechnikov and uniform kernels), are shown in Figure 19 in the Appendix; while the point estimates and their precision varies slightly across specifications, the qualitative conclusions remain the same.

5.3 Robustness

One way of examining the validity of the identifying assumptions is to explore how families' ability to pay for college evolves with their household income. If students with household AGI in a small neighborhood about the cutoff are appropriate counterfactuals for one another, then we would expect that expected family contribution to college costs is continuous through the cutoff. Figure 10 provides evidence in support of this hypothesis. Both panels show a positive relationship between households' income and their EFC, which is to be expected given that income is a major contributor to families' ability to pay for college. Re-

Figure 8: RD Estimates of Effects on Enrollment



Notes: Figure 8 shows RD coefficient and 95 percent confidence interval estimates (in percentage points) from local linear regressions of the effect of BTP eligibility on the probability of enrolling at UW-Madison, conditional on receipt of an admissions offer and Wisconsin residency. Regressions are estimated using a triangular kernel, with and without covariates, using mean square error (MSE)- and coverage error rate (CER)-optimal bandwidth selection procedures. The sample is limited to Fall 2018 admitted first-year resident applicants. Point estimates are bias-corrected, and inference is conducted using a heteroscedasticity-robust plug-in residuals variance estimator with HC3 weights (see Calonico et al., 2015, for technical details).

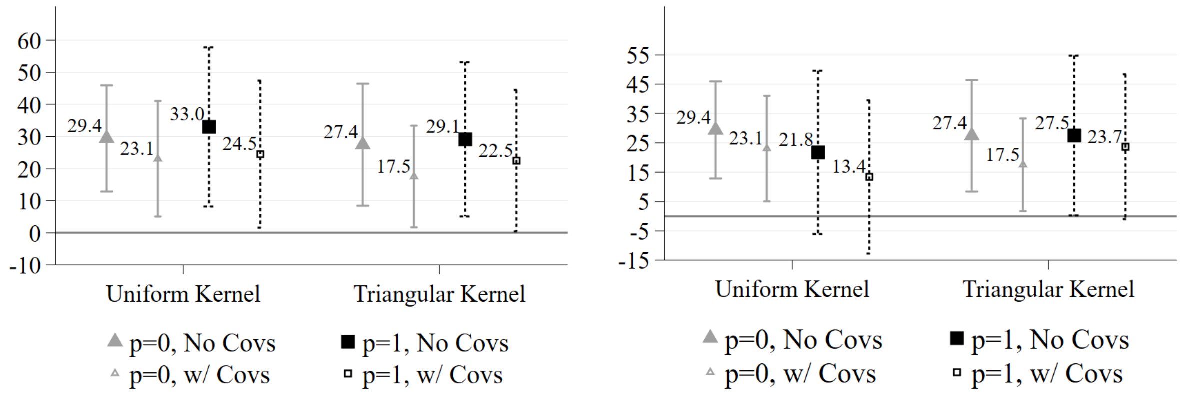
assuringly, the polynomial regressions, which are estimated separately to the left and right of the eligibility threshold, suggest that EFC evolves smoothly through the cutoff. Panels (a) and (b) depict degree 2 (quadratic) polynomial regressions, which are less likely than higher order polynomials to over-fit the data at the cutoff boundaries.

The polynomial regressions help show the overall relationship between AGI and EFC. Given that the RD design is local by nature, it also is useful to explore the variability in the raw data. I use two data-driven bin selection methods to determine the size of the bins; bins are selected using several data-driven spacings estimator methods as described in Calonico et al. (2015).[40]

The two panels in Figure 10 differ in several ways. The mimicking variance approach

[40] In panel (a), the bin sizes are chosen such that the binned sample means have an asymptotic integrated variability approximately equal to the amount of variability in the raw data; in panel (b), the bin sizes are chosen to be integrated mean-squared error minimizing (IMSE-optimal) (Calonico et al., 2015), that is, the bins are selected to trade off bias and variance in an optimal way. Both panels use quantile-partitioning, so for a given side of the cutoff, bins contain approximately the same number of observations. Results are similar if evenly-spaced bins are used. See Figure 18 in Appendix **??**.

Figure 9: RD Estimates of Effects on Enrollment, Pell-Ineligible Sample

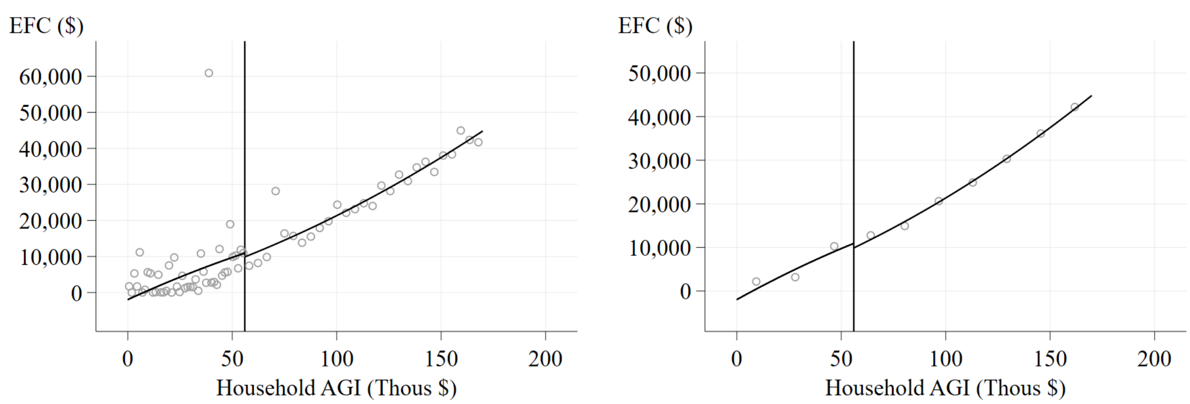


(a) MSE-Optimal Bandwidth

(b) CER-Optimal Bandwidth

Notes: Figure 9 shows RD coefficient and 95 percent confidence interval estimates (in percentage points) from kernel and local linear regressions of the effect of BTP eligibility on the probability of enrolling at UW-Madison, conditional on receipt of an admissions offer and Wisconsin residency. Regressions are estimated using rectangular (uniform) and triangular kernels, with and without covariates, using MSE- and CER-optimal bandwidth selection procedures. The sample is limited to Fall 2018 admitted first-year resident applicants who are Pell-ineligible. Point estimates are bias-corrected, and inference is conducted using a heteroscedasticity-robust plug-in residuals variance estimator with HC3 weights (see Calonico et al., 2015, for technical details).

Figure 10: How Expected Family Contribution Evolves with Household AGI



(a) Mimicking Variance Quantile Bins

(b) IMSE-Optimal Quantile Bins

Notes: Figure 10 uses quadratic polynomial regressions and binned scatter plots to visualize the evolution of expected family contribution through the household AGI cutoff. The sample includes UW-Madison admitted in-state first year applicants for Fall 2018 who submitted a FAFSA and reported HH AGI between $0 and $170,000. For panel (a), the average bin sizes are $1,273 to the left of the cutoff and $2,087 to the right; for panel (b) these values are $9,333 and $11,742, respectively. Figures are produced using the *rdplot* command described in Calonico et al. (2017).

in panel (a) is noisier by design, because bins are chosen so that the binned sample means mimic the underlying variability of the data. This method yields a large number of bins on each side of the cutoff—46 below and 45 above—with relatively narrow average and median bin lengths ($1,273 and $1,096 below the cutoff and $2,087 and $2,003 above). Consequently, each bin contains a smaller number of observations, averaging to 14 below the cutoff and 44 above. This three-fold difference in bin sample size helps explain why the data just below the cutoff appear noisier; the few outliers are not surprising with such narrow bins, as EFC takes into account family assets. In contrast, the IMSE-optimal method shown in panel (b) selects only 6 and 8 bins to the left and right of the cutoff, with average and median bin lengths $9,333 and $9,074 below the cutoff and $11,742 and $11,862 above the cutoff. With these wider bin lengths, each bin contains on average 102 observations below the cutoff and 253 above, yielding a binned scatterplot that is a smoother version of that in panel (a).

Figure 11: BTP Eligibility and Grant Aid

(a) 2018 (Post BTP) (b) 2017 (Pre BTP)

Notes: Figure 11 shows how BTP eligibility affects grant aid. The overall relationship is shown using global polynomial regression, while underlying variation in the data is portrayed using a data-driven binned scatter plot. The global polynomial is of order 2 and is estimated separately above and below the cutoff. Quantile-spaced bins are selected using a mimicking variance method with spacings estimators. Figures are produced using the *rdplot* command described in Calonico et al. (2017). See Calonico et al. (2015) for technical details.

6 Effects of Increasing Certainty in Degree Costs

6.1 Empirical Strategy: Differences-in-Differences Design

In this section I conduct an analysis to identify the effects of increased certainty in degree costs on admitted resident students' decision whether to enroll at the state flagship. I use detailed information about admitted students' financial aid offers with a DID design to separately identify the effects of the four-year tuition guarantee.

As discussed in Section 3.2 and confirmed in Figure 4, most Pell-eligible students do not experience an increase in grant aid from BTP, so their only (effective) treatment from the program is the promise of tuition coverage in subsequent years. This treatment may increase students' certainty about expected degree costs and ability to pay, which on its own may impact the enrollment decision.

To investigate these effects more precisely, I remove from the sample all BTP students who received BTP grant dollars. I then augment the 2018-19 sample with 2017-18 data, similarly excluding all students who satisfy BTP eligibility criteria and whose grant aid levels were insufficient to cover the cost of tuition (and therefore, would have received positive BTP grant dollars had the program been enacted the prior year). These individuals serve as a comparison group for the "certainty-only" BTP students in 2018. I also restrict the sample to students with household AGI between \$0 and \$80,000. I then estimate the following differences-in-differences model:

$$Y_i = \beta BTP_i^c \times Post_i + \delta BTP_i^c + \gamma Post_i + \lambda Pell_i + \varepsilon_i \tag{6}$$

where BTP_i^c is an indicator of BTP receipt of the certainty only treatment (i.e., the only BTP-eligible students in the estimation sample are those who would not receive BTP dollars), $Post$ is an indicator of the post-policy period (2018-19), $Pell_i$ is an indicator of Pell-eligibility, and ε_i is an error term. This model compares the certainty-only BTP eligible students to students with slightly higher income (i.e., who are AGI ineligible) to estimate the effect on enrollment, using prior year data to account for differences between eligible and ineligible students. The parameter of interest is β, which captures the effect of the certainty-only BTP treatment. I cluster standard errors at the high school level.

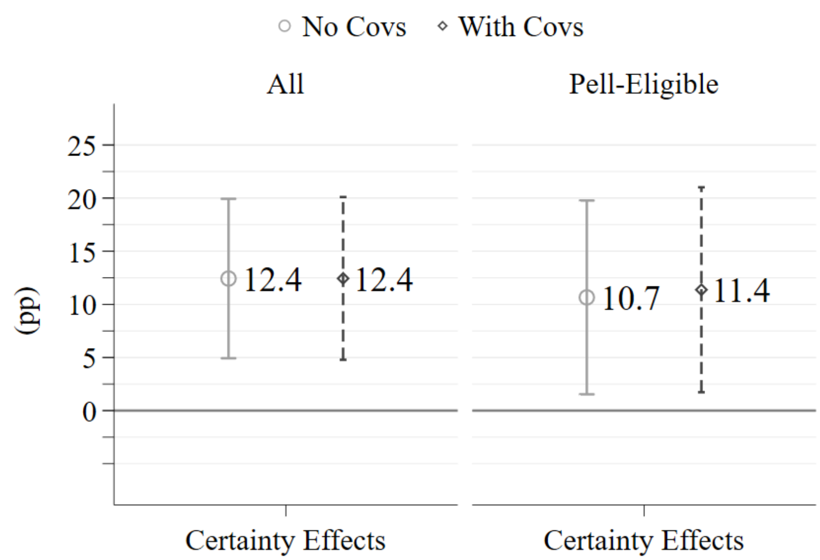
6.2 Results

I find that the certainty-only treatment is meaningful even for students who receive more generous aid packages. Results are shown in Figure 12. My coefficient estimate for β is 0.124 (SE=0.0381), which means that the BTP certainty treatment increased the probability of accepting an enrollment offer by 12 percentage points (from a base acceptance rate of 67.6 percent for non-Pell admits or 87 percent for Pell admits). Estimates are stable when covariates are included, and fall slightly to 0.114 (SE= 0.0491) when the sample is restricted to Pell-eligible students. All estimates are statistically significant at the 5 percent level.

The results indicate that providing low-income students certainty about overall degree costs impacts enrollment choices independent of the aid dollars. These findings suggest that low-income admitted students highly value the promise aspect of BTP, even when they are already receiving generous aid packages that cover the cost of tuition. More broadly, financial aid policies that increase degree cost certainty may remove barriers to enrollment arising from concerns about ability to pay, especially for low-income students. Moreover, these results suggest that tuition promises at public flagships may help close income-based gaps in the college-going behaviors of high-achieving students and increase the presence of low-income students at state flagships.

For robustness, I perform covariate balance tests to ensure that students on either side of the cutoff are appropriate counterfactuals for one another. These are performed using a differences-in-differences specification with indicators for the post-BTP year, BTP-eligibility, and their interaction, and using the covariate of interest as the outcome. The results from these tests are displayed in Table 6 and indicate that students are observationally similar on either side of the cutoff.

Figure 12: The Effects of Degree Cost Certainty on Enrollment



Notes: Figure 12 shows differences-in-differences coefficient and 95 percent confidence interval estimates (in percentage points) of the effect of BTP "certainty-only" treatment on the probability of enrolling at UW-Madison, conditional on receiving an admissions offer. Regressions are estimated with and without covariates. The sample is limited to Fall 2017 and Fall 2018 admitted first-year resident applicants whose grant aid was less than tuition and fees. Standard errors are clustered at the high school level.

Table 6: Covariate Stability Regressions

	Baseline (All)	Pell	Non-Pell	Certainty Only
Distance (mi)	−9.09	−12.76	−0.94	−12.36
	(6.50)	(11.69)	(15.62)	(7.55)
	0.16	0.28	0.95	0.10
Female	0.00	−0.08	−0.11	0.02
	(0.04)	(0.08)	(0.10)	(0.04)
	0.99	0.30	0.27	0.58
Underrepresented Minority	−0.03	−0.02	0.01	−0.04
	(0.03)	(0.06)	(0.06)	(0.03)
	0.26	0.67	0.93	0.26
Mother has BA	−0.02	0.04	−0.10	−0.00
	(0.04)	(0.07)	(0.09)	(0.04)
	0.67	0.55	0.27	1.00
Mother College Missing	−0.01	0.00	−0.10	−0.02
	(0.02)	(0.05)	(0.07)	(0.03)
	0.55	0.94	0.12	0.38
Free/Reduced Price Lunch	0.02	0.02	0.00	0.04
	(0.03)	(0.04)	(0.00)	(0.04)
	0.60	0.68	0.33	0.36
Expected Family Contrib.	−838.23	−67.32	−3,025.98	−604.87
	(464.24)	(185.29)	(2,120.79)	(492.29)
	0.07	0.72	0.15	0.22
Household Assets	10,000.61*	2,894.75	31,194.39	6,958.77
	(5,082.72)	(4,721.90)	(22,660.39)	(5,021.63)
	0.05	0.54	0.17	0.17
Household Taxes Paid	595.52*	−24.19	1,966.29	419.81
	(255.35)	(251.41)	(1,127.16)	(271.13)
	0.02	0.92	0.08	0.12
# in Family	0.02	0.24	0.20	−0.02
	(0.11)	(0.21)	(0.19)	(0.14)
	0.89	0.26	0.29	0.90
# in Family in College	−0.03	0.11	−0.20	−0.01
	(0.04)	(0.11)	(0.13)	(0.05)
	0.44	0.29	0.12	0.88
ACT Score	0.71*	−0.83	1.24	0.71
	(0.36)	(0.62)	(1.00)	(0.41)
	0.05	0.18	0.22	0.09
SAT Score	1.79	0.27	−130.70*	27.36
	(27.14)	(46.19)	(57.36)	(32.64)
	0.95	1.00	0.02	0.40
Obs.	3,998	877	3,121	3,801
ymean	89	86	90	91

Notes: Table 6 shows results from covariate balance regressions, wherein each covariate is used as the regressand in the preferred DID model. For each variable, the table shows the DID coefficient estimate, its standard error (in parentheses), and p-value. The sample includes in-state first-year applicants for Fall 2017 and 2018 who received offers of admission to UW-Madison and who completed a FAFSA. The FAFSA for Fall 2018 (2017) enrollment uses tax return data filed in 2017 (2016) for the 2016 (2015) tax year.

7 Conclusion

Tuition promises have the potential to improve college access for higher-need students by providing aid dollars and by guaranteeing minimum aid in future years. Because most tuition promise policies are limited to community colleges, little is known about how tuition promises by state flagships would affect the enrollment decisions of academically talented residents with modest means. In this paper, I study the 2018 introduction of Bucky's Tuition Promise at UW-Madison to estimate the effects of program eligibility on admitted students' financial aid offer and decision about whether to attend the flagship. I take advantage of the sharp cutoff in program eligibility based on the household adjusted gross income, which cannot exceed \$56,000 in the first year.

I find that Pell-ineligible students who fall just below the AGI cutoff (and thus are BTP-eligible) receive much larger grant aid (\$8,000) and total aid (\$7,900) offers than their Pell-ineligible counterparts whose AGI just exceeds the BTP eligibility threshold. In contrast, Pell-eligible students who are BTP-eligible receive no grant aid from the program, so the main difference relative to those above the cutoff (BTP-ineligible) is the advance tuition guarantee. Results on enrollment effects indicate that Pell-ineligible students are very responsive to BTP eligibility.

After examining effects around the AGI cutoff, I turn to examining the role of the "certainty" treatment. Using a sample of students whose non-BTP sources of grant aid exceeded tuition and fees—so that they did not (in 2018) or would not (in 2017) qualify for BTP grand aid—I estimate a difference-in-differences model to examine the effect of receiving only the certainty treatment. I find that "promise" aspect of BTP increases the probability of accepting an admissions offer by 11 percentage points, indicating that students value certainty above and beyond the aid packages they are receiving, which may be generous. My findings may capture more than enrollment effects: If students who enroll at UW-Madison because of BTP would not have attended college in absence of the policy, or would have enrolled at a school with lower overall quality or lower match-quality, then BTP may have long-run positive effects on students' persistence and earnings.

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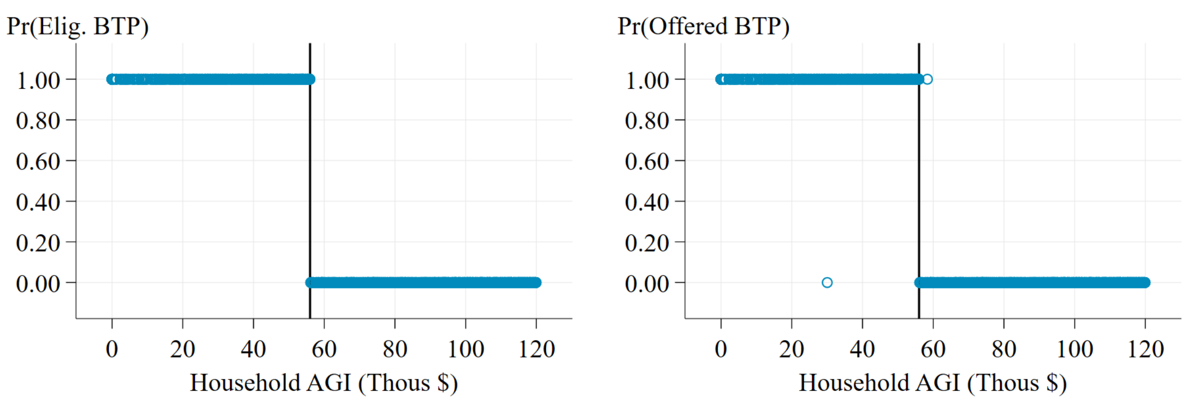
A Additional Tables and Figures

Table 7: Academic Year Tuition and Fees for UW System Schools in 2018

UW System School	Tuition and Fees ($)	Cost Relative to UW-Madison (%)
Madison	10,616	–
Milwaukee	9,638	−9.2
Eau Claire	8,721	−17.9
Green Bay	7,928	−25.3
La Crosse	8,983	−15.4
Oshkosh	7,671	−27.7
Parkside	7,439	−29.9
Platteville	7,846	−26.1
River Falls	8,075	−23.9
Stevens Point	8,289	−21.9
Stout	5,824	−45.1
Superior	8,176	−23.0
Whitewater	7,742	−27.1
Ave. excl. Madison	7,978	−24.4

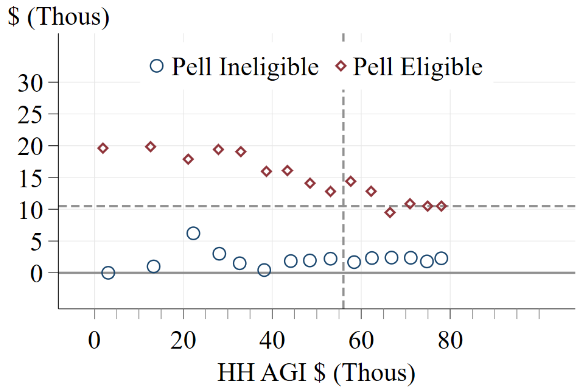
Notes: Author's calculations using data from The University of Wisconsin System Tuition Schedule 2018-2019, accessed at https://www.wisconsin.edu/budget-planning/download/tuition/tuition_schedule/academic_tuition_schedule/Tuition-Schedule-2018-19-FINAL-v3.pdf.

Figure 13: Probability of BTP Treatment Eligibility and Receipt in 2018

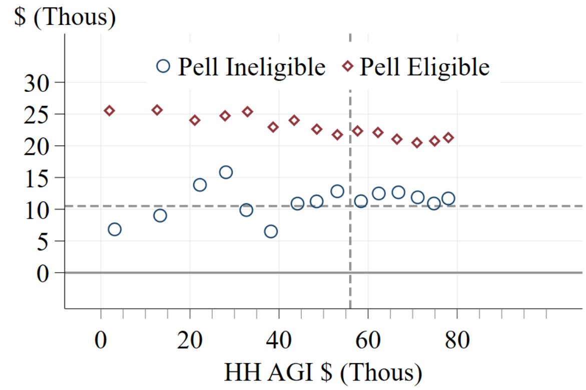


(a) BTP Eligibility (Constructed) (b) BTP Treatment (Realized)

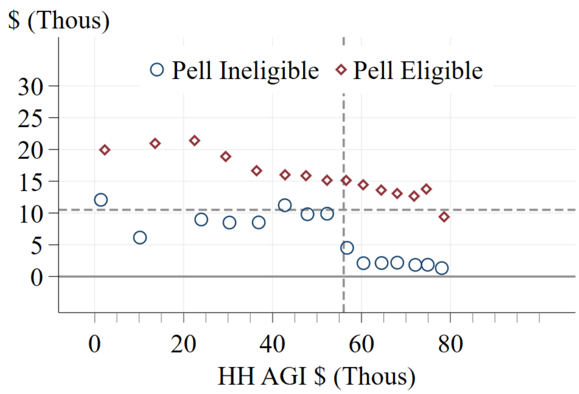
Figure 14: Grant and Total Aid Offers in 2017 and 2018, by Pell Eligibility



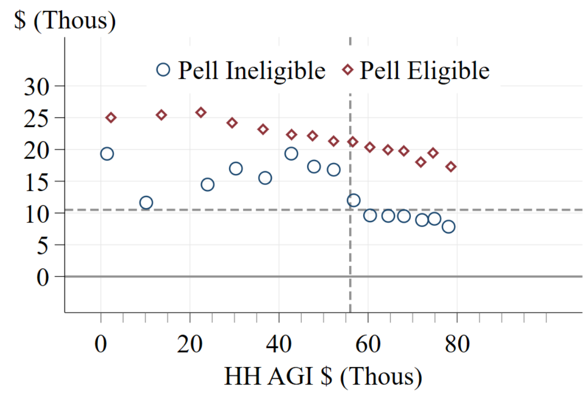
(a) Ave. Grant Aid, 2017



(b) Ave. Total Aid, 2017



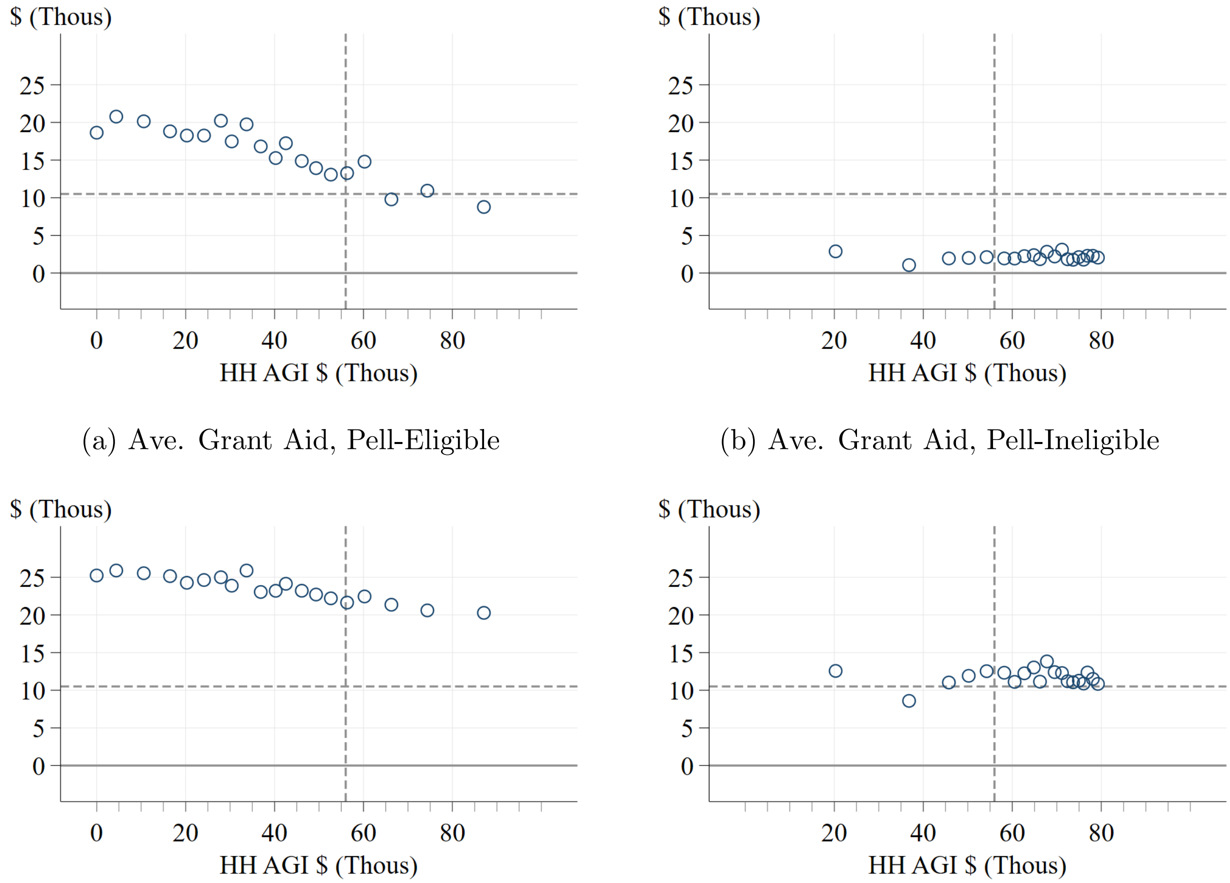
(c) Ave. Grant Aid, 2018



(d) Ave. Total Aid, 2018

Notes: Panels (a) and (b) in Figure 14 show binned scatter plots of grant and total aid offers for UW-Madison admitted resident students who applied for financial aid in academic year 2017-2018, the year preceding the introduction of BTP. The sample is restricted to those with household adjusted gross income at or below $85,000. The horizontal line delineates the level of grant aid coverage (tuition and fees, approximately $10,896) that would be provided under BTP. The vertical line shows the $56,000 household AGI eligibility cutoff used in for BTP 2018. The bottom panels (c) and (d) show binned scatter plots of grant and total aid for admitted resident students who applied for financial aid in academic year 2018-19, the year BTP is introduced. The sample is restricted to those with household adjusted gross income at or below $85,000. The horizontal line delineates the level of grant aid coverage (tuition and fees, approximately $10,896) that is guaranteed under BTP. The vertical line shows the $56,000 household AGI eligibility cutoff used in for BTP 2018.

Figure 15: Pre-BTP: Average Grant and Total Aid Offers in 2017 for Admitted Resident Students, by Pell-Eligibility Status and Household AGI



(a) Ave. Grant Aid, Pell-Eligible

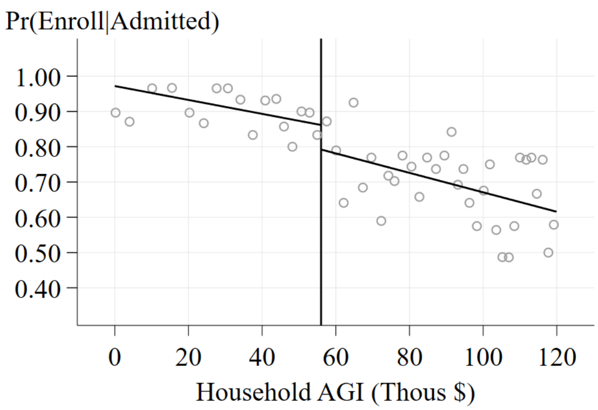
(b) Ave. Grant Aid, Pell-Ineligible

(c) Ave. Total Aid, Pell-Eligible

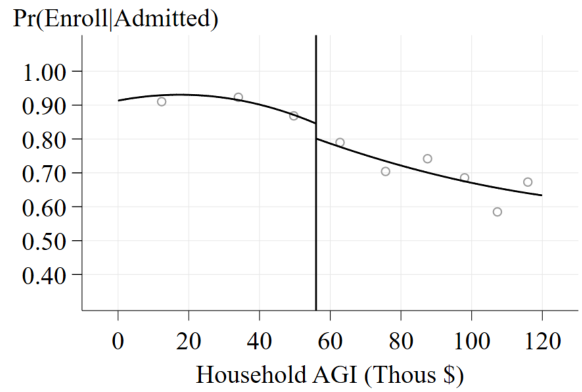
(d) Ave. Total Aid, Pell-Ineligible

Notes: Figure 15 shows scatter plots of average grant and total aid at binned values of household AGI by Pell-Eligibility status. The sample includes UW-Madison admitted in-state first year applicants for Fall 2017 (the year before BTP is introduced) who submitted a FAFSA. The sample of Pell-ineligible students is restricted to those with household adjusted gross income at or below $85,000. The horizontal dashed line delineates the level of grant aid coverage (tuition and fees, approximately $10,896) that would be provided to each eligible student (at minimum) under BTP. The vertical dashed line shows the $56,000 household AGI eligibility cutoff used for BTP 2018. Data come from the UW-Madison Office of Admissions and Recruitment and Office of Student Financial Aid.

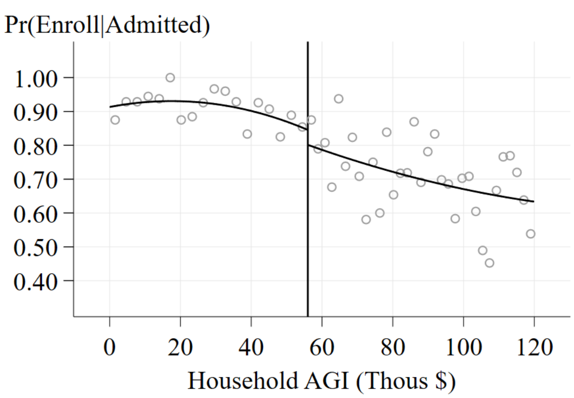
Figure 16: Conditional Probability of Enrollment by HH AGI



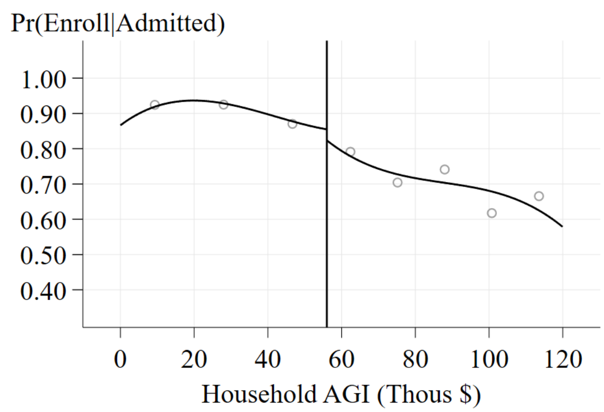
(a) Mimicking Variance Quantile Bins



(b) IMSE-Optimal Quantile Bins



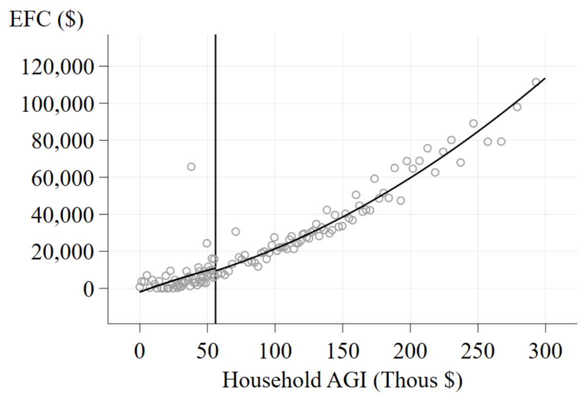
(c) Mimicking Variance Evenly-Spaced Bins



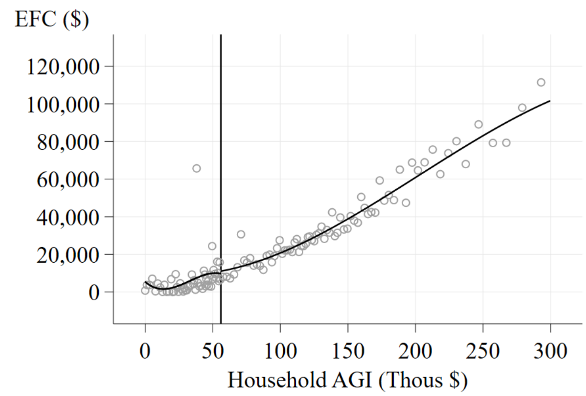
(d) IMSE-Optimal Evenly-Spaced Bins

Notes: Figure 16 provides two ways of visualizing how enrollment changes with household AGI. The overall relationship is shown using global polynomial regression, while underlying variation in the data is portrayed using a data-driven binned scatter plot. In panels (a) and (b) the polynomials are degrees 1 and 2, respectively, and quantile bins are used; in (c) and (d) the polynomials are degrees 2 and 3, respectively, and data are partitioned into evenly spaced bins. In panels (a) and (c) bins are selected using a polynomial regression-based mimicking variance method, while bins in (b) and (d) are chosen using an IMSE-optimal approach. Students with household AGI above $120,000 and below $0 are excluded. Household AGIs are reported on the 2018-2019 FAFSA using 2016 tax return data. The sample includes UW-Madison admitted in-state first year applicants for Fall 2018 who submitted a FAFSA. Data come from the UW-Madison Office of Admissions and Recruitment and Office of Student Financial Aid. Figures are produced using the *rdplot* command described in Calonico et al. (2017). See Calonico et al. (2015) for technical details.

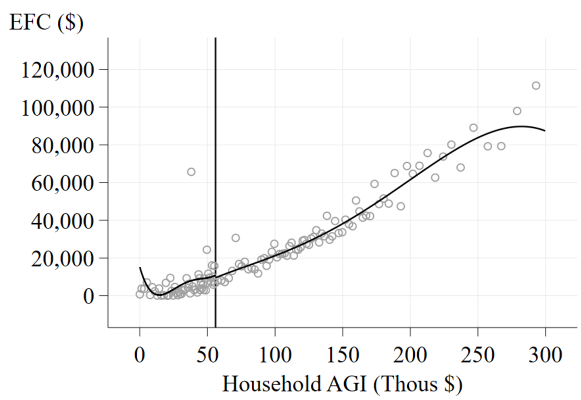
Figure 17: How Expected Family Contribution Evolves with Household AGI: Robustness to Polynomial Order



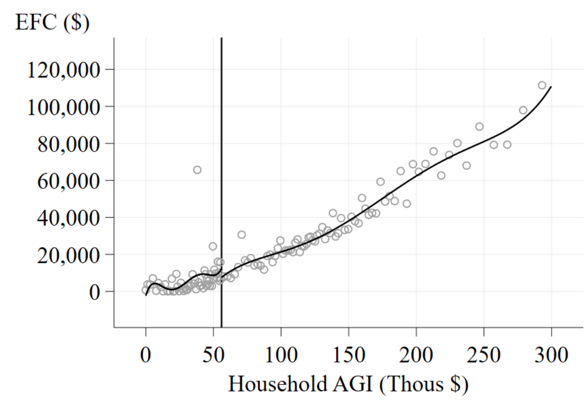
(a) Degree 2 Polynomials



(b) Degree 3 Polynomials



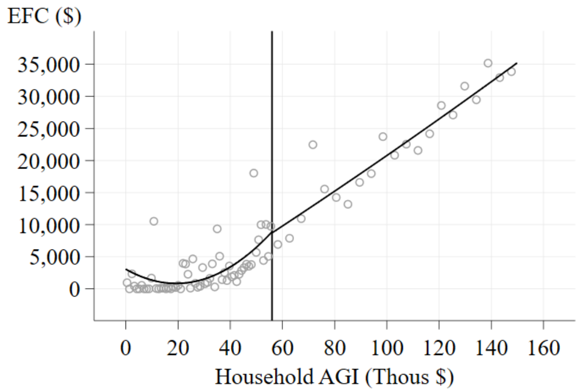
(c) Degree 4 Polynomials



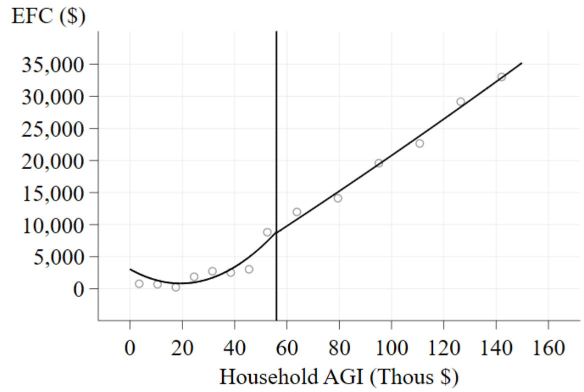
(d) Degree 5 Polynomials

Notes: Figure 17 shows how expected family contribution evolves around the household AGI cutoff for global polynomial regressions of different orders. Regressions are estimated separately to the right and left of the cutoff and capture how EFC evolves as AGI increases. Quantile-spaced bins for scatter plots are selected using a data-driven spacings estimator that mimics the underling variance in the data (Calonico et al., 2015). The sample includes UW-Madison admitted in-state first year applicants for Fall 2018 who submitted a FAFSA. Students with household AGI above $300,000 and below $0 are excluded. Household AGIs are reported on the 2018-2019 FAFSA using 2016 tax return data. Data come from the UW-Madison Office of Admissions and Recruitment and Office of Student Financial Aid. Figures are produced using the *rdplot* command described in Calonico et al. (2017).

Figure 18: Scatter Plots of EFC at Binned Values of HH AGI: Robustness to Binning Procedure



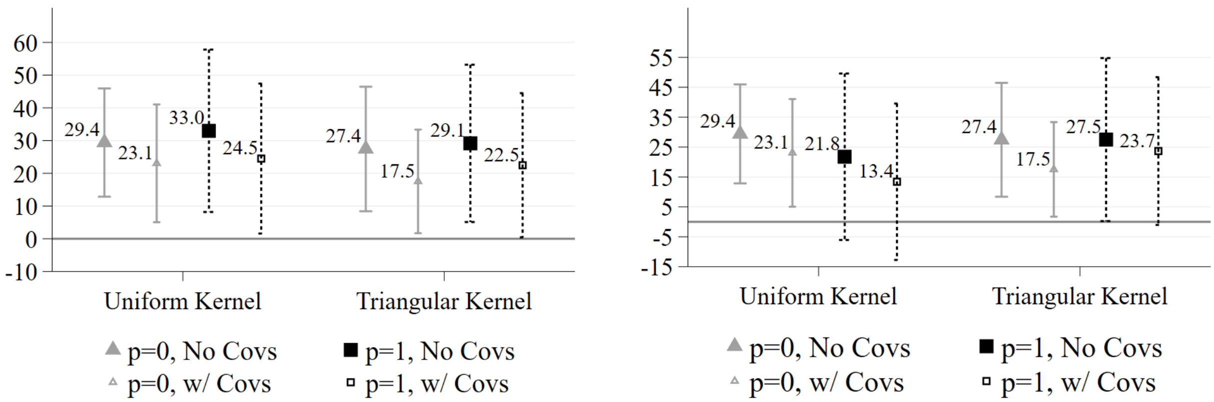
(a) Mimicking Variance Evenly-Spaced Bins



(b) IMSE Optimal Evenly-Spaced Bins

Notes: Figure 18 shows how expected family contribution evolves around the household AGI cutoff for different bin selection methods using evenly-spaced bins. Regressions are estimated separately to the right and left of the cutoff and capture how EFC evolves as AGI increases. Panel (a) uses a data-driven spacings estimator that mimics the underling variance in the data, while panel (b) uses a data-driven spacings estimator that is IMSE optimal (Calonico et al., 2015). The sample includes UW-Madison admitted in-state first year applicants for Fall 2018 who submitted a FAFSA. Students with household AGI above $300,000 and below $0 are excluded. Household AGIs are reported on the 2018-2019 FAFSA using 2016 tax return data. Data come from the UW-Madison Office of Admissions and Recruitment and Office of Student Financial Aid. Figures are produced using the *rdplot* command described in Calonico et al. (2017).

Figure 19: Robustness Estimates of the Effect of BTP Eligibility on the Conditional Probability of Enrollment for Pell-Ineligible Admitted Students



(a) Mean Square Error-Optimal Bandwidth (b) Coverage Error Rate-Optimal Bandwidth

Notes: Figure 19 shows RD coefficient and 95 percent confidence interval estimates (in percentage points) from local polynomial regressions of the effect of BTP eligibility on the probability of enrolling at UW-Madison, conditional on receipt of an admissions offer and Wisconsin residency. Regressions are estimated using degree 0 and 1 polynomials, uniform and triangular kernels, with and without covariates, using mean square error (MSE)-optimal (panel (a)) and coverage error rate-optimal (panel (b)) bandwidth selection procedures. The sample is limited to Fall 2018 admitted first-year resident applicants who are Pell-ineligible. Point estimates are bias-corrected, and inference is conducted using a heteroscedasticity-robust plug-in residuals variance estimator with HC3 weights (see Calonico et al., 2015, for technical details).