THREE ESSAYS ON THE ECONOMICS OF FINANCIAL AID

by

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This dissertation

is dedicated to my mother and Tony,

who unreservedly believed in me

and supported me along this process.

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The Toward EXcellence, Access, and Success (TEXAS) grant is the largest source of financial aid for higher education in Texas, created in 1999. In fiscal year 2017, it provided 72% of the total grants awarded by the state and granted funds to 58% of first-time freshmen who received any form of financial aid. Since its launch date, the TEXAS Grant program has been adjusted to better look after the best interest of students, institutions, and the state. Starting in fiscal year 2014, the state passed Senate Bill (SB) 28 establishing that from a pool of low-income eligible students, those deemed to be high-achievers should receive priority for initial year awards. In this dissertation I utilize descriptive statistics, statistical learning, and traditional statistical approaches to explore the financial aid situation in the state of Texas, with particular emphasis on the TEXAS Grant program and the modification included in SB 28. It is my hope that the information here included is useful to make policy decisions to ensure programs' and institutions' goals accomplishments, and guarantee students' best interest.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

The Toward EXcellence, Access, and Success (TEXAS) grant is the largest source of financial aid for higher education in Texas, created in 1999. In fiscal year 2017, it provided 72% of the total grants awarded by the state and granted funds to 58% of first-time freshmen who received any form of financial aid. Since its launch date, the TEXAS Grant program has been adjusted to better look after the best interest of students, institutions, and the state. Starting in fiscal year 2014, the state passed Senate Bill (SB) 28 establishing that from a pool of low-income eligible students, those deemed to be high-achievers should receive priority for initial year awards. In this dissertation I study explore the financial aid situation in the state of Texas, with particular emphasis on the TEXAS Grant program and the modification included in SB 28. Chapter 2 studies the process of awarding financial aid packages to Texas first-time freshman students enrolling in 4-year public colleges. I conduct a factual analysis to examine the typical financial aid package awarded to students in the last 8 years. Additionally, I utilize descriptive analysis and supervised and unsupervised statistical learning (machine learning) algorithms to i) study how universities award the TEXAS Grant to eligible students, and ii) to identify clusters of institutions according to their characteristics. Chapter 3 studies the effects of implementing the HP model on students' postsecondary outcomes via a difference-in-difference approach. My estimates suggest the modification on the originally need-based program significantly impacts the academics and finances of HP-eligible students. Chapter 4 executes a regression-discontinuity design to estimate effects of the TEXAS aid package on postsecondary outcomes. Within high-achieving students enrolling in four-year public institutions, my estimates show that aid receipt lowers the GPA of the treated and that financial aid's debt-reduction effect diminishes after the first two years of college. Heterogeneous effects and possible mechanisms are discussed individually for types of institutions.

CHAPTER 2

ON THE EXAMINATION OF FINANCIAL AID AWARDS EMPLOYING STATISTICAL LEARNING: A CLOSER LOOK AT TEXAS INSTITUTIONS

2.1 Introduction

Financial assistance is a powerful tool to improve access to higher education as many students face financial constraints that limit their ability to enroll in college. There exists a large number of programs funded from federal, state, or private resources that typically adjust allocation rules and eligibility requirements according to their specific interests. Authors utilize different experimental or quasi-experiment techniques to causally estimate the effects of grants and scholarship programs (Deming and Dynarski, 2010). Different studies find that financial aid may significantly increase enrollment and persistence (Van der Klaauw, 2002; Dynarski, 2003), rise completion rates (Dynarski and Scott-Clayton, 2013), and may also rise course withdrawal and reduce full-load enrollment and completion (Cornwell et al., 2005, 2006). Moreover, other studies indicate that financial aid programs can potentially affect performance and major choice, which can translate into an increase in earnings after graduation and better financial health even years after they complete a degree (Dee and Jackson, 1999; Andrews et al., 2016; Scott-Clayton and Zafar, 2016; Bettinger et al., 2016; Cáceres-Delpiano et al., 2018; Clotfelter et al., 2018).

Aid programs can typically be grouped into two categories: merit-based and need-based. Some are intended to reach academically able students, while others may be focused on targeting financially needy ones. There is a wide number of federal and state sources of programs available for students enrolling in college. the Pell Grant, the Federal Supplemental Educational Opportunity Grant (FSEOG), Georgia's HOPE program, and California's Cal grant are some of the most popular and studied in the literature. Like many other states in the US, Texas offers financial aid programs to its residents with the purpose of easing access to higher education. Particularly, the Toward EXcellence, Access, and Success (TEXAS) Grant is the largest program in the state that targets financially needy students. In the fiscal year 2017, it made up for nearly 72% of the total aid provided by the state and granted funding to 58% of the total state aid recipients (Texas Higher Education Coordinating Board, 2018a).

The state of Texas and the TEXAS Grant program are an interesting case of study. Particularly, not only is this Grant is one of the most important financial aid programs in the state, but it is also unique in its class as it is a hybrid between need- and merit-based aid. Additionally, the postsecondary system in Texas is similar to those in most other states and Texas has a set of public institutions that are rank among the top schools in the country, combined with a broader set of less-selective four-year schools and many open-access community colleges. These reasons make the TEXAS Grant a compelling case of study. Although some research has been examining the program focusing on students (see Johnson, 2005; Denning et al., 2018; Villarreal, 2018; Montenegro, 2019; Andrews and Montenegro, 2019), none has focused on institutions' allocation process and how they make decisions to grant TEXAS dollars. We propose to implement statistical learning algorithms to provide insight regarding this institutional process.

This paper has two objectives. The first goal is to use unsupervised statistical learning techniques to classify the Texas institutions according to different variables potentially associated with the allocation of financial aid. Fulfilling this goal allows us to generate clusters of institutions that give policymakers insight into the financial aid allocation process. The second goal is to create an evidence-based algorithm to determine which students will receive last-dollar financial aid in the Texas Educational system. We compare a traditional econometric model's classification accuracy with that of a supervised statistical learning model. The results allow us propose an algorithm to allocate last-dollar financial aid in a time-saving fashion. Our findings will be useful to education policy-makers throughout the country since this study will provide new evidence on the decisions that institutions make when given the discretion to select students from a pool of eligible low-income, high-achieving individuals.

2.2 Background

Texas has engaged in efforts like the *60x30TX*[1] to reach higher standards of excellence in teaching, research, and innovation and to help Texans get better jobs and achieve higher living standards through higher education. To attain part of *60x30TX*'s purpose, Texas offers multiple grants and scholarships that have helped its residents to enroll in colleges and universities across the state. The Top 10% Scholarship, the Texas Public Educational Grant Program (TPEG), and the Toward EXcellence, Access and Success (TEXAS) Grant are the largest programs of assistance in terms of dollars granted and benefited students. Most grants are awarded based on financial need[2], and students can apply by submitting the Free Application for Federal Student Aid (FAFSA) or the Texas Application for State Financial Aid (TASFA).

On January 18th, 1999, the House Bill 713, 76th Leg., ch. 1590[3] filed into the Texas Legislature a proposal *relating to the establishment and operation of the Toward EXcellence, Access, & Success (TEXAS) grant program [. . .]; consolidating and revising financial aid, grant, and scholarship programs [. . .]*, which was approved and became effective on the 19th

[1]This is the abbreviation of *60 percent of Generation Texas will have post secondary credential or degree by 2030*. That is, by 2030, Texas will have approximately 60 percent of its 25 to 34 year-old workforce to hold a post-secondary credential.

[2]Most institutions define financial need as part of the cost of attendance (COA) that is not covered by the expected family contribution (EFC). Usually, the COA refers to the total amount of education expenses such as tuition, books and supplies, housing and dining, transportation, among others.

[3]See Education Code, Title 3. Higher Education. Subtitle A. Higher Education in General. Chapter 56. Student Financial Assistance.

of June of the same year. The purpose of this program is to provide financial aid assistance to enable economically disadvantaged students to attend public institutions of higher education in the state. Although the program's goal has been the same ever since its establishment, its allocation rules and guidelines have been modified since its inception. The requirements to be eligible for an initial year (IY) TEXAS Grant award include being classified by the institution as Texas resident, and having a 9-month expected family contribution (EFC) of no more than a cap set each year by the THECB, which in the 2018 fiscal year was $5,430 dollars[4]. In order to receive a renewal year (RY) award, students need to maintain satisfactory academic progress (SAP) by meeting the institution's SAP policy[5] by the end of the first year. The TEXAS Grant program covers up to 150 semester credit hours, can be received for up to 6 years from the first semester it is awarded, and awards a maximum annual amount of $9,050 dollars for public universities (max. award for the 2017-18 academic year.).

This grant program gives academic institutions the discretion to award TEXAS Grant dollars provided they identified eligible students. However, the state restricted part of that autonomy with the implementation of Senate Bill (SB) 28 in 2013 as this program is over-subscribed, and many eligible students did not receive funding for college. Particularly, "*The state does not fully fund the TEXAS grant program and often there are significant numbers of students (30 percent of those eligible) who do not receive the grant. Many of these students showed academic promise while in high school. During times of budgetary constraints, the state must decide to most efficiently use limited dollars, and this change to TEXAS grants will help to maximize state grant dollars per graduate*[6]". SB 28 therefore modified its allocation

[4]The EFC cap is set as a portion of the state-wide average tuition and fees, and it is adjusted annually (see THECB (2018a)).

[5]For most institutions in Texas, this includes maintaining a 2.0 cumulative GPA, and completing 24 semester credit hours (SCH) over an academic year

[6]SB 28, Bill Analysis. By Zaffirini, W. Available at: `https://capitol.texas.gov/billlookup/text.aspx?LegSess=82R&Bill=SB28`.

rules imposing higher priority in allocation to students whom the state deemed to be higher achieving—and therefore more likely to graduate. The highest priority (HP) model started to be implemented for awards granted in the fiscal year 2014 (i.e., starting in the Fall of 2013).

Regulations on the TEXAS program prioritize renewal awards. This means that in a given year, renewal awards are granted to continuing students first. After these are allocated and if remaining resources permit, initial awards for first-time-in-college students can be assigned next. These students may fall under either type of eligibility: basic eligibility (BE) or high priority (HP) eligibility. A high school graduate qualifies for basic eligibility (BE) if: i) graduates high school within 16 months of college enrollment, ii) enrolls in college at least three-fourths full-time[7], and iii) has a 9-month EFC of no more than the determined threshold for a given fiscal year. Among those who qualify for BE, the higher priority (HP) model gives preference to high-achieving students. Under its specifications, institutions must prioritize students who had met some of requisites in the the following categories:

1. Advanced Academic Program[8] (AAP):

   12 hours of college credit (dual credit or AP courses), complete the Recommended or Advanced High School Program (or its equivalent), or complete the international baccalaureate program.

2. TSI Readiness[9] (TSIR):

   Meet the Texas Success Initiatives assessment thresholds or qualify for an exemption.

[7]Full-time status for undergraduate students is typically granted to those who enroll 12 or more credit hours per semester.

[8]These programs are standard across states and are available to students who desire more challenging work than what's offered in the standard curriculum.

[9]The Texas Success Initiative (TSI) is a state-legislated program designed to improve students' success in college. Part of the program is an assessment to determine students' basic skills in reading, mathematics and writing. Students may be eligible to TSI exception if a student obtains a qualifying score on ACT, SAT, or STAAR. Students who are not TSI exempt are required by law to take an assessment test approved by the Texas Higher Education Coordinating Board (THECB).

3. Class Standing (CS):

   Graduate in the top one-third of the high school graduating class or a grade point average of at least 3.0 on a 4-point scale.

4. Advanced Math (AM):

   Complete at least one math course beyond Algebra II or at least one advanced career and technical course (as determined by the TEA).

If a student complies with at least two of these four categories, he or she is given priority among all their peers that are only eligible under BE to receive an IY TEXAS award.

TEXAS Grant regulations also state that this program is to be awarded on a last-dollar basis. This means that institutions are obligated to fill in any remaining financial need after TEXAS dollars are awarded with non-loan sources. Universities therefore have a clear incentive to award the TEXAS Grant to students that have most aid, as this strategy reduces their cost and financial responsibility. In other words, the TEXAS Grant is designed to complement the dollars from other generous programs. To date, only one study acknowledges the fact that the TEXAS Grant is designed to be accompanied by other sources of financial aid, and therefore should be understood as a financial aid package. Montenegro (2019) studies the causal effects of receiving TEXAS Grant dollars under the HP model utilizing a Regression-Discontinuity Design. He finds that aid for marginal recipients lowers academic performance by 14 percent and cuts student loans by 28 percent. Other studies look into modification on TEXAS allocation rules. For instance, Andrews and Montenegro (2019) examine the effects of implementing the HP model via a difference-in-difference approach. Although the results for this study are preliminary, the authors find evidence that the implementation of the priority model increased the likelihood of continuous enrollment, reduced the likelihood of obtaining a GPA that is below 2.0 by the first year, and cut student loans for up to four years after initial enrollment. Other studies describe issues related to the TEXAS

Grant (see Johnson, 2005; Denning et al., 2018; Villarreal, 2018), but none of them study the direct effects of the implementation of the HP model on college outcomes.

Because the TEXAS Grant—and in general most financial aid programs—is very clear regarding eligibility, it is posible to propose different parametric models that may allow drawing causal effects of receiving TEXAS dollars or those from implementing a change in allocation rules—such as the HP model. Our objective is to explore more than just elegibility requirements. Particularly, we want to examine the fact that institutions have total discretion to choose TEXAS Grant recipients among the pool of eligible students. Because there is no guideline for this decision process, implementing traditionaly parametric methods is not useful in oder to provide insight. We intend to make use of different machine learning techniques that allow us to learn—from the data—how universities target eligible students to award TEXAS dollars.

2.3 Data

The data we use in this study come from three sources: annually administrative data from the Texas Education Agency (TEA) and annually administrative data from the Texas Higher Education Coordinating Board (THECB); and annually institutional data from the Integrated Postsecondary Education Data System (IPEDS). TEA/THECB data are housed at The University of Texas at Dallas Education Research Center (ERC) and IPEDS data is publicly available. In order to correctly identify students that meet TEXAS Grant's HP eligibility criteria, we merge TEA with THECB data to create a student-level dataset. TEA files include information on each students' work from high school until graduation. THECB files provide information on students' college admissions and financial aid. Particularly, the loans programs in the financial aid data are studied at an aggregated level according to the type of program. Table 2.1 depicts the level of aggregation used in this analysis.

Table 2.1: Loan categories

Category	Program
Subsidized loans	Subsidized federal direct Subsidized Stafford loans
Unsubsidized loans	Unsubsidized federal direct Unsubsidized Stafford loans
Other federal loans	PLUS federal direct SLS+PLUS loans Help loans Primary care loans Perkin loans
State loans	College access loans Be on time loan HB3015 loans
Private loans	Other long-term loans

Finally, we also observe student characteristics prior to their enrollment in postsecondary education such as race/ethnicity, gender, ACT score[10], COA, and indicators for free/reduced price lunch (economically disadvantaged), English proficiency, gifted and talented status, and risk of dropping out from high school[11]. These measures are taken at the time of high school graduation and prior to college enrollment. We will use data both at the institutional and student level to conduct or analyses, and will focus on 4-year public university in Texas—and first-time freshman student—between fiscal years 2010 and 2017.

2.3.1 Data Exploration

Institutions' decisions regarding students' financial aid building-process can be a complicated decision mainly because they need to comply with a number of requisites and parameters inherent to the different financial aid programs. In some cases, colleges have the discretion to

[10]Students' SAT scores were converted to ACT scale to guarantee comparability between the two tests.

[11]This a dichotomic indicator constructed from a number of variables such as being convicted of a felony, among others.

award at their discretion, conditional on meeting program guidelines, universities' strategic plans, and students' best interest. We will examine financial aid decisions—including all non-repayable and repayable forms of aid—by looking at the final allocation of financial aid awards among first-time freshman students. This analysis will be performed using two techniques. First, we will implement a Spearman's (Spearman, 1904) correlation matrix to produce a network plots that will visually depict the financial aid programs that are frequently awarded to students jointly (i.e., as a package). Second, we will produce descriptive tables depicting the most frequent financial aid programs that were given to students in the last 8 academic years finilizing in 2017.

Network plots are presented in Figure B.1. These pictures the correlation between financial aid programs in which programs granted together to a student are more highly correlated and will appear closer together and are joined by stronger paths in the graph. Paths are also colored according to the value of the correlation so that a darker color represents a stronger correlation. The proximity of the points is determined using multidimensional clustering (see Kuhn et al., 2020, for more details). The panels in Figure B.1 show us that—at least for the last 8 academic years—there are two clear clusters when analyzing the programs that are awarded together: The Pell-TEXAS cluster and the cluster of loans (including subsidized, unsubsidized, and other federal loans). The Pell-TEXAS cluster is easily identifiable—and expected—group. Recall that the TEXAS Grant is designed to complement the dollars from other generous first-dollar programs, such as the Pell Grant. Keep in mind that by the time institutions grant TEXAS dollars to a student, their tuition and fees must be covered fully by a financial aid package that does not include repayable forms of aid (i.e., student loans). All the connections of the Pell-TEXAS cluster with other programs may be considered additions to the financial aid package that covers tuition and fees. In order to have a better understanding of the amounts and the order in which the programs are granted to students, we conduct a descriptive exercise with the process of tailoring financial aid programs.

Tables A.1 through A.8 present the most frequent financial aid awards for the last 8 academic years. The dollar amounts in the tables are adjusted for inflation and are expressed in constant dollars of 2017. The first row of each table represents the most frequently awarded program among Texas first-time freshman (FTF) students. The descriptive statistics include the mean and median award for that particular program and the number of students who received such funds. The second row presents information of the second most frequent program awarded to students who were also awarded the program in row one. In other words, it is the most frequently awarded program conditional on receiving the program in the first row. Taking a look at the packages awarded to FTF students in 2017 (Table A.8), the most frequently awarded program is the Pell Grant with a total of 25,744 individuals receiving it in the—average—amount of \$4,802 dollars. Additionally, 80% of the Pell recipients also received a TEXAS award for \$5,209. Up to this point, the 20,644 students receiving a Pell-TEXAS award are being granted, on average, a total of \$10,176 dollars. Furthermore, 56%—for a total of 11,611 students, which represents about 45% of the initial Pell Grant recipients—of the Pell-TEXAS recipients borrow on average \$3,433 dollars in the form of subsidized loans. Lastly, 73% of those receiving aid and borrowing subsidized loans—and about 33% of the initial Pell recipients—also borrow \$2,642; for a total of \$16,292 dollars in FY 2017. TPEG, SEOG, and other federal loans correspond to 9%, 2%, and 0.1% of the initial Pell recipients; respectively.

Two things should be highlighted from this data exploration. First is that, taking inflation into account, awards remained relatively unchanged throughout the last 8 academic years. The most significant change was experienced by the TEXAS Grant program in 2012,where the mean award drops to 5.1 thousand from 7 thousand in the previous year, which is consistent with the implementation of a target award that suggests institutions to offer 5 thousand dollars to eligible FTF students. Second, the number of FY 2017 FTF Pell recipients increased 68% with respect to those in 2010 and the number of Pell-TEXAS recipients increased 123%;

showing the great scope and the improvement in coverage of the TEXAS Grant as a last-dollar program.

2.4 Methodology

Our objective is to identify institutions that look similar in terms of institutional and students' characteristics, and utilize this information as input, along with several other factors, to predict institutions' financial aid decisions. To conduct these two separate analyses, we will implement two different statistical learning approaches. First, we utilize an unsupervised machine learning algorithm to identify clusters of Texas universities according to institutional and student characteristics. Second, we employ a supervised machine learning algorithm to study how Texas public universities make the decision to award the TEXAS Grant among eligible students. Particularly, we run a classification exercise to identify recipients and non-recipients.

The following two sections explain in detail the approaches and algorithms we implemented to conduct the hierarchical clustering (HC) to categorize institutions, and for the gradient boosting machines (GBM) utilized to predict TEXAS Grant receipt status.

2.4.1 Hierarchical Clustering

Texas has a number of post-secondary institutions that vary greatly in size, selectivity, and student population. We use data from the Integrated Postsecondary Education Data System (IPEDS) and TEA/THECB data to conduct a clustering analysis to classify and categorize Texas 4-year colleges using aggregated collegiate variables and select characteristics for the entering cohorts of first-time freshman students (see variables[12] included in Table A.9). We make use of a hierarchical clustering algorithm in order to profile institutions and produce

[12]The total number of variables (features) included in the analysis is 117. The 27 variables presented in Table A.9 are entered in the model for the different academic years.

metrics that will allow us to provide insight on how similar colleges are to each other. Because there is not a response variable, clustering is an unsupervised method, which implies that it seeks to find relationships between the observations—in this case Texas 4-year colleges—without being trained by a response variable. These algorithms allow us to identify which observations are similar, and potentially categorize them therein. We prefer the hierarchical clustering method—as opposed to other clustering approaches such as K-means—because it does not require to pre-specify the number of clusters to be generated. Furthermore, hierarchical clustering has an added advantage as it results in a dendrogram, which is an attractive tree-based representation of the observations. Cluster are identified by making a cut across the dendrogram.

Hierarchical clustering follows a simple recursive algorithm that allows us to map a dissimilarity measure into a dendrogram. Following (James et al., 2017, p. 395), the algorithm is:

1. Consider n clusters (one for each observation) and a measure of all the $\binom{n}{2} = n(n-1)/2$ pairwise dissimilarities.

2. For $i = n, n-1, \dots, 2$:

   (a) Examine for all pairwise inter-cluster similarities among the i clusters and identify the pair of clusters that are least dissimilar (i.e., most similar). Fuse these two clusters. The dissimilarity between these two clusters indicates the height in the dendrogram at which the fusion should be pleased.

   (b) Compute the new pairwise inter-cluster dissimilarities among the $i-1$ remaining clusters.

We employ Euclidean distance in the features and a complete linkage to address dissimilarity among clusters (see James et al., 2017, Chapter 10 for more details.). In the process of selecting the appropriate number of clusters, we implement the algorithm suggested by Charrad et al. (2014) to determine the number of clusters using indices that propose the best clustering scheme. Additionally, one approach to verify whether a unit was placed correctly in a cluster is the computation of silhouette information from the clustering exercise (see Maechler et al., 2019, for more details). For each unit i, the silhouette width $s(i)$ is defined as follows:

Let $a(i)$ be the average dissimilarity between i and all other points of the cluster to which i belongs (if i is the only observation in its cluster, $s(i) = 0$ without further calculations). For all other clusters C, let $d(i, C)$ be average dissimilarity of i to all observations of C. Next, define $b(i) = \min_C d(i, C)$. $b(i)$ may be seen as the dissimilarity between i and its neighbor cluster, i.e., the nearest one to which it does not belong. Finally, silhouette may be defined as $s(i) = \frac{b(i)-a(i)}{\max[a(i),b(i)]}$. Units with $s(i) = 1$ are well clustered, $s(i) = 0$ means that the unit lies between two clusters, and units with $s(i) < 0$ are likely to be placed in the wrong cluster. Figure B.2 depicts silhouette information for different number of clusters. The evidence suggests that 3 clusters classify universities properly.

We further examine whether the features included in the clustering analysis allow to produce groups that are statistically different from one another so that 4-year colleges are similar within groups but dissimilar between groups. Because the analysis included a total of 117 features, we select 6 variables at random to conduct a visual analysis to determine whether the clusters are statistically different from each other according to the assessed features. Figure B.3 shows a boxplot for the means across the 3 clusters for the 6 randomly-selected variables. This evidence is consistent with having different means for these variables across all three clusters; therefore 4-year colleges seem to be similar within but dissimilar between clusters.

2.4.2 Classification Models

TEXAS Grant guidelines are rather clear on the eligibility requirements for a student to receive an initial year award. Texas institutions are to follow these guidelines and they are required to select recipients from a pool of eligible students. Although made up by eligible students, the set of individuals from which institutions select TEXAS Grant recipients has different sources of heterogeneity such as first-dollar financial aid received, college of enrollment, parents' education, household income, academic year, among others. With the purpose of predicting who will receive a TEXAS Grant initial year award from a pool of eligible students, we conduct a classification exercise and compare two approaches: a Logistic regression and a gradient boosting machine (GBM) model, which is a tree-based algorithm.

We will contrast our fine-tuned GBM model predictions with those of a fine-tuned Logit model. In order to train our models, we split the pool of eligible students into two groups at random: a training set (70% of the observations) and a test set (remaining 30% of the observations). Both models—GBM and step-wise Logit—were trained on the same training set and both models' performance was be assessed on the same test—or training—set. With this approach we intend to i) show each model's predictive power, ii) avoid producing over-fitted predictive models, and iii) identify students who will receive the TEXAS Grant as Initial Year award and distinguish the features that are more relevant to predict award receipt among eligible students by using the best model. In the following two sections we will describe our models.

Logistic Regression

The Logistic regression is a well-known model to estimate the probability of an event occurring. This model assumes a logistic cumulative distribution function based on a set of variables (features) to make the prediction. Formally, the Logistic model is represented as

$$F(Z_i) = \frac{e^{-Z_i}}{1 + e^{-Z_i}} = \Lambda(-Z_i) \tag{2.1}$$

where $F(\cdot)$ represents the logistic cumulative distribution function, $Z_i = X\beta + \varepsilon_i$, and X is the set of individual characteristics. Our best Logit candidate model was fine-tuned using a step-wise algorithm that recursively includes and extracts variables and evaluates each model to select the one that fits the date the best. In other words, the algorithm considers two base-points: a model that only includes a constant and a model that includes all the features available in the dataset. The algorithm recursively includes and extracts variables from X until it evaluates all possible combinations using the AIC information criterion. We utilize a forward, backward, and both-directions step-wise algorithms. Each algorithm suggest the best candidate of the Logit family. In case the three algorithms suggest different models, we will pick the best model—among those three models—using the ROC curve and AUC information, which will be explained in the next section.

Gradient Boosting Machines

Regression trees can be represented as follows:

$$f(X) = \sum_{m=1}^{M} c_m \cdot 1_{(X \in R_m)} \tag{2.2}$$

where $R_1, \ldots, R_M$ represent a partition of feature (i.e., X) space and c_m is a parameter associated with partition m. One of the advantages of boosting algorithms is that instead growing just one tree or a forest, this approach grows a set of trees with the difference that this statistical learning method that uses error from a single tree as recursive input. It fits a decision tree to the residuals from the model. That is, it fits a tree using the current residuals, rather than the outcome variable (Y) as response. The algorithm then adds such decision tree into the fitted function to update the residuals. The size of each recursive tree is determined by the number of splits (d). By fitting recursively relatively small trees to the residuals, one can slowly improve $\hat{f}$ in areas where it does not perform well. The learning rate—also referred to as shrinkage—(λ) may slow the process even more by allowing more and different trees to learn from the residuals. With this in mind, boosting has three tuning parameters: number of trees (B), learning rate (λ), and number of splits—often referred to as interaction depth—(d).

Let's modify Equation (2.2) so that $\hat{e}_i = y_i - \hat{f}(x)$. Formally, the gradient boosting algorithm is as follows:

1. Set $\hat{f}(x) = 0$ so that $\hat{e}_i = y_i$ for all i in the training set.

2. For $b = 1, 2, \ldots, B$:

   (a) Fit a tree $\hat{f}^b$ with d splits—and $d + 1$ terminal nodes—to the training data $(X, \hat{e})$.

   (b) Update $\hat{f}$ by adding in a shrunken version of the new tree:

   $$\hat{f}(x) \leftarrow \hat{f}(x) + \lambda \hat{f}^b(x)$$

   (c) Update the residuals:

   $$\hat{e}_i \leftarrow \hat{e}_i - \lambda \hat{f}^b(x)$$

3. Output the boosted model:

   $$\hat{f}(x) = \sum_{b=1}^{B} \lambda \hat{f}^b(x)$$

This statistical routine is known to perform quite well in predictive exercises. We will fine-tune GBM models by varying interaction depth (d) across three values: 1, 5, and 9; number of trees (B) across 30 values: from 50 to 1,500 with increments of 50; and learning rate (λ) for three values: 0.01, 0.05, and 0.1. In total we will produce 270 different GBM models and we select the best one using ROC curve (receiver operating characteristic curve) information. The ROC curve is a graph showing the performance of a classification by plotting two parameters: True Positive Rate (sensitivity) and false positive rate (1-specificity). Particularly, $TPR = \frac{TP}{TP+FN}$ and $FPR = \frac{FP}{FP+TN}$, where TP is the number of true positive cases, FN is the number of false negative cases, FP is the number of false positive cases, and TN denotes the number of true negative cases. The ROC curve is concave to the origin and is bounded between 0 and 1 for both parameters, and each point on the curve depicts the TPR and FPR for different classification thresholds[13]. The ROC curve is compared to a 45-degree line starting at the origin to produce a very useful metric: the area under the curve or AUC. AUC provides an aggregate measure of performance across all possible classification thresholds. In other words, AUC tells how much model is capable of distinguishing between classes. The higher the AUC, the better the model is at predicting true negatives and true positives. By analogy, higher the AUC, the better the model is at distinguishing between TEXAS Grant recipients and no recipients. Therefore, our algorithms select the best model as the one with largest AUC.

2.5 Results

In this section we discuss the findings obtained from our hierarchical clustering exercise on Texas 4-year public colleges and those from the Logit and GBM models we trained on the pool of TEXAS-eligible FTF students attending Texas public universities.

2.5.1 Institutional Classification

Our classification exercise included 25 variables presented in Table A.9. However, not all variables were available for the time window this analysis is considering. For this reason, the model may include a given variable for only certain years. In total, our HC model includes a total of 117 institutional characteristics we will classify 4-year colleges on. We included as many variables as available with the purpose of accounting for the changes over time that universities typically exhibit. For the hierarchical model, we followed the algorithm presented by Charrad et al. (2014) which suggests using a number of indices to determine the number of clusters that better fit the data. In this case, the algorithm suggested that 3 groups of

[13]The model produces a score (probability) of unit i belonging to the *success* category—in our case, TEXAS Grant receipt. The threshold is the score cut-off at which an observation will be assigned to either category.

institutions propose the best clustering scheme. The dendrogram presented in Figure B.4 depicts Texas public universities and the 3 clusters that our HC model suggested from the data. The first cluster of institutions is made up by Texas A&M University (TAMU) and The University of Texas at Austin (UT); we will refer to this group—for now—as cluster number 2. The second group of institutions includes Texas Tech University (TTU), The University of Texas at Dallas (UTD), Texas State University (TSU), The University of Texas at Arlington (UTA), The University of Texas at San Antonio (UTSA), University of North Texas (UNT), and University of Houston (UH); referred to as cluster number 3. Finally, all other Texas public universities are included in cluster number 1.

Figure B.2 depicts the silhuette extraction from the data categorizing institutions in 3 (Panel A), 4 (Panel B), 5 (Panel C), and 10 (Panel D) clusters. Recall that institutions with silhouette close to 1 are well clustered, silhouettes equal to zero means that the unit lies between two clusters, and institutions with negative silhouette are likely to be placed in the wrong cluster. Therefore, looking at the aggregated silhouette (column of numbers to the right of the plot), we are able to validate that 3 clusters seem so fit the data more properly. However, the plot in Panel A shows that institution number 26—classified in cluster number 1—seems to be misplaced in that cluster. With 4 clusters, institution number 26 is a better fit, but the overall silhouette of that group is lower. Institution number 26 is The University of Texas at El Paso (UTEP). Hence, UTEP's institutional characteristics seem to place it as an outlier within cluster 1, but it is not sufficiently similar to other institutions to be placed in clusters 2 or 3.

Because HC is an unsupervised algorithm, it is impossible to verify its classification power. However, in order to verify if Texas colleges are similar within clusters and dissimilar between clusters, we conduct a visual exercise using boxplots. Figure B.3 includes 6 different plots for randomly-selected features included in the clustering analysis. For example, TAMU and UT—in cluster number 2—invested the most in library resources in 2010, had the highest number of enrolled students in 2014, offer the highest number of Doctoral programs in 2015, had the largest number of associate professors in 2016, admitted the highest number of students in 2017, and had the largest number of instructional staff in 2017. It is easy to see in the pictures how the three clusters differ in these characteristics.

2.5.2 Financial Aid Decisions Among Eligible Students

Two models are compared in order to select the one with highest predictive power identifying potential IY TEXAS Grant recipients at public universities: The first model we have is a stepwise Logit model, which will be compared to a GBM model.

Three stepwise approaches were implemented: forward, backward, and both directions. These algorithms include and exclude variables from the model and suggest the best one according to how well they fit the data using the AIC information criterion. In this case, all three models suggested the same model, which is adventageous in this case because there is no need to select the best Logit model. For this selected model, we produced a ROC curve (Robin et al., 2011) and obtained a cut-off score of 0.801 by computing the Youden Index (see Youden, 1950). Therefore, all predicted scores above that threshold will be counted as TEXAS Grant recipients; and those at or below will be marked as non-recipients. Table 2.2 shows the confusion matrix for the Logit model predictions. According to this matrix, this model correctly predicts about 74.4% a TEXAS Grant decisions, 19.8% of the predictions are false negatives, and 5.8% are false positives. These predictions do not fall within the standards, mainly because the model disproportionately produces false negatives—i.e., the model predicts that a student will not receive the TEXAS Grant when they indeed received it. We will compare these metrics to those of the selected GBM model.

Table 2.2: Confusion matrix: Logit model

	No (true)	Yes (true)
No (predicted)	14.74	19.79
Yes (predicted)	5.82	59.65

The second model under consideration is a GBM for which we conducted a hyper-parameter tuning using 270 different combinations. Our selected model included 1,500 trees, interaction depth of 9, a shrinkage 0.05. This model predicts 88.5% of the cases correctly, which is about 14 percentage points higher that the Logit model. 2.6% of the predictions are false negatives, which is substantially lower than that of the Logit model. Additionally, 8.9% of the times, the GBM model predicts that the student will receive a TEXAS Grant when they are non-recipients, which is about 3 percentage points higher than the Logit model. Therefore, the GBM model does a better job at identifying TEXAS Grant recipients as it produces 19% more accurate predictions and 55% less inaccurate predictons than the Logit model.

Table 2.3: Confusion matrix: GBM model

	No (true)	Yes (true)
No (predicted)	11.65	2.54
Yes (predicted)	8.92	76.89

Our preferred model is the GBM for this predictive exercise, as it minimizes the off-diagonal in the confusion matrix. Next, it is important to look at the importance the different features (variables) have in the problem. Table 2.4 depicts the relative influence for every feature in the model. For instance, the School explains almost 27% of the total variation in TEXAS Grant receipt, and Pell Grant awards accounts for about 22% of the variation. Particularly, School; Pell awards, Fiscal year; TPEG awards; Total state loans; HB 3015 Grant awards; cost of attendance; and expected family contribution—that is 22% of the features in the model—account for 80% of the variation in the outcome variable. Note that all these variables are inherent to the student's financial aid situation, and do not necessarily reflect demographics or other variables that describe the background or economic/social status of the student. The demographic variable with highest importance is race/ethnicity (with 1.3%), which is relatively low predictive power.

Table 2.4: Relative influence of feature in GBM model

Variable	Relative influence (%)
School	26.74
Pell award	21.8
Fiscal year	8.35
TPEG award	6.66
Total state loans - year 1	5.36
HB 3015 award	3.65
Cost of attendance	3.59
EFC (adjusted for inflation)	3.57
Total unsubsidized loans - year 1	2.5
Institutional aid award	2.12
Total subsidized loans - year 1	1.93
Merit aid (external)	1.71
Other scholarships	1.68
Total other federal loans	1.65
Race/Ethnicity	1.31
Admision action	1.12
SEOG award	1.05
Father's education	0.91
Mother's education	0.91
Family income	0.66
ACT score	0.58
Living arrangements	0.45
Top 10 percent scholarship award	0.44
Total private loans	0.32
Household size	0.24
Economically disadvantaged	0.14
Sex	0.13
Dependent status	0.1
Institution type	0.06
Family obligation	0.06
HP Eligible	0.06
At risk of dropout	0.05
Studep award	0.04
Gifted and talented	0.04
Age	0.02
English proficient	0
BYRD award	0

2.6 Conclusion

Studies that explore causal relationships for the TEXAS Grant provide great insight on the postsecondary outcomes of different gourps of students (Villarreal, 2018; Andrews and Montenegro, 2019; Montenegro, 2019). Exploring causal inference is feasible because the

TEXAS Grant is very clear regarding eligibility, and certain sources of exogenous variations exist in order to complete those tasks. Our approach in this study is more descriptive, as we are willing to learn from the data. We make use of different machine learning techniques to provide insight on how universities target eligible students to award TEXAS dollars. This study is an effort to utilize descriptive and predictive approaches to speak to the financial aid literature and understand how institutions make financial aid decisions. We tackle this objective by conducting two different analysis. First, we classify Texas institutions into groups that look similar in terms of characteristics inherent to the university and their cohorts of first-time freshman students. Second, we explore the institutional process of granting an IY TEXAS award to first-time freshman students.

Classifying Texas institutions is a particularly useful exercise because it allows us to identify different sources of heterogeneity produced at the university level. Because of the different characteristics that 4-year public colleges possess, they might attract certain students, which might be a clear source of heterogeneity when conducting analyses that involve the pool of Texas public college students. Our hierarchical clustering analysis produces three groups of institutions that looks very similar to two groups—and a third natural one—easily identifiable in the state: flagships[14], emerging research[15], and other public universities. The only institution in our HC analysis with respect to these groups is the University of Texas at El Paso—which is not sufficiently similar to the other institutions to be placed in this group, but is not exactly similar to the other groups in the cluster it was placed either. Being able to identify this emerging research institution that looks so different than its peers is interesting case of study because this might reflect the need of a strategic plan to push

[14]Flagship universities are those leading enrollment, performance, and completion indicators. These institutions are the University of Texas–Austin and Texas A&M–College Station.

[15]Emerging research universities are those that receive extra funding to become Tier one in the state. These institutions are Texas State University, Texas Tech University, University of Houston, University of Texas–Arlington, University of Texas–Dallas, University of Texas–El Paso, University of Texas–San Antonio, and University of North Texas.

UTEP at the level of comparable institutions and make it worthy of receiving extra funding these institutions receive. However, categorizing Texas institutions will allow researchers examining the Texas educational system to group institutions correctly—with the caveat that UTEP might be a particularly different institution. Our HC results suggest that it might be a good idea to study these groups separately as they are likely to exhibit heterogeneous effects for policy implementations. Additionally, because the three groups of institutions have dissimilar characteristics, they might make decisions that differ across groups. Lastly, under a regression analysis, researchers may find useful to control for the appropriate fixed effects at the institution level.

Furthermore, we aim to also to provide insight on institutions' decision process for selecting financial aid recipients. Particularly, we examined institutions' discretion to select TEXAS Grant recipients among the pool of eligible students. Because there is no guideline for this decision process—further than targeting eligible individuals—, implementing traditionally parametric methods might not be an adequate in order to provide insight on this front. In order to show that this is the case, we compared the predictions of two fine-tuned models: an stepwise Logit and a GBM model. Our results show that the statistical learning model has higher predictive power to identify TEXAS Grant recipients than the traditional approach. Our GBM model minimizes false negatives rate from 19.8%—for the Logit model—to 2.5%. However, this reduction comes with a trade-off, as the false positive rate is slightly higher (8.9%, compared to 5.8% for the Logit model). Another trade-off we face by selecting the GBM as the *winner*, is that there is not statistical process to determine whether variables are statistically significant. To make up for this limitation, we produced metrics for the relative importance that features have in the model. Table 2.4 shows that students' institution and Pell award are the top 2 variables for relative influence. This suggests two important things. First, that decisions for TEXAS awards among eligible students highly depend on the institution, which does not come as surprise because TEXAS Grant funds are allocated to institutions according to their needs, and they are to award as many students as possible. Furthermore, because the TEXAS Grant is a last-dollar program—and therefore designed to complement other generous first-dollar programs—an important variable to predict TEXAS receipt is the amount students receive from the Pell Grant, which is the largest financial aid program at the federal level. It is interesting to see that fiscal year is an important factor because, again, it reflects the changes in money availability and budgeting inherent to these type of programs. Finally, although the institution is a very important factor to make the financial aid decision, the type of institution is not, which speaks to the high variation at the institution level—and not at the cluster level. Second, it is important to mention that institutions do not seem to base their decisions on students' demographic characteristics, which is consistent with efforts in achieving fair-awarding decisions.

This study is the first attempt to implement these types of tools to provide insight regarding Texas institutions and their financial aid decisions. The goal of this study is to close the gap in the literature of how financial aid appropriations are used in the state to increase the debate on how institutions allocate state resources effectively. One practical implication of this exercise is that an institution could use our findings to accompany the financial aid decision. We suggest the following algorithm:

Step 1: Collect data on—recently admitted—students presented in Table 2.4.

Step 2: Enter data into the GBM model

Step 3: Obtain predicted outcome (i.e., binary outcome for whether students under analysis should receive an IY TEXAS Grant award.

Step 4: Make the financial aid decision using prediction obtained from the GBM model.

By implementing this algorithm, institutions can potentially reduce waiting and administrative costs in the financial aid decision process. This is our effort to contribute to this difficult task.

There are still a number of different issues to tackle, but it is our desire that our findings make the research agenda on financial aid decisions and fairness more active.

CHAPTER 3

ESTABLISHING AN ALLOCATION PRIORITY MODEL FOR HIGH-ACHIEVING STUDENTS: EVIDENCE FROM AN STATE NEED-BASED GRANT

3.1 Introduction

Financial assistance is a powerful tool to improve access to higher education as many students face financial constraints that limit their ability to enroll in college. There exists a large number of programs funded from federal, state, or private resources which typically adjust allocation rules and eligibility requirements according to their specific interests. Authors utilize different experimental or quasi-experiment techniques to causally estimate the effects grants and scholarship programs (Deming and Dynarski, 2010). Different studies find that financial aid may significantly increase enrollment and persistence (Van der Klaauw, 2002; Dynarski, 2003), rise completion rates (Dynarski and Scott-Clayton, 2013), and may also boost course withdrawal and reduces full-load enrollment and completion (Cornwell et al., 2005, 2006). Moreover, other studies indicate that financial aid programs can potentially affect performance and major choice, which can translate into an increase in earnings after graduation and better financial health even years after they complete a degree (Dee and Jackson, 1999; Andrews et al., 2016; Scott-Clayton and Zafar, 2016; Bettinger et al., 2016; Cáceres-Delpiano et al., 2018; Clotfelter et al., 2018).

Aid programs can typically be grouped in two categories: merit- and need-based. Some are intended to reach academically able students, while other may be focused on targeting financially needy ones. Goldrick-Rab et al. (2012) shows that higher completion of a full-time credit load and rates of re-enrollment for a second year of college can be achieved when need-based college financial aid program is distributed among first-year Pell Grant recipients at select public Wisconsin universities. This is evidence compatible with the idea that need-based aid may boost student success in college. Additionally, Toutkoushian and Shafiq (2009) examine the choice that states make between giving appropriations to public colleges or need-based financial aid to students, showing that the latter might lead to higher enrollment. Realistically, both forms are needed to guarantee financial sustainability for both states and institutions. However, this type programs seem to be understudied in the literature relative to merit-based. Very little is know about the their effects on postsecondary outcomes and whether their effectiveness can be improved by selecting subgroups of financially needy students. This study examines a need-based financial aid program in Texas and a particular change in its allocation rules that provides higher priority to academically promising students.

The Toward EXcellence, Access, and Success (TEXAS) Grant is the largest program in the state that targets financially needy students. In fiscal year 2017, it made up for nearly 72% of the total aid provided by the state and granted funding to 58% of the total state aid recipients (Texas Higher Education Coordinating Board, 2018a). This grant program gives academic institutions the discretion to award TEXAS Grant dollars following program guidelines. However, the state restricted part of that autonomy with the implementation of Senate Bill (SB) 28. Because this program is over-subscribed, many eligible students did not receive funding for college. Particularly, "*The state does not fully fund the TEXAS grant program and often there are significant numbers of students (30 percent of those eligible) who do not receive the grant. Many of these students showed academic promise while in high school. During times of budgetary constraints, the state must decide to most efficiently use limited dollars, and this change to TEXAS grants will help to maximize state grant dollars per graduate*[1]". SB 28 therefore modified its allocation rules imposing higher priority in allocation to students who the state deemed to be higher achieving—and therefore more likely

[1]SB 28, Bill Analysis. By Zaffirini, W. Available at: `https://capitol.texas.gov/billlookup/text.aspx?LegSess=82R&Bill=SB28`.

to graduate. The highest priority (HP) model started to be implemented for awards granted in the fiscal year 2014 (i.e., starting in the Fall of 2013). This paper studies the effects of implementing the HP model on students' postsecondary outcomes via a difference-in-difference approach to assess whether TEXAS dollars are being allocated more efficiently following HP rules.

The TEXAS Grant is therefore a very interesting case of study as its allocation rules include both need and merit components, which is unusual for state-funded programs. Particularly, it is interesting to study the decisions of low-income, high-achieving students because this group exhibits behavior that is typical of students of their income rather than typical of students of their achievement. For this reason, low-income high achievers are unlikely to enroll in academically matched institutions (Hoxby and Turner, 2013; Hoxby and Avery, 2013). However, selecting from a pool of low-income, high-achieving students is a complicated task because this exercise may be subjective. For instance, Gurantz et al. (2019) identify high achievers using SAT distribution and low-income status by fee waiver usage and SAT questionnaire responses. From a randomized control trial, this study finds that virtual advising may increase enrollment in high graduation rate colleges. The authors argue that having access to a more informed application and enrollment decision may reduce the mismatch that is typical in this group of students. It is important to identify these groups of students, however it may be hard to determine the parameters guiding this decision.

To date, only one study examines the causal effects of receiving TEXAS Grant dollars under the HP model. Montenegro (2019) finds that aid for marginal recipients lowers academic performance by 14 percent and cuts student loans by 28 percent. Other studies describe issues related to the TEXAS Grant (see Johnson, 2005; Denning et al., 2018; Villarreal, 2018), but none of them study the direct effects of the implementation of the HP model on college outcomes. We contribute to the empirical literature on the Economics of Education in two ways. First, we help to close a gap in the financial aid literature by examining a large state need-based program. Second, we shed light on the debate about whether aid programs should grant priority to high-achieving students and its potential effects on postsecondary outcomes. The implementation of the HP model might be interpreted as the state's disagreement with the allocation decisions institutions were making. Thus, the main goal of this paper is to offer a better understanding of how the HP model affects postsecondary outcomes and how this policy changes the educational outlook of students receiving the grant.

3.2 Background

Texas has engaged in efforts like the *60x30TX*[2] to reach higher standards of excellence in teaching, research, and innovation and to help Texans get better jobs and achieve higher living standards through higher education. To attain part of *60x30TX*'s purpose, Texas offers multiple grants and scholarships that have helped its residents to enroll in colleges and universities across the state. The Top 10% Scholarship, the Texas Public Educational Grant Program (TPEG), and the Toward EXcellence, Access and Success (TEXAS) Grant are the largest programs of assistance in terms of dollars granted and benefited students. Most grants are awarded based on financial need[3], and students can apply by submitting the Free Application for Federal Student Aid (FAFSA) or the Texas Application for State Financial Aid (TASFA).

On January 18th, 1999, the House Bill 713, 76th Leg., ch. 1590[4] filed into the Texas Legislature a proposal *relating to the establishment and operation of the Toward EXcellence,*

[2]This is the abbreviation of *60 percent of Generation Texas will have post secondary credential or degree by 2030*. That is, by 2030, Texas will have approximately 60 percent of its 25 to 34 year-old workforce to hold a post-secondary credential.

[3]Most institutions define financial need as part of the cost of attendance (COA) that is not covered by the expected family contribution (EFC). Usually, the COA refers to the total amount of education expenses such as tuition, books and supplies, housing and dining, transportation, among others.

[4]See Education Code, Title 3. Higher Education. Subtitle A. Higher Education in General. Chapter 56. Student Financial Assistance.

Access, & Success (TEXAS) grant program [...]; consolidating and revising financial aid, grant, and scholarship programs [...], which was approved and became effective on the 19th of June of the same year. The purpose of this program is to provide financial aid assistance to enable economically disadvantaged students to attend public institutions of higher education in the state. Although the program's goal has been the same ever since its establishment, its allocation rules and guidelines have been modified since its inception. The requirements to be eligible for an initial year (IY) TEXAS Grant award include being classified by the institution as Texas resident, and having a 9-month expected family contribution (EFC) of no more than a cap set each year by the THECB, which in the 2018 fiscal year was $5,430 dollars[5]. In order to receive a renewal year (RY) award, students need to maintain satisfactory academic progress (SAP) by meeting the institution's SAP policy[6] by the end of the first year. The TEXAS Grant program covers up to 150 semester credit hours, can be received for up to 6 years from the first semester it is awarded, and awards a maximum annual amount of $9,050 dollars for public universities (max. award for the 2017-18 academic year.).

This grant program gives academic institutions the discretion to award TEXAS Grant dollars provided they identified eligible students. However, the state restricted part of that autonomy with the implementation of Senate Bill (SB) 28 in 2013 as this program is over-subscribed, and many eligible students did not receive funding for college. Particularly, "*The state does not fully fund the TEXAS grant program and often there are significant numbers of students (30 percent of those eligible) who do not receive the grant. Many of these students showed academic promise while in high school. During times of budgetary constraints, the state must decide to most efficiently use limited dollars, and this change to TEXAS grants will*

[5]The EFC cap is set as a portion of the state-wide average tuition and fees, and it is adjusted annually (see THECB (2018a)).

[6]For most institutions in Texas, this includes maintaining a 2.0 cumulative GPA, and completing 24 semester credit hours (SCH) over an academic year

help to maximize state grant dollars per graduate[7]". SB 28 therefore modified its allocation rules imposing higher priority in allocation to students whom the state deemed to be higher achieving—and therefore more likely to graduate. The highest priority (HP) model started to be implemented for awards granted in the fiscal year 2014 (i.e., starting in the Fall of 2013).

Regulations on the TEXAS program prioritize renewal awards. This means that in a given year, renewal awards are granted to continuing students first. After these are allocated and if remaining resources permit, initial awards for first-time-in-college students can be assigned next. These students may fall under either type of eligibility: basic eligibility (BE) or high priority (HP) eligibility. A high school graduate qualifies for basic eligibility (BE) if: i) graduates high school within 16 months of college enrollment, ii) enrolls in college at least three-fourths full-time[8], and iii) has a 9-month EFC of no more than the determined threshold for a given fiscal year. Among those who qualify for BE, the higher priority (HP) model gives preference to high-achieving students. Under its specifications, institutions must prioritize students who had met some of requisites in the the following categories:

1. Advanced Academic Program[9] (AAP):

   12 hours of college credit (dual credit or AP courses), complete the Recommended or Advanced High School Program (or its equivalent), or complete the international baccalaureate program.

[7] SB 28, Bill Analysis. By Zaffirini, W. Available at: `https://capitol.texas.gov/billlookup/text.aspx?LegSess=82R&Bill=SB28`.

[8] Full-time status for undergraduate students is typically granted to those who enroll 12 or more credit hours per semester.

[9] These programs are standard across states and are available to students who desire more challenging work than what's offered in the standard curriculum.

2. TSI Readiness[10] (TSIR):

   Meet the Texas Success Initiatives assessment thresholds or qualify for an exemption.

3. Class Standing (CS):

   Graduate in the top one-third of the high school graduating class or a grade point average of at least 3.0 on a 4-point scale.

4. Advanced Math (AM):

   Complete at least one math course beyond Algebra II or at least one advanced career and technical course (as determined by the TEA).

If a student complies with at least two of these four categories, he or she is given priority among all their peers that are only eligible under BE to receive an IY TEXAS award.

With these allocation rules, SB 28 attempts to more adequately allocate dollars toward financially needy students who are more likely to succeed, by providing priority to high-achieving high school graduates who enroll in college.

3.3 Data

The data we use in this study come from two sources: annually administrative data from the Texas Education Agency (TEA) and annually administrative data from the Texas Higher Education Coordinating Board (THECB). These data are housed at The University of Texas at Dallas Education Research Center (ERC). In order to correctly identify students that meet TEXAS Grant's HP eligibility criteria, we merge TEA with THECB data to create a student-level panel. TEA files include information on each students' work from

[10] The Texas Success Initiative (TSI) is a state-legislated program designed to improve students' success in college. Part of the program is an assessment to determine students' basic skills in reading, mathematics and writing. Students may be eligible to TSI exception if a student obtains a qualifying score on ACT, SAT, or STAAR. Students who are not TSI exempt are required by law to take an assessment test approved by the Texas Higher Education Coordinating Board (THECB).

high school until graduation. THECB files provide information on students' admissions, course load, performance, and financial aid. This dataset allows us to follow students from high school through college—provided they remain in Texas—, allowing to control for relevant student characteristics prior to their enrollment in postsecondary education such as race/ethnicity, gender, ACT score[11], COA, and indicators for free/reduced price lunch (economically disadvantaged), English proficiency, gifted and talented status, and risk of dropping out from high school[12]. These measures are taken at the time of high school graduation and prior to college enrollment. Because TEXAS Grant IY awards are distributed at the beginning of the fiscal year, we only consider cohorts enrolling the Fall semester of each academic year. The sample for this paper is made up of low-income Texas residents who complete a FAFSA application and enroll in a 4-year public university in Texas for the first time between 2009 and 2016 (i.e., fiscal years 2010–2017). The timing in our data allows us to follow the first HP-eligible cohort in the post-period for up to four years.

3.4 Methodology and Identification Strategy

We select the set of low-income students who qualify for basic eligibility (BE). These are all the students who are Texas residents, enroll in college within 16 months of high school graduation, and have an EFC at or bellow the annual cap[13]. Within the pool of BE students, we flag high-achieving individuals who would qualify for higher priority under TEXAS Grant rules. We therefore identify the HP-eligibility effect on the outcomes of interest by contrasting the responses of eligible students before and after implementation of SB 28 with those who

[11]Students' SAT scores were converted to ACT scale to guarantee comparability between the two tests.

[12]This a dichotomic indicator constructed from a number of variables such as being convicted of a felony, among others.

[13]EFC cap for fiscal year 2017 is $5,233 dollars. Table A.10 contains caps for each year considered in our sample.

are ineligible. Our control group is made up by low-income student who do not qualify for higher priority.

In a regression context, this means estimating empirical models of the form

$$y_{isc} = \alpha(HP_i \times \mathbf{1}(Cohort_i \geq 2013)) + \gamma HP_i + \delta \mathbf{1}(Cohort_i \geq 2013) + \boldsymbol{\psi}'\boldsymbol{X} + \eta_s + \theta_c + \varepsilon_i \quad (3.1)$$

where y_{isc} is a behavioral response measure for student i at school s in cohort c; HP_i is an HP-eligibility dummy; $\mathbf{1}(Cohort_i \geq 2013)$ is an indicator function that is set to one for students who enrolled in a cohort after SB 28 was enforced; and X is a matrix of control variables. η_s and θ_c are school and cohort fixed effects, respectively. The coefficient of interest is α as it represents the effect of implementing the HP model in this two-by-two difference-in-difference approach.

Texas has a number of post-secondary institutions that vary greatly in size, selectivity, and student population. These and other statistics dramatically differ across institutions, but tend to look much more alike when grouped in these three categories: flagships[14], emerging research[15], and other universities. For this reason, we will produce estimates for students attending Texas institutions that belong to those particular groups, as well as overall estimates.

3.5 Results

The HP model is intended to prioritize dollar allocation toward students that the state deems to be more likely to be successful in college. We estimate the effects of receiving

[14]Flagship universities are those leading enrollment, performance, and completion indicators. These institutions are the University of Texas–Austin and Texas A&M–College Station.

[15]Emerging research universities are those that receive extra funding to become Tier one in the state. These institutions are Texas State University, Texas Tech University, University of Houston, University of Texas–Arlington, University of Texas–Dallas, University of Texas–El Paso, University of Texas–San Antonio, and University of North Texas.

HP-eligibility on the academics and finances of low-income students enrolling in 4-year public colleges in Texas. Our results suggest that HP-model implementation significantly impacts the academics and finances of eligible students, along with the fact that there seems to be high heterogeneous effects across students enrolling in different type of institutions. We produce estimates controlling for different exogenous student characteristics, as well as a set of fixed effects. Our preferred specification includes covariates, cohort fixed effects, and college fixed effects.

3.5.1 Academics

Panel A in Tables 3.2, 3.3, and 3.4 show the point estimates for the impact of the HP model for students enrolling in flagships, emerging research institutions, and all other institutions. Table 3.1 presents overall estimates.

Our results suggest that implementation of the HP model had a positive effect in the likelihood of receiving an IY TEXAS award. Particularly, HP-eligible students at flagship universities are 2.8 percentage points (about 3.8 percent) more likely to receive an award than the counterfactual. Within students attending emerging research institutions, the effect is 5.8 percentage points higher (7.3 percent percent) and for students attending other institutions is 2.7 percentage points (about 4 percent). Implementation of the HP model also impacted students' academic attainment. HP-eligible students attending flagship institutions obtain lower GPA (8 percent) and attempt 7.4 percent more credit hours by the second year of college than their ineligible peers; however, these results are not statistically significant. Additionally, eligible students at emerging research institutions attain 9.8 percent higher GPA by the end of the first year of college and those attending other public universities 2 percent higher GPA. HP-eligible students also attempt 10 percent more credit hours at emerging institutions, but 6.8 percent less at other universities. Finally, the implementation of the HP model increased the likelihood of continuous enrollment for students in emerging

Table 3.1: Estimated effects of HP-eligibility on academics and finances: All institutions

A. Academics				
	(1)	(2)	(3)	(4)
Receives Texas Grant	0.067**	0.065**	0.068**	0.063**
[0.741]	(0.028)	(0.029)	(0.031)	(0.028)
Switches major	-0.029***	-0.027***	-0.037***	-0.033***
[0.346]	(0.007)	(0.007)	(0.007)	(0.007)
Cummulative GPA - semester 1	0.083***	0.053***	0.070***	0.071***
[2.394]	(0.019)	(0.018)	(0.018)	(0.018)
Cummulative GPA - year 1	0.064***	0.034**	0.051***	0.059***
[2.339]	(0.017)	(0.016)	(0.017)	(0.017)
Cummulative credit hours attempted - year 1	-1.025***	-1.232***	-1.221***	-0.985***
[25]	(0.158)	(0.150)	(0.150)	(0.132)
Cummulative credit hours attempted - year 2	-0.545***	-0.706***	-0.590***	-0.286*
[53]	(0.172)	(0.169)	(0.170)	(0.170)
Continuous enrollment - year 1	0.037***	0.037***	0.022***	0.023***
[0.976]	(0.004)	(0.004)	(0.004)	(0.004)
Continuous enrollment - year 2	0.031***	0.034***	0.039***	0.042***
[0.912]	(0.008)	(0.008)	(0.007)	(0.008)
Studies and works	-0.018**	-0.015**	-0.012*	-0.015**
[0.307]	(0.007)	(0.007)	(0.007)	(0.007)

B. Finances				
	(1)	(2)	(3)	(4)
Total financial aid received - year 1	282***	396***	513***	286***
[11154]	(72)	(71)	(69)	(63)
Cummulative loans - year 1	-408***	-265***	-154**	-152***
[3477]	(71)	(64)	(63)	(57)
Cummulative loans - year 2	-1,302***	-948***	-889***	-601***
[7914]	(181)	(158)	(158)	(145)
Observations - year 1		150,723		
Observations - year 2		94,306		
Covariates	Yes	No	No	Yes
Cohort FE	No	Yes	No	Yes
School FE	No	No	Yes	Yes

1 Standard errors in parentheses are clustered at high school level. * p <0.1, ** p <0.05, *** p <0.01.
2 Counterfactual mean in square brackets.
3 Number of observations for major switch and Switches from STEM to other majors correspond to those for year 1.
4 The set of covariates includes gender, race/ethnicity, at risk of dropping out from high school, free/reduced price lunch, English proficiency, gifted and talented status, ACT scores, and cost of attendance.

Table 3.2: Estimated effects of HP-eligibility on academics and finances: Flagship institutions

A. Academics				
	(1)	(2)	(3)	(4)
Receives Texas Grant	0.013*	0.017**	0.028**	0.028**
[0.744]	(0.006)	(0.007)	(0.012)	(0.012)
Switches major	0.007	0.010	-0.002	-0.001
[0.389]	(0.106)	(0.109)	(0.108)	(0.105)
Cummulative GPA - semester 1	0.040	-0.079	-0.016	-0.020
[2.638]	(0.219)	(0.204)	(0.208)	(0.203)
Cummulative GPA - year 1	-0.156	-0.266	-0.209	-0.212
[2.655]	(0.183)	(0.166)	(0.169)	(0.165)
Cummulative credit hours attempted - year 1	-0.654	-0.416	-0.820	-0.815
[26]	(1.787)	(1.677)	(1.683)	(1.693)
Cummulative credit hours attempted - year 2	3.928*	4.017*	4.010*	4.162*
[56]	(2.329)	(2.311)	(2.323)	(2.357)
Continuous enrollment - year 1	-0.026	-0.032	-0.035	-0.035
[0.973]	(0.058)	(0.058)	(0.056)	(0.056)
Continuous enrollment - year 2	0.069	0.071	0.081	0.082
[0.888]	(0.116)	(0.116)	(0.116)	(0.116)
Studies and works	-0.167**	-0.168**	-0.169**	-0.169**
[0.180]	(0.080)	(0.082)	(0.082)	(0.082)

B. Finances				
	(1)	(2)	(3)	(4)
Financial aid received - year 1	1,190	1,637	1,360	1,367
[13748]	(1,104)	(1,071)	(1,073)	(1,064)
Cummulative loans - year 1	78	108	148	146
[2710]	(120)	(157)	(126)	(134)
Cummulative loans - year 2	455	481	497	462
[7853]	(434)	(412)	(413)	(420)
Observations - year 1	21,802			
Observations - year 2	16,649			
Covariates	Yes	No	No	Yes
Cohort FE	No	Yes	No	Yes
School FE	No	No	Yes	Yes

[1] Standard errors in parentheses are clustered at high school level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

[2] Counterfactual mean in square brackets.

[3] Number of observations for major switch and Switches from STEM to other majors correspond to those for year 1.

[4] The set of covariates includes gender, race/ethnicity, at risk of dropping out from high school, free/reduced price lunch, English proficiency, gifted and talented status, ACT scores, and cost of attendance.

Table 3.3: Estimated effects of HP-eligibility on academics and finances: Emerging research institutions

A. Academics				
	(1)	(2)	(3)	(4)
Receives Texas Grant	0.065***	0.068***	0.075***	0.058***
[0.790]	(0.014)	(0.014)	(0.014)	(0.014)
Switches major	0.017	0.023	0.006	0.001
[0.348]	(0.019)	(0.019)	(0.019)	(0.019)
Cummulative GPA - semester 1	0.273***	0.163***	0.196***	0.255***
[2.450]	(0.041)	(0.037)	(0.038)	(0.038)
Cummulative GPA - year 1	0.265***	0.156***	0.183***	0.234***
[2.404]	(0.039)	(0.035)	(0.035)	(0.035)
Cummulative credit hours attempted - year 1	3.509***	2.294***	2.294***	2.412***
[24]	(0.379)	(0.346)	(0.347)	(0.296)
Cummulative credit hours attempted - year 2	0.921***	0.441	0.617*	0.799**
[52]	(0.346)	(0.316)	(0.319)	(0.318)
Continuous enrollment - year 1	0.029***	0.033***	0.023***	0.023***
[0.973]	(0.010)	(0.011)	(0.008)	(0.008)
Continuous enrollment - year 2	0.028**	0.032**	0.023**	0.037**
[0.894]	(0.012)	(0.014)	(0.011)	(0.018)
Studies and works	-0.041**	-0.024	-0.019	-0.015
[0.344]	(0.016)	(0.016)	(0.016)	(0.015)

B. Finances				
	(1)	(2)	(3)	(4)
Financial aid received - year 1	852***	704***	408***	420***
[11004]	(122)	(122)	(119)	(116)
Cummulative loans - year 1	-710***	-550***	-662***	-543**
[4161]	(171)	(158)	(158)	(226)
Cummulative loans - year 2	-1,048**	-772**	-753**	-1,050**
[8775]	(417)	(383)	(382)	(416)
Observations - year 1	50,997			
Observations - year 2	31,595			
Covariates	Yes	No	No	Yes
Cohort FE	No	Yes	No	Yes
School FE	No	No	Yes	Yes

[1] Standard errors in parentheses are clustered at high school level. * p <0.1, ** p <0.05, *** p <0.01.
[2] Counterfactual mean in square brackets.
[3] Number of observations for major switch and Switches from STEM to other majors correspond to those for year 1.
[4] The set of covariates includes gender, race/ethnicity, at risk of dropping out from high school, free/reduced price lunch, English proficiency, gifted and talented status, ACT scores, and cost of attendance.

Table 3.4: Estimated effects of HP-eligibility on academics and finances: Other institutions

A. Academics				
	(1)	(2)	(3)	(4)
Receives Texas Grant	0.022**	0.024**	0.025**	0.027**
[0.711]	(0.010)	(0.010)	(0.011)	(0.012)
Switches major	-0.030***	-0.028***	-0.035***	-0.032***
[0.296]	(0.008)	(0.008)	(0.008)	(0.008)
Cummulative GPA - semester 1	0.048**	0.036*	0.049**	0.049**
[2.288]	(0.021)	(0.021)	(0.021)	(0.021)
Cummulative GPA - year 1	0.031**	0.022**	0.035**	0.042**
[2.206]	(0.013)	(0.09)	(0.015)	(0.019)
Cummulative credit hours attempted - year 1	-1.994***	-1.950***	-1.932***	-1.508***
[22]	(0.140)	(0.124)	(0.126)	(0.114)
Cummulative credit hours attempted - year 2	-0.730***	-0.792***	-0.623***	-0.308
[48]	(0.209)	(0.203)	(0.203)	(0.202)
Continuous enrollment - year 1	0.031***	0.032***	0.015***	0.016***
[0.977]	(0.005)	(0.005)	(0.005)	(0.005)
Continuous enrollment - year 2	0.013	0.015*	0.022**	0.024***
[0.924]	(0.009)	(0.009)	(0.009)	(0.009)
Studies and works	-0.015*	-0.022***	-0.021**	-0.011
[0.343]	(0.009)	(0.009)	(0.009)	(0.008)

B. Finances				
	(1)	(2)	(3)	(4)
Financial aid received - year 1	311***	289***	289***	151**
[10466]	(84)	(80)	(78)	(72)
Cummulative loans - year 1	-695***	-369***	-266***	-243***
[3297]	(76)	(69)	(68)	(63)
Cummulative loans - year 2	-1,684***	-985***	-897***	-713***
[7375]	(195)	(168)	(167)	(155)
Observations - year 1		77,924		
Observations - year 2		46,062		
Covariates	Yes	No	No	Yes
Cohort FE	No	Yes	No	Yes
School FE	No	No	Yes	Yes

[1] Standard errors in parentheses are clustered at high school level. * p <0.1, ** p <0.05, *** p <0.01.

[2] Counterfactual mean in square brackets.

[3] Number of observations for major switch and Switches from STEM to other majors correspond to those for year 1.

[4] The set of covariates includes gender, race/ethnicity, at risk of dropping out from high school, free/reduced price lunch, English proficiency, gifted and talented status, ACT scores, and cost of attendance.

research and other institutions. Particularly, eligible students are 2.3 percent more likely to show up the following semester and 4 percent more likely to show up at least the following year. The figures for other universities are 1.6 and 2.6 percent; respectively. Lastly, one important finding is that HP-eligible students are less likely to work and study at the same time. Particularly, eligible students at flagship universities are 93 percent less likely to work. The estimates are smaller and less precisely estimated for emerging research and other universities (4.3 and 3.4 percent, respectively).

3.5.2 Finances

The implementation of the HP model had an important impact on the finances of Texas first-time freshman students. Panel B of Tables 3.1 through 3.4 depict the effects on total financial aid received and student loans. HP-eligible students at emerging research and other universities received $420 (3.9 percent) and $151 (1.4 percent) more generous financial aid packages during the first year of college, respectively. The figure for students at flagship universities is 10 percent, but the point estimate is not precisely estimated. Additionally, the HP model helped cut amounts borrowed during the first two years of college. HP-eligible students at emerging research institutions borrow 13 and 12 percent less during the first and second year, respectively. For those at other universities, the effects are 7.3 and 9.7 percent. The point estimate for students at flagship universities is $462 dollars, but is not statistically significant.

3.5.3 Robustness Checks

It is our interest to investigate these empirical relationships and to understand which correlations speak to a causal relationship, and which do not. Therefore, with the purpose of providing evidence that is consistent with the parallel trend assumption—necessary to produce an adequate counterfactual for this difference-in-difference identification strategy—we conduct an event study using the following specification

$$y_{isc} = \beta(HP_i \times \mathbf{1}(Cohort_i = t)) + \pi HP_i + \rho\mathbf{1}(Cohort_i = t) + \boldsymbol{\phi}'\boldsymbol{X} + \eta_s + \theta_c + \epsilon_i \quad (3.2)$$

where $\mathbf{1}(Cohort_i = t)$ is a an indicator function that takes on value of 1 when a student enrolls in cohort t, for $t = 2010, \cdots, 2017$. Our parameter of interest is β, as it represents the effect of being HP-eligible in cohort t. Figures 3.1 through 3.5 depict the effects of being HP-eligible in each cohort for the different outcomes[16]. Particularly, Figure 3.1 shows the difference in the likelihood of receiving the TEXAS Grant between HP-eligible and -ineligible students (i.e., treatment and control groups, respectively). HP-eligible students are about 2.8, 58, 2.7 percentage points (for flagships, emerging research, and other institutions; respectively) more likely to receive TEXAS dollars than the countefactual in the post-period. The two groups are observationally equivalent in the pre-period—as they show no statistically significant differences—which lines up with the purpose of this priority model.

Similarly, in order to understand the relationships presented in Tables 3.1 through 3.4 as causal effects from HP model implementation, we should observe that HP-eligible students remain unaffected by eligibility status in the pre-period (i.e., before 2013). Figures 3.2 through 3.5 show case-study plots for the outcomes. There is some important heterogeneity across the groups of universities and therefore the event-case studies must be analyzed separately. Focusing on the overall results (all institutions), the panels in Figure 3.2 show that HP-eligible students are always less likely to switch majors, obtain higher GPAs, and attempt less semester credit-hours. Additionally, our event-study plots suggest that the effects on the likelihood of studying and working (negative), continuous enrollment (positive), total financial aid received (positive) and on loans (negative) may also be attributed to the

[16]Figures 3.1 through 3.5 plot the estimate for β in Equation 3.2 for each cohort and their corresponding confidence interval.

implementation of the priority model. The different panels in Figure 3.2 show that HP-eligible students are statistically similar before the HP model was implemented. Therefore, the effects may be attributed to the implementation of the TEXAS priority model. The case is similar for flagship, emerging research, and other institutions.

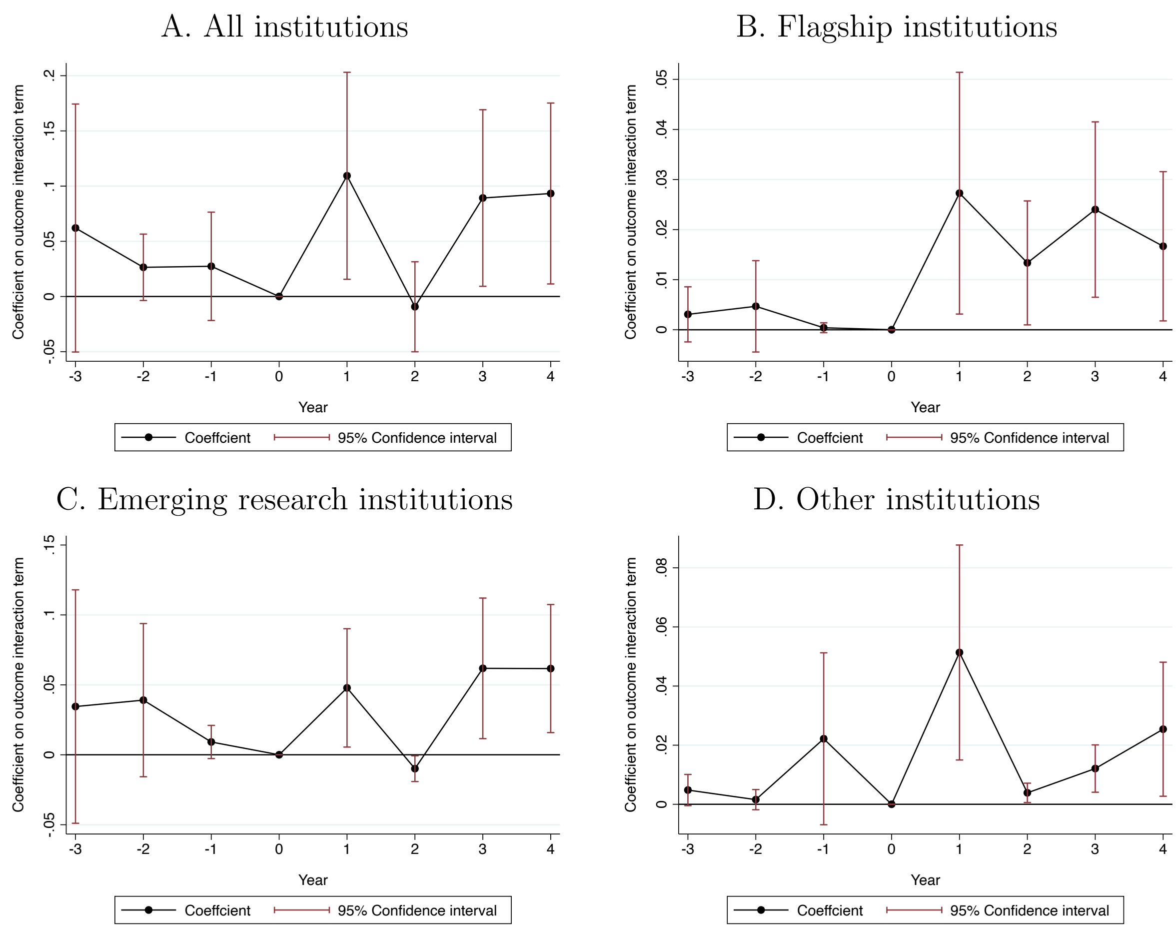


Figure 3.1: Event-case study plots for the probability of receiving the TEXAS Grant

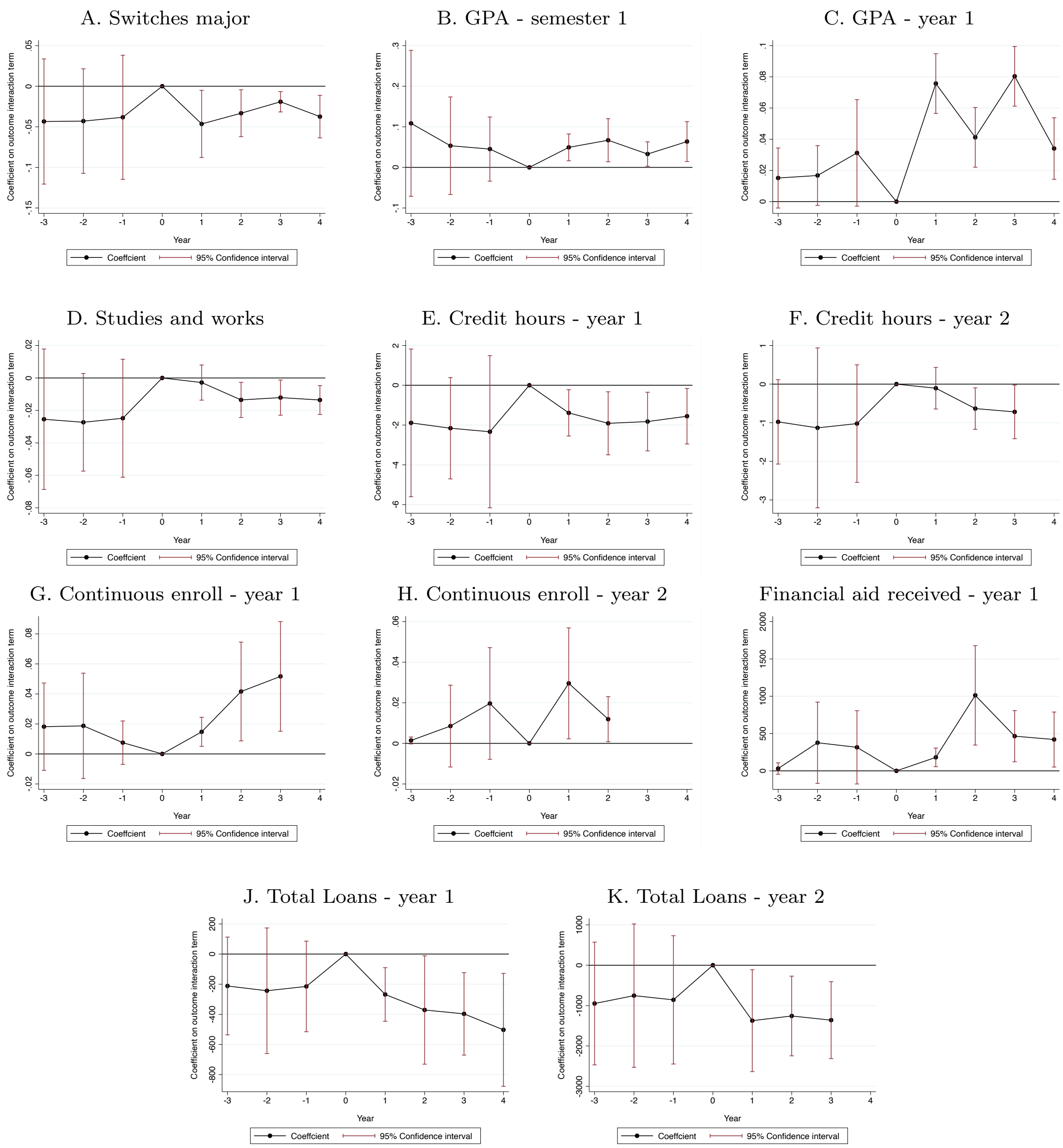


Figure 3.2: Event-case study plots for select outcomes: All institutions

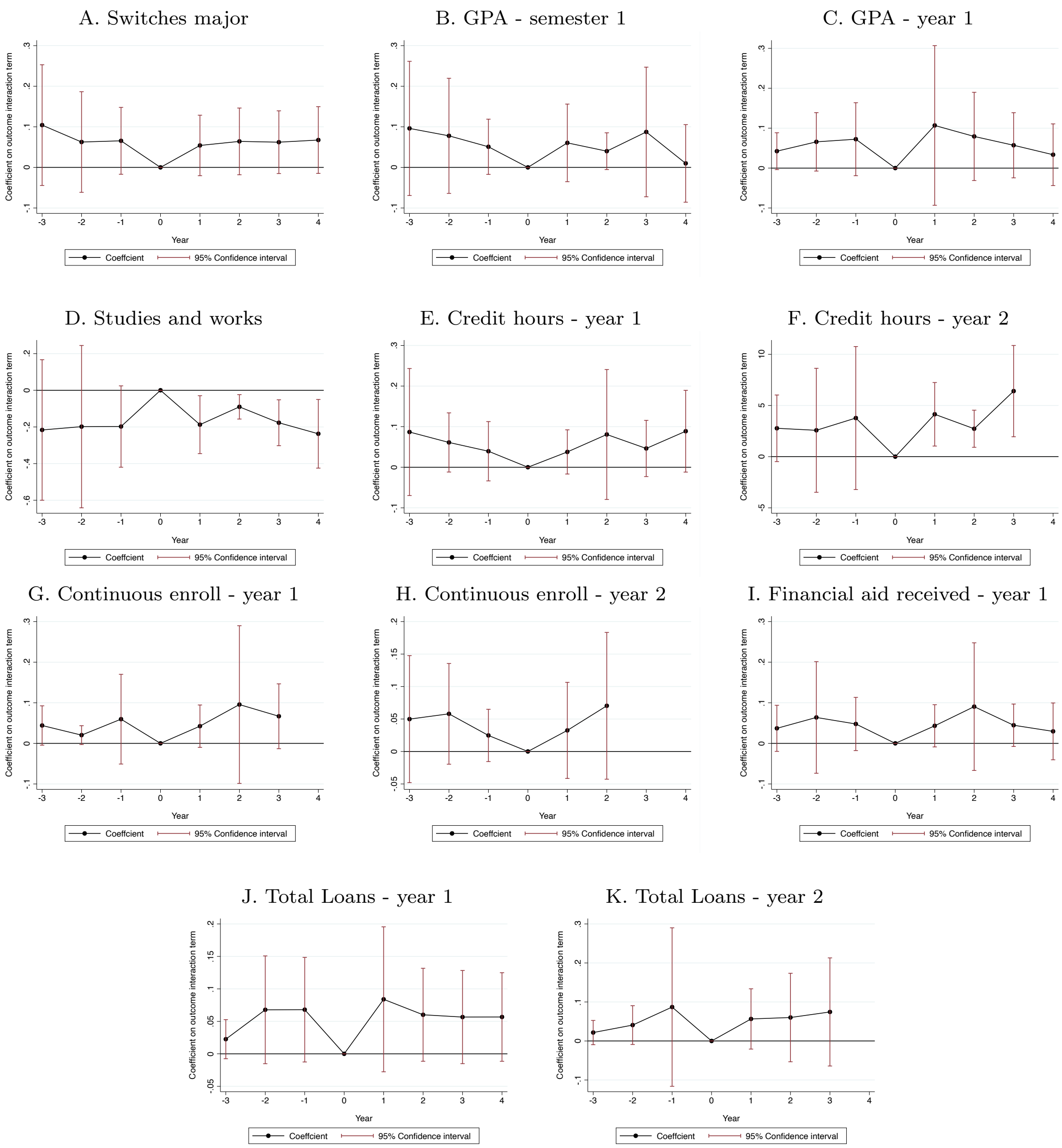


Figure 3.3: Event-case study plots for select outcomes: Flagship institutions

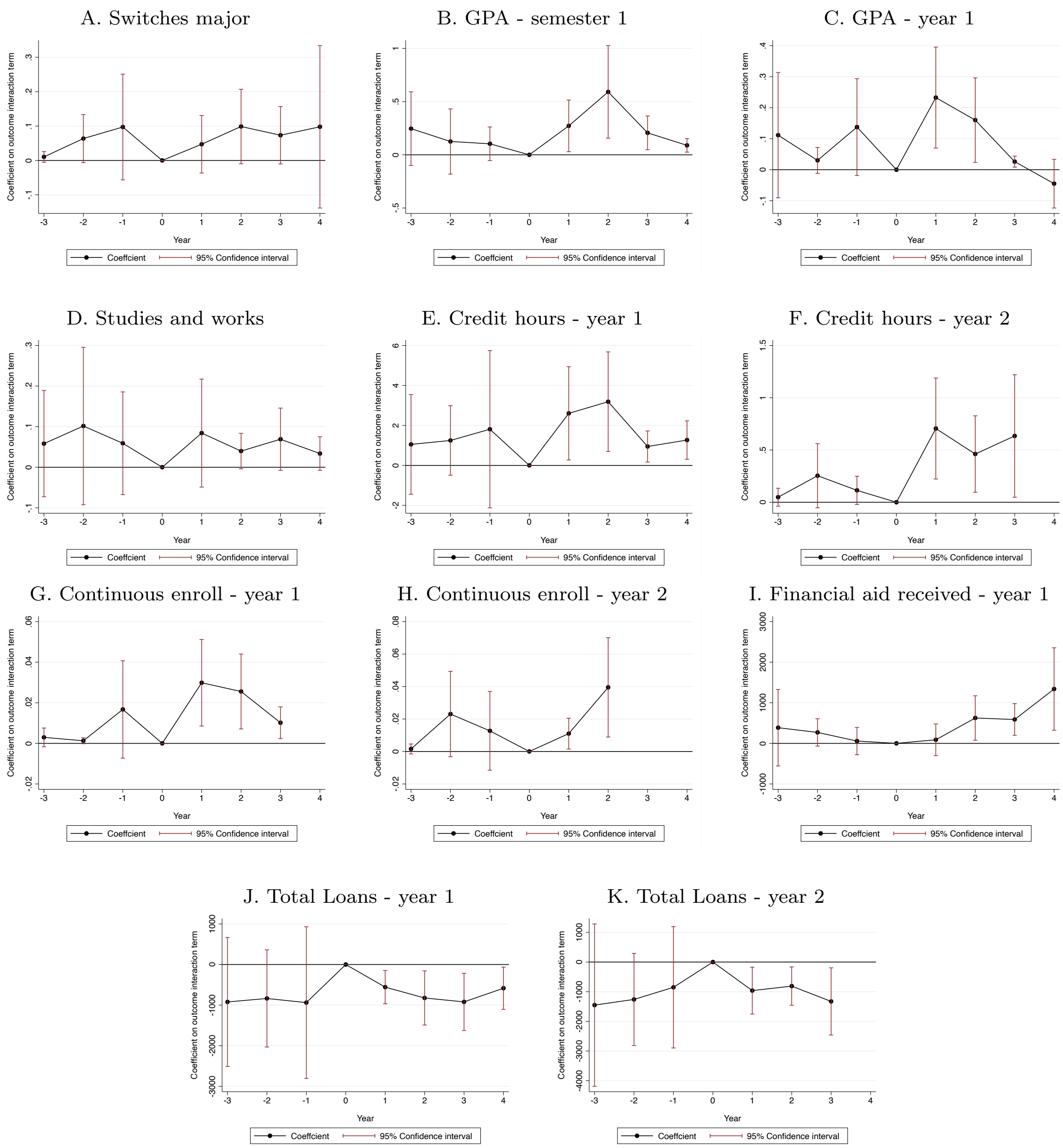


Figure 3.4: Event-case study plots for select outcomes: Emerging research institutions

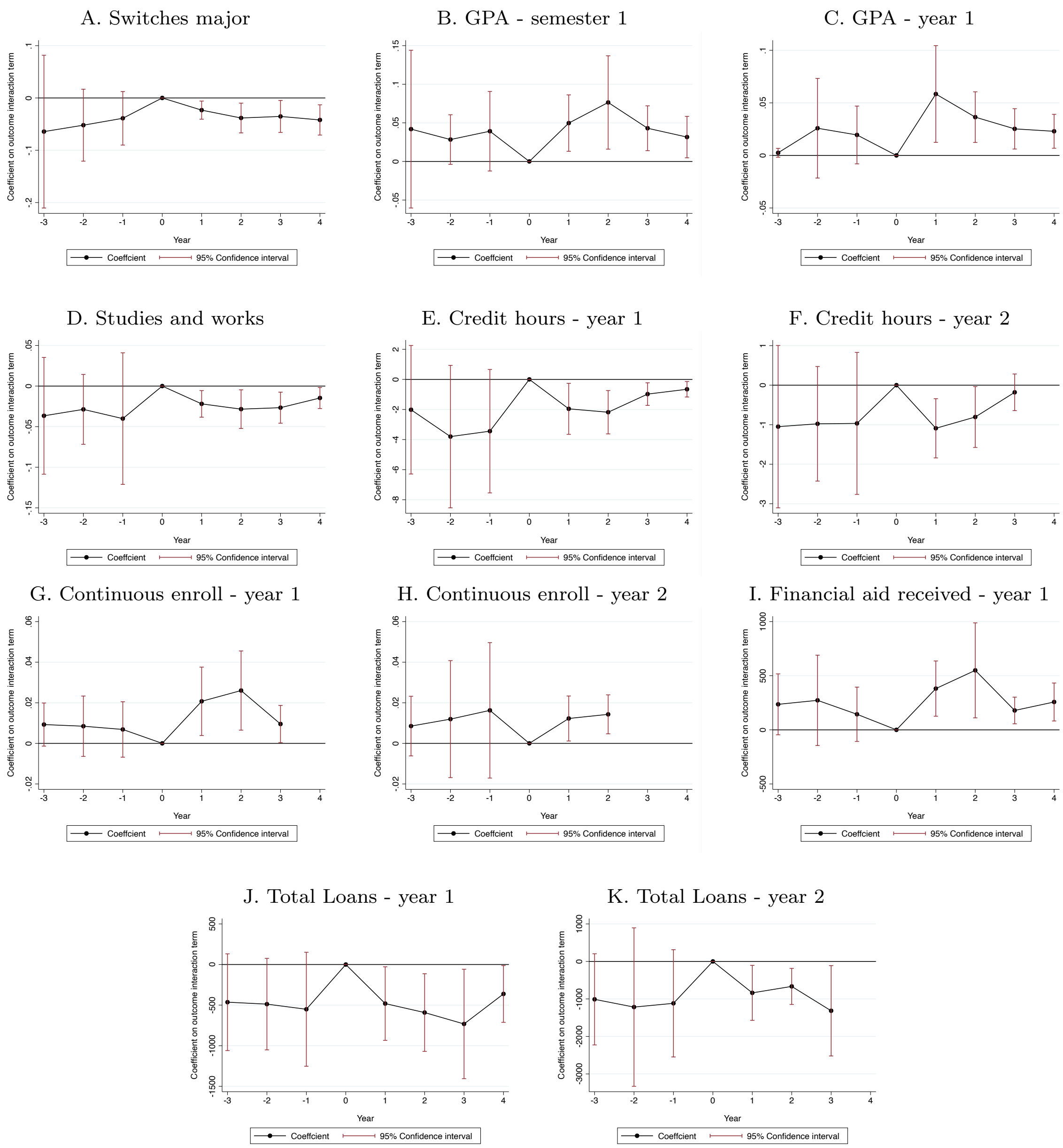


Figure 3.5: Event-case study plots for select outcomes: Other institutions

3.5.4 Discussion

The HP-model flags a set of high-achieving students from a pool of Texas low-income high school graduates making use of different student characteristics that the state deems to be a signal of academic promise in college. However, selecting from a pool of low-income, high-achieving students is a complicated task. Although being high-achievers and capable of succeeding in college, the decisions they make look very similar to those of low-income students (Hoxby and Turner, 2013; Hoxby and Avery, 2013; Gurantz et al., 2019).

Our overall estimates show that HP-eligible students are 8.5 percent more likely to receive TEXAS funds in the post-period. This is consistent with the scope and objective of the implementation of the priority model, as SB 28 intended to increase priority among those who are eligible for it. Additionally, the same group of students receives 2.5 percent more financial aid during the first year of college. The fact that more eligible students are receiving the TEXAS Grant should be accompanied with more funding for those students, as this is a last daughter program. Our results show that HP-eligible students in the post-period receive 2.6 percent larger financial aid packages than their ineligible peers.

Implementation of the HP model also significantly impacted the academic outcome of Texas first-time freshman students. Our results suggest that within the pool of low-income students, high achievers perform better in college. Particularly, the HP model is consistent with -eligible obtaining cumulative GPAs that are between 2.5 and 3 percent higher than -ineligible students, decreased the number of attempted credit hours of -eligible students by 4 percent, and reduced the likelihood of switching majors by 10 percent. All this is consistent with the purpose of the highest-priority model where the state wanted to better target students deemed to be more academically promising and ensure they receive funds to help them succeed in college. That being said, the implementation of the priority model also increased the likelihood of continuous enrollment up to 4.6 percent, and decreased the likelihood of working while studying by about 5 percent; which is consistent with students who are committed with their good academic progress in college. Finally, HP eligibility decreases student loans by up to 7.6 percent. Within low-income students, the HP model is likely to reduce the amount borrowed because eligible students are highly likely to receive funding from the TEXAS Grant program (see Montenegro, 2019, for discussion).

3.6 Conclusion

The Toward Excellence Access, and Success (TEXAS) Grant is the largest financial aid program in the state of Texas. Since its creation in 1999, the program has benefited financially needy students with the purpose of reducing their cost of attending higher education. In 2013, the TEXAS Grant included a merit component that gives priority to low-income, high achievers by enforcing the higher priority model (HP model). Therefore, the TEXAS Grant is an interesting and unique state program that combines need and merit eligibility criteria. We use administrative data from the 2009–2016 entering college cohorts and conduct a two-by-two difference-in-difference approach to study the effects of implementing the HP model on students' post-secondary outcomes. Our results suggest that HP model increased the likelihood of receiving TEXAS Grant funding among eligible students by 8.5 percent, significantly improved their academic outcomes, and cut student loans by up to 7.6 percent. We also conduct an event-study analysis in order to provide robustness to our causal estimates and to support the parallel trend assumption.

Something we need to highlight from out results is the heterogeneity of the HP-eligibility impact on postsecondary outcomes of Texas students enrolling in different types of 4-year public colleges. Particularly, it is interesting to see that students at flagship institutions do not experience a large impact on their academic or finances from the implementation of the HP model. However, there is a very large—both in size and statistical significance—effect on the reduction of the likelihood of working while studying. One may attribute the lack of significant effects to two things. First, on academics, flagship universities attract the most academically promising students in the state. Therefore, the counterfactual group is more likely to look much similar to the pool of low-income, high-achievers eligible for higher priority than those at emerging research or other public universities. Second, on finances, flagship universities tend to have much more financial aid available than emerging research and other institutions. Therefore, the relative more availability of financial resources might be reducing the HP model effects on the finances of eligible first-time freshman students. These sources of heterogeneity make a rather interesting topic to study that is our of the scope of this study, but will remain in our research agenda.

This paper is the first attempt to examine the effects of implementing the TEXAS Grant HP model on academics and finances. Although the maturity of the cohorts only allows us to track the first HP cohort for up to 4 years, our estimates provide succinct evidence that the priority model has beneficial short-run effects associated to it. We require more cohorts exposed to the HP model in order to determine effects on longer-run outcomes such as graduation and earnings. This study contributes to build knowledge for a particularly interesting group of students: low-income, high achievers. This set of college enrollees is interesting because the decisions they make look very similar to those of low-income students (Hoxby and Turner, 2013; Hoxby and Avery, 2013). Further research should be produced to provide more insight in this regard and that include longer-run outcomes in academics and finances is something that should be included in future studies.

CHAPTER 4

ON NEED-BASED AID AND UNEXPECTED EFFECTS: A REGRESSION-DISCONTINUITY ANALYSIS OF A GRANT PACKAGE FOR COLLEGE ACCESS AND SUCCESS

4.1 Introduction

Financial constraints are probably the top-of-mind in students' limitations to enroll in college. The reduction of their relative cost of attendance via financial aid is unquestionably a powerful tool to improve access to higher education. Financial aid programs and their impacts on student outcomes is a broadly studied topic in the literature. Particularly, studies emphasize that aid programs do not only increase enrollment in postsecondary education, but they may potentially improve in-college outcomes such as completion rates (Dynarski and Scott-Clayton, 2013). Authors utilize different experimental or quasi-experiment techniques to causally estimate the effects of state and privately funded grants and scholarship programs (see Deming and Dynarski, 2010, for a detailed list of studies that examine financial aid programs). Studies find that financial aid may significantly increase enrollment and persistence (Van der Klaauw, 2002; Dynarski, 2003), and may also boost course withdrawal and reduces full-load enrollment and completion (Cornwell et al., 2005, 2006). It may also benefit the labor market, as large scale financial aid may lead to long term benefits in the labor market and for the financial health of recipients even years after they complete a degree (Scott-Clayton and Zafar (2016); Bettinger et al. (2016)). Moreover, other studies indicate that financial aid programs can potentially affect performance and major choice, which can translate into an increase in earnings after graduation (Dee and Jackson, 1999; Andrews et al., 2016; Cáceres-Delpiano et al., 2018; Clotfelter et al., 2018).

It is important to study financial aid programs—especially if they are generous—because doing so gives great insight into whether they produce any effects, target enrollees correctly, and are producing the desired results. Nguyen et al. (2019) present a meta-analysis of available evidence of the effect of grant aid on postsecondary persistence and degree attainment, suggesting that grant aid increases the probability of student persistence and degree completion between 2 and 3 percentage points. When considering the dollar amount of aid, they estimate an additional $1,000 of grant aid improves persistence and attainment by 1.5 to 2 percentage points. In despite of these expected results, there are studies showing that sometimes financial aid programs have unexpected effects associated to their roll-out. Particularly, Cohodes and Goodman (2014); Clotfelter et al. (2018); Park and Scott-Clayton (2018) show that programs may produce non-positive effects on GPA and course load, and may lower completion rates and persistence.

As many other states in the US, Texas offers financial aid programs to its residents with the purpose of easing access to higher education. The largest program offered by the state is the Toward EXcellence, Access, and Success (TEXAS) Grant, which in the 2017 fiscal year made up nearly 72% of the total aid provided by the state and granted funding to 58% of the total state aid recipients (THECB (2018b)). This program has been adjusted to properly satisfy the needs of both students and institutions. Particularly, in 2011, Senate Bill (SB) 28 modified its allocation rules, imposing two changes: First, an expected family contribution[1] (EFC) cap was created by the Texas legislature[2]. Second, higher priority in allocation was granted to high-achieving students who the state deemed to be more likely to graduate. The highest priority (HP) model started to be implemented for awards granted in the 2014 fiscal year (i.e., starting in the Fall of 2013). Under the rules presented in SB 28, a student is entitled to receive higher priority for aid receipt if he or she meets a number of

[1] Defined as the amount that students and their families can reasonably be expected to pay for postsecondary expenses for a given award year.

[2] The Texas Higher Education Coordinating Board (THECB) used EFC cap as allocation rule since its creation in 1999, but its implementation was not regulated by law.

requisites[3] that are associated with high academic achievement by the time of high school graduation. With these allocation rules, SB 28 attempts to more adequately allocate dollars toward financially needy high school students who are more likely to succeed in college. This paper studies the effects of eliminating the financial need—with respect to the total of tuition and fees—under HP allocation rules for students attending public universities in Texas.

Even though the TEXAS Grant is the largest source of financial aid provided by the state, very little is known about how it affects students. The Texas Higher Education Coordinating Board (THECB) presents reports on total amounts awarded and completion indicators for TEXAS Grant recipients. However, these reports do not permit researchers to draw causal effects or analyze impacts on academics or finances. To date, three studies have studied this grant in further detail. Johnson (2005) presents a descriptive and correlational analysis of the TEXAS Grant for the 2000–2002 fiscal years. This study indicated that there was greater persistence rate among TEXAS Grant recipients than that of other state programs. Denning et al. (2018) investigate the effect of qualifying for automatic zero EFC eligibility[4] on the amount of TEXAS Grant dollars awarded. However, this grant program is not the main interest of this paper and direct causal effects of grant receipt are not investigated. Chapter 3 in Villarreal (2018) studies the effect of receiving the TEXAS Grant on postsecondary outcomes by implementing a regression-discontinuity design (RDD) for students who enrolled in a Texas public university for the first time in the fall semesters of 2004 to 2013. This paper finds that receiving the TEXAS Grant reduces student loans in the first year by 30 percent, increases the probability of continuous enrollment by 7 percent, and rises the number credit hours attempted by 2,3 percent. This paper also examines other longer-run outcomes, but does not include the effects on academic attainment—such as GPA. However, Villarreal

[3]These requisites will be discussed in Section 4.2 in more detail.

[4]One of the main criteria to qualify for an automatic zero EFC is to fall below a year-specific income threshold. See Denning et al. (2018) for further details.

(2018) does not acknowledge important aspects that may threaten the identification strategy. The TEXAS Grant is typically not enough to cover for the total of tuition and fees for a given year—i.e., it is not a full-ride program. Rather, TEXAS dollars are designed to complement other generous programs. It is therefore necessary to view and understand the aid package as a whole. Additionally, it lacks a robust discussion regarding the identifying assumptions and methodological issues such as bandwidth selection and sensitivity of RD estimates.

I re-examine Villarreal's (2018) research and contribute to the empirical literature on the economics of education in the following aspects. First, I study the impacts of receiving aid on financially needy students under the HP model and shed light on the debate about whether the TEXAS Grant is producing desired impacts on recipients. Second, I explore the heterogeneous treatment effects of receiving financial assistance by academic institutions. I find succinct evidence that filling in financial need using TEXAS dollars has important effects on academics and finances. Recipients earn lower average GPA during the first two semesters of college and are disproportionately more likely to fail with satisfactory academic progress (SAP) at the end of the first year of college. Additionally, recipients cut student loans by 28 percent during the first two years of college. The main goal of this paper is to offer a better understanding of how the TEXAS Grant is affecting students who receive it and how this program changes the educational outlook of students in Texas. The remainder of this paper is organized as follows: Section 4.2 contains details on the background and changes to the TEXAS grant. Sections 4.3 and 4.4 present the data and the identification strategy. Section 4.5 discusses the results and mechanisms. Section 4.6 concludes.

4.2 Background

Texas has engaged in efforts like the *60x30TX*[5] to reach higher standards of excellence in teaching, research, and innovation and to help Texans get better jobs and achieve a higher living standards through higher education. To attain part of *60x30TX*'s purpose, Texas offers multiple grants and scholarships that have helped its residents to enroll in colleges and universities across the state. The Top 10% Scholarship, the Texas Public Educational Grant Program (TPEG), and the Toward EXcellence, Access and Success (TEXAS) Grant are the largest programs of assistance in terms of dollars granted and number of students benefited. Most grants are awarded on the basis of financial need[6] and students can apply by submitting the Free Application for Federal Student Aid (FAFSA) or the Texas Application for State Financial Aid (TASFA).

On January 18th, 1999, the House Bill 713, 76th Leg., ch. 1590[7] filed into the Texas Legislature a proposal *relating to the establishment and operation of the Toward EXcellence, Access, & Success (TEXAS) grant program [. . .]; consolidating and revising financial aid, grant, and scholarship programs [. . .]*, which was approved and became effective on the 19th of June of the same year. The purpose of this program is to provide financial aid assistance to enable economically disadvantaged students to attend public institutions of higher education in the state. Although the goal of the program has been the same ever since its establishment, its allocation rules and guidelines have been modified since its inception. The requirements to be eligible to receive an initial year (IY) TEXAS Grant award include being classified

[5] This is the abbreviation of *60 percent of Generation Texas will have post secondary credential or degree by 2030*. That is, by 2030, Texas will have approximately 60 percent of its 25 to 34 year-old workforce to hold a post-secondary credential.

[6] Most institutions define financial need as the part of the cost of attendance (COA) that is not covered by the expected family contribution (EFC). Usually the COA refers to the total amount of education expenses such as tuition, books and supplies, housing and dining, transportation, among others.

[7] See Education Code, Title 3. Higher Education. Subtitle A. Higher Education in General. Chapter 56. Student Financial Assistance.

by the institution as a Texas resident, and having a 9-month expected family contribution (EFC) of no more than a cap set each year by the THECB, which in the 2018 fiscal year was $5,430 dollars[8]. Table A.10 shows TEXAS Grant's EFC eligibility thresholds over the years since its creation. In order to receive a renewal year (RY) award, students need to maintain satisfactory academic progress (SAP) by meeting institution's SAP policy[9] by the end of the first year. The TEXAS Grant program covers up to 150 semester credit hours, can be received for up to 6 years from the first semester it is awarded, and awards a maximum annual amount of $9,050 dollars for public universities (max. award for the 2017-18 academic year).

Regulations on the TEXAS program prioritize renewal awards. This means that in a given year, renewal awards are granted to continuing students first. After these were allocated and if remaining resources permit, initial awards for first-time-in-college students can be assigned next. These students may fall under either type of eligibility: basic eligibility (BE) or high priority (HP) eligibility. A high school graduate qualifies for basic eligibility (BE) if: i) graduates high school within 16 months of college enrollment, ii) enrolls in college at least three-fourths full-time[10], and iii) has a 9-month EFC of no more than the determined threshold for a given fiscal year. Among those who qualify for BE, the higher priority (HP) model gives preference to high-achieving students. Under its specifications, institutions must prioritize students who had met the requirements under the following categories: i) have earned 12 hours of college credit courses[11] by the time of high school graduation; or have

[8]The EFC cap is set as a portion of the state-wide average tuition and fees and it is adjusted annually (see THECB (2018a)).

[9]For most institutions in Texas, this includes maintaining a 2.0 cumulative GPA, and completing 24 semester credit hours (SCH) over an academic year

[10]Full-time status for undergraduate students is typically granted to those who enroll 12 or more credit hours per semester.

[11]I.e., dual credits or advanced placement classes (AP)

graduated under the distinguished level of achievement High School plan or the international baccalaureate program[12], ii) have completed a math course beyond Algebra II, iii) have ranked in the top one-third of their high school graduating class or graduate with a GPA of at least 3.0 on a 4-point scale, or iv) have achieved a college readiness score above the threshold determined by the Texas Success Initiative[13]. If a student complies with at least two of these four categories, he or she is given priority among all their peers that are only eligible under BE to receive an IY TEXAS award. I will focus on the subset of students who are HP-eligible.

TEXAS Grant regulations also state that this program is to be awarded on a last-dollar basis. This means that institutions are obligated to fill in any remaining financial need after TEXAS dollars are awarded with non-loan sources. Universities therefore have a clear incentive to award the TEXAS Grant to students that have most aid, as this strategy reduces their cost and financial responsibility. In other words, the TEXAS Grant is designed to complement the dollars from other generous programs. For instance, the most common aid package that institutions build for first-time-in-college students is made up by the federal-funded Pell Grant and the TEXAS Grant[14] (see Denning et al., 2018, for discussion). Between 2013 and 2016, 48% of Texas high school graduates enrolling in four-year colleges for the time received a Pell grant and 40% were awarded the TEXAS Grant (see Table A.12). Moreover, 99.7% of the TEXAS Grant recipients were also awarded a Pell grant. The average Pell-TEXAS package is $10,225, where the latter makes up for 51% of the total. This is a

[12]These programs are standard across states and are available to students who desire more challenging work than what's offered in the standard curriculum.

[13]The Texas Success Initiative (TSI) is a state-legislated program designed to improve students' success in college. Part of the program is an assessment to determine students' basic skills in reading, mathematics and writing. Students may be eligible to TSI exception if a student obtains a qualifying score on ACT, SAT, or STAAR. Students who are not TSI exempt are required by law to take an assessment test approved by the Texas Higher Education Coordinating Board (THECB).

[14]Both programs are need-based and use EFC as allocation rule. The Pell Grant uses a function of COA and EFC to determine eligibility and dosage.

generous amount as it represents about 43% of the total COA for this group. However, the aid total package may differ student-by-student in both amounts and programs included.

4.3 Data

The data I use in this study come from two sources: annually administrative data from the Texas Education Agency (TEA), and annually administrative data from the Texas Higher Education Coordinating Board (THECB). These data are housed at the University of Texas at Dallas Education Research Center (ERC). In order to correctly identify students that meet TEXAS Grant's HP eligibility criteria, I merge TEA with THECB data to create a student-level panel. TEA files include information on each students' work from high school until graduation. THECB files provide information on students' admissions, course load, performance, and financial aid. This dataset allows me to follow students from high school through college—provided they remain in Texas—, allowing me to control for relevant student characteristics prior to their enrollment in postsecondary education such as race/ethnicity, gender, ACT score[15], COA, and indicators for free/reduced price lunch (economically disadvantaged), English proficiency, gifted and talented status, and risk of dropping out from high school[16]. These measures are taken at the time of high school graduation and prior to college enrollment. Because TEXAS Grant IY awards are distributed at the beginning of the fiscal year, I only consider cohorts enrolling the Fall semester of each academic year. The sample for this paper is made up of students who complete a FAFSA application and enroll in a 4-year public university in Texas for the first time between 2013 and 2016 (i.e., fiscal years 2014–2017). Finally, it is worth mentioning two characteristics of these data. First, they only allow me to observe financial aid for students who enroll in a

[15]Students' SAT scores were converted to ACT scale to guarantee comparability between the two tests.

[16]This a dichotomic indicator constructed from a number of variables such as being convicted of a felony, among others.

given institution. Records of aid packages offered to students who did not accept them are not observed in the data. Second, the timing allows me to follow the first HP-eligible cohort for up to four years.

As explained in Section 4.2, a student qualifies for HP eligibility if: i) is eligible under BE, and ii) meets the requirements for at least two of the four categories of academic achievement (these students will be referred to as *high-achieving* thereafter). Even though the TEA and THECB data are quite rich, I am not able to perfectly identify all items in the list presented above. In particular, these data does not allow me to distinguish between regular and AP courses, or whether students receive college credit from AP courses. Additionally, TEA files do not report grades for high school courses, or students' raking in their graduating class. Therefore, my indicator for AAP compliance is based on whether the high school graduate completed 12 credits of dual enrollment, completed the advanced high school program, or completed the IB program. My indicator for CS compliance is based on a THECB indicator for students who are admitted into college and graduate in the top 25% of their high school class. Indicators for TSIR and AM compliance are fully identified.

Dual-enrollment is widely adopted by institutions. According to U.S. Department of Education surveys, in the 2003 fiscal year, three-quarters of high schools reported that they had students taking college courses, fifty-seven percent of the colleges reported that they had high school students taking their courses, and 98% of the public two-year colleges reported participating in dual-enrollment (see Hughes et al., 2005; Karp et al., 2007; Karp and Hughes, 2008). Additionally, students seem to prefer dual-credit classes over AP as the former gives a final grade on a college transcript, whilst the latter requires an end-of-course examination for granting college credit (Hughes, 2010). This suggests that the indicators I implement for advanced academic program (i.e., first category in the list presented in Section 4.2) should be a good proxy of the unobserved characteristics.

The number of Texas first-time-in-college students attending public 4-year universities who complete a FAFSA and enroll in the Fall semesters between 2013 and 2017 is close to

161,000 students, from which about 88%—or 141,966 to be exact—are high-achieving. Table A.12 presents summary statistics for outcomes and control variables for this sub-population. The proportion of high-achieving students might seem too large but it is not if put in context. The level of stratification at which I am conditioning the observations adds self-selection on different levels that make this group of students more likely to show up in the sample. Additionally, the vast majority (99% of students) enroll in college full time, which is to be expected from students who are recent high school graduates receiving financial aid. Table A.13 depicts summary statistics for the sub-sample corresponding students whose EFC is at a distance of no more than $1,428[17] dollars above or below the annual threshold for eligibility. These summary statistics show that 54% fall below the EFC threshold (henceforth eligible students), 71% of eligible students receive an IY TEXAS award, 90% receive an IY Pell grant, and 70% receive both. Additionally, 56% of the students are females, 42% are Hispanic, 12% are Black, and 8% are Asian. Mean estimates for the underlying sub-sample are similar to those for the complete sample of students, which is consistent with it being *randomly* drawn from the population.

4.4 Methodology and identification strategy

Students are not typically interested in the name of the financial aid program they receive. In fact, it is common that money from programs remain unspent, or even worse, that eligible students do not even apply to college (Tierney and Venegas, 2009). Those who seek financial aid may be rather interested in the total stipend they receive that allows them to enroll in college. Moreover, numerous programs—including federal, state, and institutional—may be available for students, making it possible for some of them to receive funding from more than one only source. Because the TEXAS Grant is a last-dollar program, its allocation rules for

[17] This is the optimum bandwidth selected for this specification. See Section 4.4.2 for details on the bandwidth selection process.

IY awards allow me to predict the receipt of the aid package that eliminates the financial need with respect to the total of tuition and fees. However, it is important to acknowledge the fact that students who receive TEXAS dollars may be likely receive those from other programs. For now, I will only focus on the financial aid package that is topped off with TEXAS dollars, which I henceforth refer to as the *TEXAS Grant package*. This issue will be discussed in more depth in Section 4.4.1.

TEXAS Grant receipt conditioned on Texas residency, three-fourths through full time enrollment, and stating college within 16 month of high school graduation depends on two variables: EFC and HP-eligibility. This is, not all HP-eligible individuals are entitled to receive aid, and not all students with EFC below the threshold are entitled to receive aid. Rather than modeling the bi-dimensional response, I subset the data by HP status in a fuzzy frontier RD fashion (see Reardon and Robinson, 2012). I therefore select students who comply with at least two of the four requirements presented in Section 4.2. I next use location at the EFC threshold to predict aid receipt. Eligible students are those who fall below the EFC threshold. Because they comply with all the requirements to receive TEXAS Grant's last-dollars, they are highly likely to be granted funding. Those who fall above the threshold are ineligible, and therefore highly unlikely to receive aid. The *fuzziness* of this RDD takes place because of the existence of eligible students who do not receive aid, and because some ineligible students wind up receiving it. Under these settings, the counterfactual group may be understood as those students who are not eligible top off their financial aid package with TEXAS Grant dollars. My identification strategy relies on two ideas: first, eligible students are disproportionately more likely to receive the TEXAS aid package (also referred to as being treated or receiving treatment throughout the paper) than those ineligible. Second, comparable eligible students who fall just below the EFC threshold are interchangeable with eligible students who fall just above it. Subsection 4.4.2 explains the procedure I employ to determine the bandwidth around EFC cut-off that allows for the latter property.

I use an instrumental variable approach by employing 2SLS to estimate the causal impact of aid package receipt on various postsecondary outcomes which include major choice, GPA, number of credit hours attempted, likelihood of continuous enrollment, student loans, and others.

I estimate a linear model as follows:

$$Y_i = \alpha A_i + k(S_i) + \boldsymbol{\psi}' X + \omega_i \tag{4.1}$$

where Y_i denotes student i's postsecondary outcome; A_i is an indicator for aid receipt that takes on a value of one if student i receives grant dollars; X is a matrix of controls; $k(S_i)$ is a continuous function of the scoring variable; and S_i refers to student i's EFC (centered at the eligibility threshold, such that students with negative values of S_i are eligible to receive TEXAS Grant's last-dollars). I instrument for aid receipt, A_i in equation 4.1, with student's eligibility—i.e., falling below the EFC cap.

Formally, the specification is:

$$A_i = \delta D_i + l(S_i) + \boldsymbol{\phi}' X + \varepsilon_i \tag{4.2}$$

where D_i is an indicator for student's aid package eligibility. Namely, $D_i = 1(S_i \leq 0)$. The control function—$k(S_i)$ in (4.1), $l(S_i)$ in (4.2), and $m(S_i)$ in (4.4)—is quadratic polynomial in the centered running variable which is continuous at the threshold—i.e., where $S_i = 0$—and is interacted with D_i, allowing the function to take different slope on either side of the threshold. In other words, this function is modeled using a flexible parametric approach which uses a power series estimation for $k(S_i) = \sum_{j=1}^{J} \eta_{0,j} \tilde{S}_i^{\,j} + \sum_{j=1}^{J} \eta_{1,j} \tilde{S}_i^{\,j} D_i$. I produce estimates using quadratic specifications—that is, $J = 2$ (see Newey et al., 1990; Gelman and Imbens, 2018, for a dicussion on the topic).

This approach is able to solve the endogeneity problem caused by the fuzziness in aid receipt as long as the identifying assumptions are satisfied. As mentioned before, given

TEXAS Grant's design and allocation rules, one should expect an indicator for eligibility—that is, falling below the EFC threshold—to be a good instrument for aid receipt, provided it is uncorrelated with ω_i. Note that the coefficient of interest for the first stage (equation 4.2) is δ, which denotes the effect of eligibility on the likelihood of receiving the aid package. In the second stage (equation 4.1), we are interested in α, as it represents the total effect of receiving the TEXAS package on outcome Y_i. The following Section explains the assumptions in which this identification strategy is based on and the procedure for bandwidth selection.

4.4.1 Identifying assumptions

Different requirements need to be assessed and discussed to argue that an RDD produces unbiased estimates (see Imbens and Angrist, 1994; Lee and Lemieux, 2009, for discussion). In this Section I discuss how these assumptions relate to the TEXAS Grant package and allocation rules to causally estimate its associated effects.

Non-manipulability of scoring variable

A student cannot do anything that can put her at a desired side of the threshold. This assumption is likely to hold in this setting since students and families do not know the specific EFC cap at which a student can attain eligibility. Additionally, EFC is computed using tax returns information in FAFSA or TASFA applications. This assumption allows me to believe that students are assigned to experimental conditions at random within an optimal bandwidth. Manipulation tests related to continuity of the running variable density function and bandwidth selection process are presented in Section 4.4.2.

Local randomization

Control variables in the model should be unaffected by the discontinuity. That is, variables included in matrix X (equations 4.1 and 4.2) should vary smoothly across the threshold.

This is verified using two approaches: first, by plotting graphs of covariates as function of the scoring variable. Second, by running a system of seemingly unrelated regressions (SUR) as suggested by Lee and Lemieux (2009). The system of equations to be estimated is as follows:

$$\begin{pmatrix} x_1 \\ \vdots \\ x_J \end{pmatrix} = (I_J \otimes K) \begin{pmatrix} \boldsymbol{\theta}_1 \\ \vdots \\ \boldsymbol{\theta}_J \end{pmatrix} + \begin{pmatrix} e_1 \\ \vdots \\ e_J \end{pmatrix} \tag{4.3}$$

where J is the number of covariates—thus, number of equations in the system—, $K = (D_i, S_i)_{n\times 2}$, and $\boldsymbol{\theta}_j = (\theta_{j1}, \theta_{j2})'$ are the coefficients for the j-th equation. I jointly test the hypothesis that $\theta_{j1} = 0$ for $j = 1, \cdots, J$. Table A.17 presents SUR coefficients for D_i and a χ^2 statistic for the joint test, and Figure B.8 depicts means of the covariates for bins of the scoring variable. This set of figures and SUR estimations show that covariates vary smoothly across the threshold, suggesting that variations in the outcomes may be attributed to aid receipt.

Strong first stage

Instrumental variable estimations using 2SLS require a valid and strong first stage. Table 4.1 presents estimates for equation 4.2. Two things need to be highlighted: first, falling below the EFC cut-off makes a student nearly 50 percentage points more likely to receive aid. This result is highly statistically significant. Second, the Wald-statistic allows to conclude that the instrument is not week[18]. These two facts provide evidence that eligibility is a valid instrument for aid receipt.

Monotonicity

Eligibility weakly increases (or decreases) treatment likelihood. Table A.13 shows that eligible students—i.e., those falling below the cut-off—are 35 times more likely than ineligible students

[18]Following Staiger and Stock (1997) and Stock and Yogo (2002)

to receive aid. Additionally, students who are offered the TEXAS aid package are highly likely to accept it because doing so does not imply financial liability and, in only specific cases, students might have to repay all or part of it. My observations are conditioned on enrollment, meaning that I observe the final result of the aid package offer and take-up process. Thus, under the scenarios here outlined, being eligible for aid only increases the likelihood of receiving it and the possibility of having treatment defiers may be ruled out.

Excludability (or exclusion)

The endogenous predictor may only impact outcomes through the instrument variable to obtain unbiased causal estimates (see Jones, 2015). That is, eligibility must not affect outcomes through any other variables, including receipt of other programs awarded after TEXAS dollars are granted. Recall that per allocation rules, institutions are required to cover any remaining need with respect to tuition and fees after TEXAS dollars are awarded. This means that federal and other state programs[19] are awarded first, TEXAS dollars are awarded at last, and institutional aid covers for any remaining need should there be any. The evidence suggests that the only program that is disproportionately effected by TEXAS eligibility is Pell (see Table A.18). My overall estimates indicate that eligible students are 18 percentage points more likely to receive Pell funding and that are granted \$179 dollars more than ineligible students. These results should come as no surprise for two reasons. First, because TEXAS Grant dollars are meant to complement those of other—rather generous—first-dollar programs such as Pell. Second, because the maximum EFC eligibility threshold for the Pell Grant is close to that for the TEXAS Grant[20]. Although the aid package whose last dollars come form TEXAS

[19] These include Federal Supplemental Educational Opportunity Grant (FSEOG), Texas Public Educational Grant (TPEG) , Tuition Equalization Grant Program (TEG), appropriations from HB 3015, The top 10% scholarship, and others.

[20] The Pell EFC eligibility cut-off for the 2019 fiscal year is \$5,328 whereas that for the TEXAS Grant is \$5,609. That is a difference of only \$281 dollars that is necessarily captured by the selected bandwidth across specifications.

appropriations may not include Pell, on average these two programs are highly likely to be awarded jointly. Institutions are rather likely to prefer students with larger financial aid when awarding TEXAS dollars as doing so will minimize the amount of institutional that would need to be provided to recipients should there be any remaining financial need. In fact, Table A.18 shows that eligibility does not affect the likelihood of receiving institutional aid or its dose.

It is important to mention that Texas and its colleges can only roll-out the program, but they cannot compel students' take-up. For this reason, it is also interesting to explore the effects of financial aid package eligibility on postsecondary outcomes. Assumptions 4.4.1 through 4.4.1 are required to identify the intent-to-treat effect, which captures the effect of TEXAS eligibility on the outcomes of interest. The underlying equation becomes:

$$Y_i = \eta D_i + m(S_i) + \boldsymbol{\xi}' X + \omega_i \tag{4.4}$$

where η corresponds to the ITT causal effect. Moreover, if assumptions 4.4.1 through 4.4.1 hold, α in equation 4.1 can be interpreted as the local average treatment effect (LATE) associated with receiving the TEXAS aid package (see Imbens and Angrist, 1994). I focus on the LATE throughout this document and present ITT estimates for cohesion.

4.4.2 Bandwidth selection

Selecting a bandwidth that is consistent with the assumption that individuals just below and just above the threshold are interchangeable is crucial for conducting an RDD. The selected bandwidth around the running variable's cut-off that allows for this property is referred to as *optimal*. I select a symmetric window—such that its length is twice the optimal bandwidth—employing a triangular kernel density function following Calonico et al. (2018)[21]. Table A.19

[21]I use the `bwselect` command from the `rdrobust` Stata package to calculate the optimal bandwidth (see Calonico et al., 2017).

presents the optimal bandwidths used for these estimations. As suggested by Imbens and Lemieux (2008), these optimal bandwidths were obtained by selecting the minimum between those corresponding to the first and second stage depicted in equations 4.1 and 4.2. For this exercise, the first-stage bandwidth is always smaller in magnitude than that for the second stage across outcomes and specifications. Once an optimal bandwidth is selected, running variable's non-manipulatibily should be verified. Figure B.5 and Table A.19 present visual and statistical tests assessing the continuity of the EFC density function (see McCrary, 2008; Cattaneo et al., 2019).

4.5 Results

The TEXAS Grant program is designed to complement dollars coming from other forms of financial aid. I take advantage of its allocation rules to causally estimate the effect of eliminating the financial need with respect to the total of tuition and fees using TEXAS dollars for students enrolling in public universities. Table A.11 presents general characteristics for groups four-year public colleges in Texas. The statistics show that the overall cohort graduation rate is 55 percent. This and other statistics dramatically differ across institutions, but tend to look much more alike when grouped in these three categories: flagships[22], emerging research[23], and other universities. Those rates by groups of institutions are 79 (flagships), 48 (emerging research), and 38 (other institutions) percent. Because of the evident heterogeneity, I run this quasi-experiment separately by types of four-year institutions. The underlying bandwidths are \$1,428 (all institutions), \$3,130 (flagship institutions), \$1,668 (emerging research institutions), and \$1,654 (other institutions) dollars (see Table A.19).

[22]Flagship universities are those leading enrollment, performance, and completion indicators. These institutions are the University of Texas–Austin and Texas A&M–College Station.

[23]Emerging research universities are those that receive extra funding to become Tier one in the state. These institutions are Texas State University, Texas Tech University, University of Houston, University of Texas–Arlington, University of Texas–Dallas, University of Texas–El Paso, University of Texas–San Antonio, and University of North Texas.

Table 4.1 presents estimates for the eligibility effect on the probability of receiving the TEXAS aid package. These results suggest that eligibility increases the likelihood of receiving aid between 44 and 67 percentage points depending on the type of institution the sample is conditioned on. The overall eligibility effect is 49 percentage points. The following sections describe the effects of aid receipt on outcomes presented in Tables 4.2 though 4.5 and Tables A.20 through A.23.

Table 4.1: Estimated effect of eligibility on TEXAS package receipt

	All Institutions				Flagship			
Elegible for TEXAS Grant	0.492***	0.501***	0.492***	0.501***	0.678***	0.675***	0.676***	0.675***
	(0.021)	(0.022)	(0.020)	(0.022)	(0.030)	(0.036)	(0.030)	(0.036)
Observations	11,951				4,574			
Covariates	Yes	No	No	Yes	Yes	No	No	Yes
Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes
School FE	No	No	Yes	Yes	No	No	Yes	Yes
F-statistic	551.4	518.1	581.7	536.0	498.7	350.5	502.3	352.0

	Emerging Research				Other			
Elegible for TEXAS Grant	0.439***	0.438***	0.438***	0.435***	0.507***	0.515***	0.506***	0.515***
	(0.032)	(0.036)	(0.032)	(0.036)	(0.030)	(0.034)	(0.029)	(0.033)
Observations	5,351				6,101			
Covariates	Yes	No	No	Yes	Yes	No	No	Yes
Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes
School FE	No	No	Yes	Yes	No	No	Yes	Yes
F-statistic	190.0	147.7	190.4	145.1	276.9	235.5	300.1	245.6

[1] Standard errors in parentheses are clustered at values of EFC. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[2] The set of covariates includes gender, race/ethnicity, at risk of dropping out from high school, free/reduced price lunch, English proficiency, gifted and talented status, ACT scores, and cost of attendance.

4.5.1 Effects on academics

Overall estimates suggest that TEXAS package receipt has significantly large effects on academic attainment. Treated students obtain cumulative GPAs that are lower by 0.32 (11 percent) and 0.25 (8.7 percent) grade-points than those for non-recipients in the first and second semesters, respectively. They are also 13 percentage points (93 percent) more likely to obtain a GPA that is below the 2.0 threshold for satisfactory academic progress (SAP) compliance by the end of the freshman year. These estimates are driven by emerging research and other institutions, and no significant effects are found for students conditional on enrolling in flagship institutions. Additionally, aid does not have significant effects on continuous enrollment or four-year graduation for any group of institutions. Treated students conditional on enrolling in emerging research universities obtain lower GPA by about 0.44 and 0.38 grade-points (16 and 14 percent) by the end of their first and second semesters, respectively; and are 1.4 times more likely to obtain a GPA below 2.0 by the end of the first year. Finally, aid recipients that attend other public institutions attain cumulative GPAs that are 0.37 grade-points (13 percent) lower than non-recipients in the first semester, and 0.26 grade-points (9.4 percent) lower in the second semester, attempt 5 credit hours (9 percent) more than the counterfactual by the end of the second year, and are 0.19 percentage points (1.3 times) more likely to fall under the first-year GPA threshold for SAP.

Table 4.2: Estimated effects of TEXAS package receipt: All institutions

Panel A: Academics								
	LATE				ITT			
Switches major	0.070	0.051	0.069	0.053	0.035	0.026	0.034	0.027
[0.24]	(0.056)	(0.059)	(0.056)	(0.059)	(0.028)	(0.030)	(0.028)	(0.030)
Switches from STEM to other majors	0.096***	0.095***	0.096***	0.092***	0.065***	0.066***	0.067***	0.069***
[0.091]	(0.036)	(0.032)	(0.033)	(0.034)	(0.025)	(0.029)	(0.029)	(0.021)
Cummulative GPA - semester 1	-0.338***	-0.300***	-0.369***	-0.320***	-0.167***	-0.150***	-0.182***	-0.160***
[2.827]	(0.107)	(0.111)	(0.105)	(0.109)	(0.052)	(0.055)	(0.051)	(0.054)
Cummulative GPA - year 1	-0.261**	-0.234**	-0.286***	-0.250**	-0.129***	-0.117**	-0.141***	-0.126**
[2.846]	(0.103)	(0.105)	(0.101)	(0.104)	(0.050)	(0.052)	(0.049)	(0.052)
GPA below 2.0 - year 1	0.139***	0.122***	0.146***	0.127***	0.068***	0.061***	0.072***	0.064***
[0.137]	(0.043)	(0.045)	(0.042)	(0.045)	(0.021)	(0.022)	(0.020)	(0.022)
Panel B: Finances								
	LATE				ITT			
Financial aid received - year 1	5,028***	5,199***	5,108***	5,271***	2,472***	2,605***	2,511***	2,643***
[4,265]	(2226)	(2302)	(2262)	(2334)	(196)	(213)	(190)	(206)
Cummulative loans - year 1	-2,399***	-2,171***	-2,432***	-2,279***	-1,179***	-1,088***	-1,195***	-1,143***
[8,599]	(603)	(625)	(590)	(619)	(298)	(316)	(292)	(312)
Cummulative loans - year 2	-5,365***	-3,950***	-5,166***	-3,913***	-2,877***	-2,131**	-2,785***	-2,122**
[16,004]	(1,387)	(1,507)	(1,349)	(1,499)	(764)	(829)	(746)	(828)
Cummulative loans - year 3	-613	1,069	-749	965	-337	565	-419	518
[24,087]	(2,772)	(3,410)	(2,683)	(3,402)	(1,529)	(1,794)	(1,507)	(1,820)
Cummulative loans - year 4	-1,490	1,663	-519	2,989	-869	884	-310	1,689
[31,110]	(5,565)	(10,046)	(5,385)	(9,715)	(3,258)	(5,336)	(3,219)	(5,480)
Observations - year 1	11,951							
Observations - year 2	6,923							
Observations - year 3	3,789							
Observations - year 4	1,402							
Covariates	Yes	No	No	Yes	Yes	No	No	Yes
Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes
School FE	No	No	Yes	Yes	No	No	Yes	Yes

[1] Standard errors in parentheses are clustered at values of EFC. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[2] Counterfactual mean in square brackets.
[3] Number of observations for major switch and Switches from STEM to other majors correspond to those for year 1.
[4] The set of covariates includes gender, race/ethnicity, at risk of dropping out from high school, free/reduced price lunch, English proficiency, gifted and talented status, ACT scores, and cost of attendance.
[5] Optimal bandwidths is $1,428 dollars.

Table 4.3: Estimated effects of TEXAS package receipt: Flagship institutions

Panel A: Academics								
	LATE				ITT			
Switches major	0.094	0.097	0.095	0.097	0.063	0.065	0.064	0.065
[0.257]	(0.062)	(0.070)	(0.062)	(0.070)	(0.042)	(0.047)	(0.042)	(0.047)
Switches from STEM to other majors	0.130**	0.138*	0.142**	0.142**	0.090**	0.092*	0.097**	0.095**
[0.185]	(0.061)	(0.075)	(0.058)	(0.073)	(0.041)	(0.050)	(0.039)	(0.048)
Cummulative GPA - semester 1	-0.016	-0.002	-0.027	-0.004	-0.011	-0.001	-0.019	-0.003
[3.019]	(0.105)	(0.120)	(0.102)	(0.117)	(0.071)	(0.081)	(0.069)	(0.079)
Cummulative GPA - year 1	0.022	0.054	0.013	0.052	0.015	0.036	0.009	0.035
[3.059]	(0.099)	(0.109)	(0.096)	(0.107)	(0.067)	(0.074)	(0.065)	(0.072)
GPA below 2.0 - year 1	-0.015	-0.026	-0.013	-0.025	-0.010	-0.017	-0.009	-0.017
[0.068]	(0.037)	(0.043)	(0.037)	(0.043)	(0.025)	(0.029)	(0.025)	(0.029)
Panel B: Finances								
	LATE				ITT			
Financial aid received - year 1	1,780	1,125	1,726	1,113	1,156	686	1,122	672
[5,273]	(1483)	(865)	(1438)	(883)	(875)	(486)	(863)	(516)
Cummulative loans - year 1	-668	-500	-700	-506	-452	-337	-473	-342
[9,779]	(804)	(933)	(804)	(934)	(545)	(630)	(544)	(630)
Cummulative loans - year 2	-376	301	-438	262	-290	233	-340	203
[18,579]	(1,645)	(2,001)	(1,641)	(1,997)	(1,274)	(1,548)	(1,274)	(1,548)
Cummulative loans - year 3	5,975*	7,624*	5,955*	7,543*	4,561*	6,102*	4,548*	6,075*
[27,372]	(3,253)	(4,379)	(3,251)	(4,366)	(2,434)	(3,403)	(2,435)	(3,415)
Cummulative loans - year 4	3,004	13,363	2,938	12,723	2,348	10,034	2,298	9,648
[34,040]	(5,672)	(10,644)	(5,650)	(10,547)	(4,451)	(7,871)	(4,441)	(7,912)
Observations - year 1				4,574				
Observations - year 2				3,087				
Observations - year 3				1,940				
Observations - year 4				867				
Covariates	Yes	No	No	Yes	Yes	No	No	Yes
Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes
School FE	No	No	Yes	Yes	No	No	Yes	Yes

[1] Standard errors in parentheses are clustered at values of EFC. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
[2] Counterfactual mean in square brackets.
[3] Number of observations for major switch and Switches from STEM to other majors correspond to those for year 1.
[4] The set of covariates includes gender, race/ethnicity, at risk of dropping out from high school, free/reduced price lunch, English proficiency, gifted and talented status, ACT scores, and cost of attendance.
[5] Optimal bandwidths is $3,130 dollars.

Table 4.4: Estimated effects of TEXAS package receipt: Emerging research institutions

Panel A: Academics								
	LATE				ITT			
Switches major	0.219**	0.171**	0.210**	0.175**	0.098**	0.076**	0.094**	0.078**
[0.263]	(0.093)	(0.075)	(0.093)	(0.077)	(0.041)	(0.049)	(0.041)	(0.047)
Switches from STEM to other majors	0.121**	0.126**	0.126**	0.136**	0.040**	0.058**	0.039**	0.062**
[0.089]	(0.054)	(0.055)	(0.054)	(0.060)	(0.019)	(0.029)	(0.019)	(0.031)
Cummulative GPA - semester 1	-0.442**	-0.464**	-0.466**	-0.438**	-0.195**	-0.108**	-0.205**	-0.115**
[2.784]	(0.196)	(0.208)	(0.206)	(0.194)	(0.081)	(0.054)	(0.081)	(0.057)
Cummulative GPA - year 1	-0.380**	-0.413**	-0.403**	-0.382**	-0.168**	-0.074**	-0.178**	-0.082**
[2.79]	(0.182)	(0.183)	(0.184)	-0.169	(0.078)	(0.037)	(0.079)	(0.041)
GPA below 2.0 - year 1	0.202***	0.203***	0.210***	0.219***	0.089***	0.049***	0.092***	0.052***
[0.159]	(0.078)	(0.089)	(0.079)	(0.096)	(0.033)	(0.018)	(0.033)	(0.019)
Panel B: Finances								
	LATE				ITT			
Financial aid received - year 1	5,498***	5,500***	5,435***	5,456***	3,918***	4,134***	3,871***	4,124***
[4,128]	(522)	(584)	(519)	(586)	(382)	(436)	(372)	(427)
Cummulative loans - year 1	-3,394***	-3,100***	-3,376***	-3,282***	-1,489***	-1,358***	-1,478***	-1,428***
[8,309]	(993)	(1,133)	(954)	(1,134)	(434)	(492)	(417)	(488)
Cummulative loans - year 2	-4,820**	-3,670	-4,515**	-3,480	-2,363**	-1,814	-2,201**	-1,717
[15,117]	(2,241)	(2,625)	(2,166)	(2,579)	(1,128)	(1,317)	(1,087)	(1,294)
Cummulative loans - year 3	-756	3,956	-558	4,699	-375	1,823	-276	2,110
[23,026]	(4,778)	(7,014)	(4,616)	(7,136)	(2,378)	(3,188)	(2,289)	(3,145)
Cummulative loans - year 4	7,028	15,437	5,783	18,146	3,438	6,205	2,909	7,433
[29,652]	(11,384)	(28,395)	(11,401)	(29,622)	(5,447)	(11,341)	(5,627)	(11,859)
Observations - year 1	5,351							
Observations - year 2	2,961							
Observations - year 3	1,528							
Observations - year 4	474							
Covariates	Yes	No	No	Yes	Yes	No	No	Yes
Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes
School FE	No	No	Yes	Yes	No	No	Yes	Yes

[1] Standard errors in parentheses are clustered at values of EFC. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
[2] Counterfactual mean in square brackets.
[3] Number of observations for major switch and Switches from STEM to other majors correspond to those for year 1.
[4] The set of covariates includes gender, race/ethnicity, at risk of dropping out from high school, free/reduced price lunch, English proficiency, gifted and talented status, ACT scores, and cost of attendance.
[5] Optimal bandwidths is $1,668 dollars.

Table 4.5: Estimated effects of TEXAS package receipt: Other institutions

Panel A: Academics								
	LATE				ITT			
Switches major	-0.018	-0.043	-0.023	-0.046	-0.009	-0.022	-0.012	-0.024
[0.22]	(0.072)	(0.081)	(0.071)	(0.081)	(0.036)	(0.041)	(0.036)	(0.041)
Switches from STEM to other majors	0.075**	0.068**	0.071**	0.073**	0.039**	0.036**	0.029**	0.037**
[0.069]	(0.033)	(0.030)	(0.031)	(0.032)	(0.019)	(0.018)	(0.013)	(0.017)
Cummulative GPA - semester 1	-0.404***	-0.361**	-0.415***	-0.366**	-0.205***	-0.186**	-0.211***	-0.189**
[2.769]	(0.144)	(0.159)	(0.141)	(0.156)	(0.071)	(0.081)	(0.070)	(0.080)
Cummulative GPA - year 1	-0.315**	-0.265*	-0.318**	-0.264*	-0.160**	-0.137**	-0.162**	-0.137**
[2.786]	(0.142)	(0.154)	(0.139)	(0.151)	(0.071)	(0.068)	(0.069)	(0.067)
GPA below 2.0 - year 1	0.171***	0.181**	0.173***	0.195**	0.087***	0.057**	0.088***	0.059**
[0.149]	(0.061)	(0.081)	(0.061)	(0.086)	(0.030)	(0.027)	(0.030)	(0.029)
Panel B: Finances								
	LATE				ITT			
Financial aid received - year 1	4,755***	5,124***	5,067***	5,267***	2,409***	2,637***	2,563***	2,714***
[3,635]	(396)	(424)	(375)	(401)	(253)	(275)	(242)	(267)
Cummulative loans - year 1	-1,861**	-1,250	-1,887**	-1,388	-943**	-643	-955**	-715
[8,531]	(852)	(886)	(832)	(876)	(432)	(458)	(421)	(453)
Cummulative loans - year 2	-6,814***	-6,224**	-7,062***	-7,335***	-3,398***	-3,089**	-3,512***	-3,643***
[15,799]	(2,107)	(2,429)	(2,011)	(2,427)	(1,066)	(1,217)	(1,010)	(1,202)
Cummulative loans - year 3	-4,559	-10,384*	-5,066	-11,653**	-2,375	-5,227*	-2,733	-6,080**
[23,382]	(4,013)	(5,888)	(3,680)	(5,563)	(2,126)	(2,995)	(2,029)	(2,925)
Cummulative loans - year 4	-8,105	-17,525	-6,529	-20,024	-5,188	-11,560	-4,232	-13,893*
[30,558]	(7,524)	(12,515)	(7,064)	(12,232)	(4,903)	(8,178)	(4,641)	(8,092)
Observations - year 1	6,101							
Observations - year 2	3,427							
Observations - year 3	1,814							
Observations - year 4	681							
Covariates	Yes	No	No	Yes	Yes	No	No	Yes
Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes
School FE	No	No	Yes	Yes	No	No	Yes	Yes

[1] Standard errors in parentheses are clustered at values of EFC. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
[2] Counterfactual mean in square brackets.
[3] Number of observations for major switch and Switches from STEM to other majors correspond to those for year 1.
[4] The set of covariates includes gender, race/ethnicity, at risk of dropping out from high school, free/reduced price lunch, English proficiency, gifted and talented status, ACT scores, and cost of attendance.
[5] Optimal bandwidths is $1,654 dollars.

4.5.2 Effects on finances

Estimates that include all institutions suggest an increase in total financial aid received and a reduction on student loans as consequence of IY TEXAS aid package receipt. Point estimates indicate an increase of non-repayable financial aid from the first year of college of $5,271 (1.23 times higher than the counterfactual. Additionally, there is evidence of a reduction in the amount borrowed equal to $2,279 (26 percent) and $3,913 (24 percent) dollars by the end of the first and second years of college, respectively. Effects for the third year and on are less precisely estimated. Effects are quite different when types of institutions are examined individually. For instance, for students at flagship universities, there is no statistically significant effect in the total amount of aid received. Particularly, TEXAS Grant recipients at these institutions seem to borrow more money by the end of the third year of college, but the effect is weakly statistically significant. Aid recipients who attend emerging research institutions receive $5,456 (1.3 times) more total aid than ineligible students, and borrow $3,282 and $3,480 dollars (39 and 23 percent) less than non-recipients during the first and second years after entry, respectively. Lastly, treated students in other institutions receive $5,267 (1.4 times) more total aid, and take out $1,388 and $7,335 dollars (16 and 49 percent) less in loans than the counterfactual for the first and second year of college, respectively.

4.5.3 Mechanisms

My findings show that receiving aid significantly reduces academic attainment and cumulative student loans, but only when conditioned on attending emerging research or other institutions. No significant effects are evidenced for students that enroll in flagships. In this Section, I explore potential mechanisms through which aid receipts could generate these effects and explanations for the heterogeneity by type of institution.

The null effects on GPA for students enrolling in flagship universities might be explained by major choice of the treated. Aid recipients attending flagships are 50 percent more likely to have a first major in Liberal Arts, 1.2 times less likely to have it in Business and Management, and 1 time more likely to switch away from STEM majors than non-recipients. Additionally, treated students remain to be 95 percent less likely to have a final major in Business and Management, but the likelihood for Liberal Arts as final major is zero. This evidence is consistent with the idea that aid recipients might be choosing their initial major strategically, as enrolling in Liberal Arts majors might increase their chance of being admitted. This initial strategy might be followed by switching to their major of preference. Additionally, Rothstein and Rouse (2011) show that as undergraduate students take out more loans, they are more likely to end up in higher paying jobs and non-governmental work. It is possible that students switch away from STEM majors because doing so reduces the money necessary to cover it cost, which might help to explain the lack of statistical significant impacts on cumulative loans for years 1 and 2.

The negative impact on GPA for students attending emerging research universities might also be explained by their choice of major. In particular, treated students attending these institutions are 95 percent less likely to enroll in Liberal Arts majors, and although imprecisely estimated, 24 percent more likely to have it in STEM. The effects for this as final major are not statistically significant. Aid receipt also increases the likelihood of switching majors by 66 percent and that for switching away from STEM majors by 1.5 times. It is possible that treated students might be enrolling in college without a full understanding of their major choice, which is consistent with evidence that they end up switching to a different major; particularly the effect is rather strong for students who initially started in a STEM major. This behavior is also consistent with the relative improvement in their GPA. Newly enrolled students might show a preference for STEM degrees due to the higher future earnings these degrees represent (Melguizo and Wolniak, 2012; Webber, 2014; Noonan, 2017). However, enrolling in a major where students take classes that are heavy on mathematics and technical knowledge may harm the performance of the treated, more so if students are not well prepared. This evidence is consistent with literature suggesting that financial aid programs reduce the likelihood that recipients will earn a STEM degree (Sjoquist and Winters, 2015). It is possible that changing majors to one that fits student's preferences and abilities more adequately is behind the relative improvement in performance from the second year and on.

The case for the set of students attending other public universities is similar. TEXAS recipients are 1 time more likely to switch away from STEM majors than their ineligible peers. Additionally, treated students attempt disproportionately more credit hours. Aid recipients attempt 7 and 9 percent more credits by the end of the first and second year, respectively. Ineligible students attempt 56 credit hours by the end of the second year, which translates to an average of 14 credits per semester. This evidence shows that treated students are attempting more than the number of credit hours required for full-time enrollment. This behavior suggests that the lower GPA of the treated might be a response to the initial major choice and the possible higher amount of credit hours they attempt to get back on track and keep up with their peers.

Villarreal (2018) does not examine all the academic outcomes here discussed, but his debt-reduction effects are fairly similar in magnitude to those fund in this study at least for the first year. The TEXAS Grant package cuts student loans by 28 percent during the first two years of college. Effects for the third and fourth years are indistinguishable from zero. It is particularly interesting that the estimated effects conditional on flagship enrollment are imprecisely estimated for all first four years of college. This is consistent with the fact that flagship institutions offer more institutional aid and have more resources available than other public institutions in Texas for all their students—not only those economically disadvantaged.

Note that the typical IY package that includes the TEXAS Grant for the RD sample across institutions is \$9,575 and the in-state average tuition and fees totals \$8,444[24]. The overall debt-reducing effects may not seem large, but the average aid package is enough to cover recipients' tuition and fees at virtually any university in the state. This shows that the treated have other significant costs to face, which is to be expected as tuition and fees are only a portion of the total cost of attendance. Students bear expenses that they need to cover using their own money such as food, housing, book, and others. This might explain the fact that eligible first-time-in-college students to borrow on average \$7,038 dollars during the first

[24]Total of tuition and fees for the 2013–2014 academic year reported by the U.S. Department of Education's 2017-2018 IPEDS Survey.

year (see Table A.13). The lack of statistically significant effects in years 3 and 4 for students at emerging research and other institutions is also an interesting result to discuss. The lack of statistically significant effects for later years is consistent with a systematic reduction in the rate of renewal awards across types of institutions, but also with a reduction in the number of observations—which is something that should be addressed in future research.

My RD sample indicates the TEXAS[25] renewal rate is 66 percent in the second year of college, 46 percent in the third year, and 40 percent in the fourth. This is also consistent with the disproportionate increase in the likelihood of failing with first-year SAP compliance of the treated. Finally, TEXAS Grant recipients receive significantly more financial aid—from non-repayable sources—than their ineligible peers. This is consistent with the last-dollar design of this program. The effects for students attending flagship institutions are both small and imprecisely estimated, consistent with the relative higher financial leverage these type of institutions have that allows them to offer more financial aid—not only to those who are eligible for a particular program such as the TEXAS Grant.

4.5.4 Robustness Checks

I perform different checks to verify the robustness of my estimates. I first examine whether the estimates are robust to the selection of bandwidth. Figures B.9 through B.12 present the average *p*-value for different values under the null hypothesis across different bandwidths. This procedure suggests that the estimates are fairly robust to bandwidth selection for overall estimates as well as those for flagship, emerging research, and other institutions.. Additionally, Figures B.13 through B.16 depict point estimates' statistical power under the optimal bandwidth showing evidencing power greater than 80 percent for most outcomes.

[25] A student receiving an IY TEXAS Grant award is guaranteed to receive funding from the program for up to 6 years, conditional on meeting satisfactory academic progress and having unmet need. This is in contrast to the Pell Grant, which considers student's family circumstances for renewal awards.

Second, I provide both ITT and LATE estimates that include covariates for all outcomes. The evidence shows that these results are highly robust to alternative specifications.

4.6 Conclusion

The Toward EXcellence, Access and Success (TEXAS) Grant is the largest need-based financial aid program in the state of Texas. This last-dollar Grant complements the funding from other aid programs and is designed to eliminate students' financial need with respect to the total of tuition and fees. After federal and any other types of aid are awarded to students, institutions may utilize TEXAS appropriations to tailor an aid package provided they eliminate awardees' financial need—should there be any—with institutional aid. Table A.18 shows that TEXAS eligibility increases the likelihood of receiving Pell awards, but does not affect the likelihood for any other type of aid. This evidence suggests that, on average, four-year public universities only use TEXAS dollars to complement those from the federal-funded Pell Grant[26] to obliterate financial need. Moreover, low-income students who receive Pell Grants get more funding than those who are Pell-ineligible. This means that both federal and state efforts interact in synergy to make college fully affordable for economically disadvantaged students.

I use administrative data from the 2013–2016 entering college cohorts and take advantage of a discontinuity in aid receipt to examine the in-college effects of receiving financial aid in Texas. My overall estimates depict two sets of results: the unexpected and the expected effects associated to this program. In the unexpected group of results I find that that aid receipt does not affect continuous enrollment or four-year graduation and reduces first-year GPA by 8 percent. For the expected group of results, my estimates show that financial aid cuts student

[26]The typical IY Pell-TEXAS award for first-time enrollees totals 10.2 thousand dollars and the 2018 average tuition and fees in Texas were about 5.7 thousand dollars. This aid package therefore allows needy recipients access higher education, as it provides more than the necessary to enroll in the average 4-year college.

loans up to the second year of enrollment by 28 percent. These effects are driven by emerging research and other universities whose GPA and loans reduction effects are 9 and 32 percent, respectively. Additionally, aid receipt significantly increases the likelihood of failing with first-year SAP compliance, which is necessary to receive a renewal year award. This evidence is compatible with the lower renewal rates within emerging research and other universities. Students enrolling in flagship institutions do not experience significant effects as consequence of aid receipt. It is important to mention that this study is not the first to find unexpected results associated to the roll-out of a financial aid program. Cohodes and Goodman (2014) study the Massachusetts' Adams Scholarship, which is a merit aid program, and find that students are remarkably willing to forgo college quality and that scholarship use actually lowered college completion rates. Clotfelter et al. (2018) study a low-income institutional program in North Carolina and find little to no evidence that program eligibility improved postsecondary progress, performance, or completion. And finally, Park and Scott-Clayton (2018) examine the impact of Pell Grant eligibility for community college students, finding that it reduces academic attainment in early stages of their college career.

These results—and those from similar studies—may rise some concern, as it is not straightforward to estimate the effects associated to aid receipt for two reasons. First, financial aid programs do not typically cover the total of tuition and fees, which makes them rather likely to be awarded as an aid package that includes two or more Grant programs. Secondly, students often care about what their awards cover rather than the specific sources. Although my identification strategy does not allow me to disentangle and attribute the effects that correspond to each program that makes up the financial aid package, it allows me to identify the causal effect of eliminating financial need with an aid package that includes TEXAS Grant dollars. In spite of the fact that it is impossible to make an assessment on unobservables, the evidence here presented suggests that eligibility only makes students more likely to receive the Pell-TEXAS package. Particularly, eligible students are not more—or less—likely to receive other sources of financial aid that may be awarded after TEXAS Grant dollars are allocated such as institutional aid. If the evidence I provide are enough to argument that the exclusion assumption is binding—i.e., eligibility does not affect any other outcomes besides aid receipt (see assumption 4.4.1)—, then my strategy identifies the effects of receiving whatever the aid package is whose last-dollars come from TEXAS appropriations. Moreover, this quasi-experimental design is consistent with the compliance of the required assumptions to produce ITT estimates—which should be interpreted as the causal effect of being TEXAS-eligible—(see assumptions 4.4.1 through 4.4.1). Whether institutions award the TEXAS Grant or not is more than eligibility per se. It might be an strategy to ensure that recipients enroll and are successful in college, which could aid to explain the heterogeneous effects by types of institutions here found. This is an additional reason why one should also care about the ITT estimates. I provide both LATE and ITT estimates for completeness.

Per rules and award amounts, the TEXAS Grant program is similar to many state need-based programs such as the New Mexico's Student Incentive Grant (up to $2,500 per year), the Arizona's AzLEAP program (up to $2,500 per year), the Colorado Student Grant (up to $5,000 per year), and the Virginia's Commonwealth Award and Guaranteed Assistance Program (up to total of tuition and fees). The effects of these low-income programs on student outcomes have not been examined, so it is not possible to analyze how TEXAS Grant effects compare. Other state merit-aid programs such as the Georgia's HOPE program and the West Virginia's PROMISE scholarship have been further studied. For instance, Scott-Clayton (2011) studies the latter and finds that aid receipt significantly increases degree attainment and in-college performance. Although need- and merit-based programs are not necessarily comparable, one should expect that both boost students' college success. This paper is the first attempt to examine the effects of the TEXAS Grant under the HP model on academics and finances. Although the maturity of the cohorts only allows me to track the first HP cohort for up to 4 years, my RD estimates provide succinct evidence that the TEXAS package has unexpected effects associated to it. However, it is still premature to conclude that aid receipt does not produce positive effects on attainment. Effects on outcomes such as graduation, continuous enrollment, and cumulative loans for later years might also increase in size as more cohorts are included. Additional to the unexpected findings, aid package receipt produces highly heterogeneous effects across institutions which limits my ability of attributing a singular mechanism for overall estimates. Institutions might implement differential selection mechanisms that may be the origin of the heterogeneous effects. Further studies that provide more insight in this regard and that include longer-run outcomes in academics and finances is something that should be included in the research agenda.

CHAPTER 5

CONCLUSION

The TEXAS Grant is the largest financial aid program in the state of Texas. All the findings and results embedded in this dissertation are intended to provide insight in different aspects of this important program. First, I present an algorithm intended to help the TEXAS Grant decisions by making use of statistical learning approaches, designed to best fit the data. Second, I examine an important change to the TEXAS Grant program, which makes it a very particular state grant as it considers both need- and merit-based components. Finally, I focus on the effects of receiving the TEXAS Grant and its impacts on postsecondary outcomes such as academics and finances.

It is my wish that academics and policy makers use these findings as input to make further adjustments to this program and assure that the financial aid in the state of Texas, other states in the U.S. and those at the federal level, remain focused on needy students and their best interest.

APPENDIX A

ADDITIONAL TABLES

Table A.1: Financial aid package for first-time freshman students: Fiscal year 2010

Program	Median	Mean	Cum. Mean	Students
Pell	6,261	5,204	5,204	15,325
TEXAS	7,115	6,469	12,059	9,263
Subsidezed	4,077	3,448	16,133	1,973
Unsubsidized	2,328	2,518	18,782	1,148
TPEG	852	981	20,170	164
Other federal loans	2,853	3,184	22,722	34
SEOG	500	600	23,581	5

Table A.2: Financial aid package for first-time freshman students: Fiscal year 2011

Program	Median	Mean	Cum. Mean	Students
Pell	6,332	5,167	5,167	17,018
TEXAS	7,806	7,091	12,753	11,904
Subsidezed	4,011	3,475	16,437	6,145
Unsubsidized	2,291	2,527	19,090	3,876
Other federal loans	2,303	3,028	20,685	454
TPEG	2,000	1,496	20,517	87
SEOG	500	488	20,748	45

Table A.3: Financial aid package for first-time freshman students: Fiscal year 2012

Program	Median	Mean	Cum. Mean	Students
Pell	6,140	4,825	4,825	20,194
TEXAS	5,582	5,175	10,491	14,316
Subsidezed	3,889	3,538	14,057	9,302
Unsubsidized	2,221	3,002	17,194	6,513
TPEG	1,500	1,528	18,362	1,425
Other federal loans	2,130	2,925	20,316	382
SEOG	500	543	19,781	63

Table A.4: Financial aid package for first-time freshman students: Fiscal year 2013

Program	Median	Mean	Cum. Mean	Students
Pell	5,796	4,773	4,773	21,583
TEXAS	5,468	5,092	10,272	15,718
Subsidezed	3,790	3,460	13,804	9,375
Unsubsidized	2,165	3,240	17,181	6,635
TPEG	1,200	1,264	17,826	1,000
SEOG	500	592	19,132	220
Other federal loans	1,640	1,661	18,362	54

Table A.5: Financial aid package for first-time freshman students: Fiscal year 2014

Program	Median	Mean	Cum. Mean	Students
Pell	6,030	4,821	4,821	21,995
TEXAS	5,389	5,230	10,274	18,114
Subsidezed	3,733	3,449	13,748	10,745
Unsubsidized	2,134	3,020	16,854	7,845
TPEG	1,199	1,374	17,362	1,330
Other federal loans	3,533	3,919	20,451	227
SEOG	500	544	21,456	28

Table A.6: Financial aid package for first-time freshman students: Fiscal year 2015

Program	Median	Mean	Cum. Mean	Students
Pell	5,919	4,790	4,790	26,030
TEXAS	5,303	5,123	10,139	20,606
Subsidezed	3,674	3,397	13,564	11,690
Unsubsidized	2,100	2,851	16,490	8,295
TPEG	1,400	1,506	17,243	1,687
Other federal loans	4,243	4,721	20,921	314
SEOG	500	522	21,025	40

Table A.7: Financial aid package for first-time freshman students: Fiscal year 2016

Program	Median	Mean	Cum. Mean	Students
Pell	6,065	4,863	4,863	26,662
TEXAS	5,297	5,130	10,106	22,587
Subsidezed	3,670	3,461	13,540	13,055
Unsubsidized	2,097	2,667	16,253	9,594
TPEG	1,275	1,505	16,841	2,563
SEOG	600	783	18,469	609
Other federal loans	2,419	3,275	21,722	64

Table A.8: Financial aid package for first-time freshman students: Fiscal year 2017

Program	Median	Mean	Cum. Mean	Students
Pell	5,926	4,802	4,802	25,744
TEXAS	5,231	5,209	10,176	20,644
Subsidezed	3,624	3,433	13,602	11,611
Unsubsidized	2,071	2,642	16,292	8,459
TPEG	1,290	1,582	17,247	2,288
SEOG	500	667	19,094	387
Other federal loans	2,092	1,832	20,060	32

Table A.9: Variables included in clustering analysis

Variable	Discription	Source
gini_txg	Gini coefficient for FTF TEXAS awards	TEA/THECB
theil_txg	Theil coefficient for FTF TEXAS awards	TEA/THECB
hhi_txg	HHI coefficient for FTF TEXAS awards	TEA/THECB
gini_pell	Gini coefficient for FTF Pell awards	TEA/THECB
theil_pell	Theil coefficient for FTF Pell awards	TEA/THECB
hhi_pell	HHI coefficient for FTF Pell awards	TEA/THECB
Library_expenditures	Institutional expenditure in library resources and improvements	IPEDS
Student.to.faculty_ratio	Student-to-faculty ratio	IPEDS
Bachelor_prog_offered	Number of bachelor programs offered	IPEDS
Masters_prog_offered	Number of Master programs offered	IPEDS
Doctoral_prog_offered	Number of doctoral programs offered	IPEDS
Associate	Number of associate professors	IPEDS
Assistant	Number of assistant professors	IPEDS
Intructors	Number of instructors	IPEDS
Lecturers	Number of lecturers	IPEDS
Applicants_total	Number of applicants	IPEDS
Admissions_total	Numbers of admitted students	IPEDS
Enrolled_total	Number of enrolled students (all programs)	IPEDS
Enrolled_FT_total	Number of full-time students	IPEDS
FTFT_undergraduate	Number of enrolled students (undergraduate programs)	IPEDS
Enrolled_PT_total	Number of part-time students	IPEDS
State_tuit_fees	Total of tuition and fees for residents	IPEDS
FT_retention	First-time freshman retention	IPEDS
FTFT_fad	Total financial aid received by first-time freshman students	TEA/THECB
FTFT_pell	Pell Grant awards received by first-time freshman students	TEA/THECB

Table A.10: TEXAS Grant parameters for public universities

Fiscal year	EFC eligibility threshold ($)	Tuition and fees coverage[2](%)
2000	5,000	100.0
2001	5,000	100.0
2002	5,000	80.5
2003	8,500	73.1
2004	8,500	63.0
2005	4,000	67.0
2006	4,000	70.3
2007	4,000	72.2
2008	4,000	75.2
2009	4,000	73.2
2010	4,000	79.1
2011	4,000	84.2
2012	4,000	61.9
2013	4,000	59.2
2014	4,620	60.0
2015	4,800	58.2
2016	5,088	57.4
2017	5,233	54.9

[1] Source: THECB (2018a). SB 28 granted priority status to eligible students for initial year awards stating in Fall 2011. A high school graduate qualifies for basic eligibility (BE) if: i) graduates high school within 16 months of college enrollment, ii) enrolls in college at least three-fourths full-time, and iii) has a 9-month EFC of no more than the determined threshold for a given fiscal year. Among those who qualify for BE, the higher priority (HP) model gives preference to high-achieving students. Under its specifications, institutions must prioritize students who had met the requirements for advanced academic program (AAP), TSI readiness (TSIR), class standing (CS), or advanced math (AM).

[2] Percentage of the state average tuition and fees that is covered by the TEXAS grant. These values are obtained from THECB reports and do not necesarily compare to those obtained in this study.

Table A.11: General characteristics for public universities by type of institution

	All institutions	Flagship	Emerging research	Other
Total price for in-state students living on campus	21,868	23,604	21,616	20,383
In-state tuition and fees	8,444	9,152	8,397	7,784
Graduation rate total cohort	55	79	48	38
Graduation rate - Bachelor degree within 4 years	31	50	24	20
Graduation rate - Bachelor degree within 5 years	50	75	42	33
Graduation rate - Bachelor degree within 6 years	55	79	48	38
Applicants total	18,066	34,774	14,340	5,083
Admissions total	10,499	18,569	9,618	3,310
Enrolled total	4,584	8,745	3,811	1,196
First-time degree-seeking undergraduate enrollment	4,454	8,745	3,745	871
Number of students receiving a Bachelor's degree	5,201	9,386	5,129	1,087
SAT Math 25th percentile score	506	570	508	441
SAT Math 75th percentile score	612	685	610	541
ACT Math 25th percentile score	21	25	22	18
ACT Math 75th percentile score	27	31	27	23

[1] Source: U.S. Department of Education. Institute of Education Sciences, National Center for Education Statistics.
[2] The group of Flagship institutions include the University of Texas–Austin and Texas A&M–College Station. These are universities leading enrollment, performance, and completion indicators. The group of emerging research include Texas State University, Texas Tech University, University of Houston, University of Texas–Arlington, University of Texas–Dallas, University of Texas–El Paso, University of Texas–San Antonio, and University of North Texas. These are institutions that receive extra funding to become Tier one in the state. The group of all other institutions includes all remaining public universities.

Table A.12: Summary statistics: Population of first-time freshmen (fall cohorts 2013–2016)

Panel A: Covariates						
	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Eligible	0.491 (0.5)	141,966	-		-	
Female	0.564 (0.496)	141,966	0.582 (0.493)	69,691	0.547 (0.498)	72,275
Asian	0.087 (0.282)	141,966	0.085 (0.278)	69,691	0.089 (0.285)	72,275
Black	0.109 (0.312)	141,966	0.152 (0.359)	69,691	0.068 (0.252)	72,275
Hispanic	0.404 (0.491)	141,966	0.543 (0.498)	69,691	0.271 (0.444)	72,275
White	0.362 (0.481)	141,966	0.188 (0.391)	69,691	0.529 (0.499)	72,275
Other race/ethnicity	0.038 (0.19)	141,966	0.032 (0.177)	69,691	0.043 (0.202)	72,275
At risk[2]	0.127 (0.333)	141,966	0.179 (0.384)	69,691	0.076 (0.265)	72,275
Free/Reduced price lunch	0.353 (0.478)	141,966	0.64 (0.48)	69,691	0.076 (0.264)	72,275
English proficient	0.989 (0.104)	141,966	0.98 (0.141)	69,691	0.998 (0.042)	72,275
Gifted and talented	0.244 (0.429)	141,966	0.204 (0.403)	69,691	0.282 (0.45)	72,275
Cost of attendance	24170 (4875)	141,966	23486 (4915)	69,691	24830 (4743)	72,275
ACT score	22.2 (4.7)	141,966	20.6 (4.2)	69,691	23.7 (4.6)	72,275
Flagship universities[3]	0.228 (0.42)	141,966	0.153 (0.36)	69,691	0.302 (0.459)	72,275
Emerging research universities[4]	0.384 (0.486)	141,966	0.384 (0.486)	69,691	0.383 (0.486)	72,275
Other universities	0.388 (0.487)	141,966	0.463 (0.499)	69,691	0.316 (0.465)	72,275

Panel B: Select outcomes						
	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Switches major[5]	0.254 (0.435)	130,233	0.261 (0.439)	64,244	0.247 (0.431)	65,989
Switches from STEM to other majors[6]	0.105 (0.306)	111,746	0.102 (0.302)	56,175	0.108 (0.31)	55,571
Cummulative GPA - semester 1	2.828 (0.945)	138,053	2.663 (0.987)	67,609	2.986 (0.874)	70,444
Cummulative GPA - year 1	2.85 (0.845)	131,658	2.689 (0.878)	63,557	3.001 (0.785)	68,101
GPA below 2.0 - year 1	0.138 (0.344)	131,658	0.175 (0.38)	63,557	0.1 (0.3)	68,101
Cummulative loans - year 1[7]	8231 (5810)	77,426	6175 (3262)	37,522	10164 (6912)	39,904
Cummulative loans - year 2[7]	14782 (10929)	59,364	10677 (6584)	29,772	18912 (12727)	29,592
Cummulative loans - year 3[7]	21770 (16237)	37,258	15702 (10347)	19,306	28296 (18704)	17,952
Cummulative loans - year 4[7]	27818 (20329)	16,551	20443 (13664)	9,013	36636 (23268)	7,538

Panel C: TEXAS aid package						
	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Receives IY TEXAS grant	0.392 (0.488)	141,966	0.796 (0.403)	69,691	0.002 (0.04)	72,275
IY TEXAS award	5207 (1293)	57,908	5205 (1291)	57,795	6059 (1616)	113
IY Pell award	4861 (1620)	68,560	4911 (1567)	67,727	837 (293)	833
IY Pell award — receiving TEXAS	5019 (1506)	55,514	5027 (1497)	55,409	1123 (615)	105
IY Pell award — not receiving TEXAS	4191 (1897)	13,046	4391 (1757)	12,318	796 (175)	728
IY package award	9233 (4807)	88,780	10899 (3874)	68,238	3699 (3188)	20,542
IY package award — receiving TEXAS	11822 (3115)	55,614	11827 (3114)	55,501	9232 (2932)	113
IY package award — not receiving TEXAS	4891 (3936)	33,166	6853 (4248)	12,737	3669 (3163)	20,429
RY award (2nd year)[8]	0.731 (0.443)	35,973	0.731 (0.443)	35,926	0.532 (0.504)	47
RY award (3nd year)[8]	0.534 (0.499)	21,301	0.534 (0.499)	21,267	0.324 (0.475)	34
RY award (4nd year)[8]	0.479 (0.5)	9,264	0.479 (0.5)	9,254	0.4 (0.516)	10

[1] Standard deviation in parenthesis.
[2] Corresponds to a variable indicating if a student is at risk of being a high school dropout.
[3] Flagship universities are those leading enrollment, performance, and completion indicators. These institutions are the University of Texas–Austin and Texas A&M–College Station.
[4] Emerging research universities are those that receive extra funding to become Tier one in the state. These institutions are Texas State University, Texas Tech University, University of Houston, University of Texas–Arlington, University of Texas–Dallas, University of Texas–El Paso, University of Texas–San Antonio, and University of North Texas.
[5] Corresponds to a variable indicating if a student switches major.
[6] Corresponds to a variable indicating if a student switches away from STEM majors.
[7] Conditional on values greater than zero.
[8] Conditional on IY TEXAS receipt.

Table A.13: Summary statistics: All institutions ($1,428 bandwidth)

Panel A: Covariates

	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Eligible	0.542 (0.498)	11,424	-		-	
Female	0.559 (0.497)	11,424	0.567 (0.496)	6,194	0.55 (0.498)	5,230
Asian	0.085 (0.278)	11,424	0.08 (0.271)	6,194	0.09 (0.287)	5,230
Black	0.118 (0.322)	11,424	0.122 (0.327)	6,194	0.112 (0.316)	5,230
Hispanic	0.419 (0.493)	11,424	0.438 (0.496)	6,194	0.396 (0.489)	5,230
White	0.338 (0.473)	11,424	0.317 (0.465)	6,194	0.363 (0.481)	5,230
Other race/ethnicity	0.041 (0.199)	11,424	0.043 (0.204)	6,194	0.039 (0.193)	5,230
At risk[2]	0.112 (0.316)	11,424	0.115 (0.319)	6,194	0.109 (0.312)	5,230
Free/Reduced price lunch	0.273 (0.445)	11,424	0.315 (0.465)	6,194	0.223 (0.416)	5,230
English proficient	0.995 (0.069)	11,424	0.995 (0.072)	6,194	0.996 (0.066)	5,230
Gifted and talented	0.249 (0.433)	11,424	0.245 (0.43)	6,194	0.255 (0.436)	5,230
Cost of attendance	24020 (4744)	11,424	24018 (4748)	6,194	24022 (4739)	5,230
ACT score	22 (4.4)	11,424	21.9 (4.3)	6,194	22.2 (4.4)	5,230
Flagship universities[3]	0.203 (0.402)	11,424	0.199 (0.399)	6,194	0.207 (0.405)	5,230
Emerging research universities[4]	0.398 (0.49)	11,424	0.404 (0.491)	6,194	0.391 (0.488)	5,230
Other universities	0.399 (0.49)	11,424	0.397 (0.489)	6,194	0.402 (0.49)	5,230

Panel B: Select outcomes

	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Switches major[5]	0.251 (0.434)	10,471	0.261 (0.439)	5,701	0.24 (0.427)	4,770
Switches from STEM to other majors[6]	0.097 (0.296)	9,080	0.102 (0.303)	4,933	0.091 (0.288)	4,147
Cummulative GPA - semester 1	2.806 (0.941)	11,112	2.788 (0.946)	6,012	2.827 (0.935)	5,100
Cummulative GPA - year 1	2.829 (0.843)	10,556	2.814 (0.849)	5,713	2.846 (0.835)	4,843
GPA below 2.0 - year 1	0.139 (0.346)	10,556	0.141 (0.348)	5,713	0.137 (0.344)	4,843
Cummulative loans - year 1[7]	7794 (4898)	7,444	7038 (4050)	3,840	8599 (5552)	3,604
Cummulative loans - year 2[7]	14151 (9227)	5,681	12533 (7892)	3,033	16004 (10243)	2,648
Cummulative loans - year 3[7]	21335 (14107)	3,671	18993 (12315)	1,983	24087 (15515)	1,688
Cummulative loans - year 4[7]	27819 (17706)	1,676	25034 (15725)	908	31110 (19293)	768

Panel C: TEXAS aid package

	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Receives IY TEXAS grant	0.392 (0.488)	11,424	0.706 (0.455)	6,194	0.021 (0.142)	5,230
IY TEXAS award	5555 (1483)	4,672	5542 (1479)	4,564	6104 (1563)	108
IY Pell award	1565 (560)	6,638	1670 (514)	5,813	828 (209)	825
IY Pell award — receiving TEXAS	1700 (507)	4,467	1715 (501)	4,366	1054 (282)	101
IY Pell award — not receiving TEXAS	1289 (564)	2,171	1536 (529)	1,447	796 (175)	724
IY package award	6621 (4055)	9,772	8137 (3844)	5,947	4265 (3149)	3,825
IY package award — receiving TEXAS	9575 (2660)	4,483	9584 (2655)	4,375	9217 (2866)	108
IY package award — not receiving TEXAS	4118 (3274)	5,289	4109 (3773)	1,572	4121 (3039)	3,717
RY award (2nd year)[8]	0.659 (0.474)	2,382	0.662 (0.473)	2,336	0.522 (0.505)	46
RY award (3nd year)[8]	0.458 (0.498)	1,518	0.462 (0.499)	1,485	0.303 (0.467)	33
RY award (4nd year)[8]	0.398 (0.49)	664	0.398 (0.49)	654	0.4 (0.516)	10

[1] Standard deviation in parenthesis.
[2] Corresponds to a variable indicating if a student is at risk of being a high school dropout.
[3] Flagship universities are those leading enrollment, performance, and completion indicators. These institutions are the University of Texas–Austin and Texas A&M–College Station.
[4] Emerging research universities are those that receive extra funding to become Tier one in the state. These institutions are Texas State University, Texas Tech University, University of Houston, University of Texas–Arlington, University of Texas–Dallas, University of Texas–El Paso, University of Texas–San Antonio, and University of North Texas.
[5] Corresponds to a variable indicating if a student switches major.
[6] Corresponds to a variable indicating if a student switches away from STEM majors.
[7] Conditional on values greater than zero.
[8] Conditional on IY TEXAS receipt.

Table A.14: Summary statistics: Flagship institutions ($3,130 bandwidth)

Panel A: Covariates						
	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Eligible	0.575 (0.494)	5,296	-		-	
Female	0.545 (0.498)	5,296	0.55 (0.498)	3,045	0.538 (0.499)	2,251
Asian	0.154 (0.361)	5,296	0.153 (0.36)	3,045	0.156 (0.363)	2,251
Black	0.063 (0.242)	5,296	0.068 (0.252)	3,045	0.056 (0.229)	2,251
Hispanic	0.366 (0.482)	5,296	0.393 (0.489)	3,045	0.33 (0.47)	2,251
White	0.383 (0.486)	5,296	0.352 (0.478)	3,045	0.426 (0.495)	2,251
Other race/ethnicity	0.033 (0.18)	5,296	0.034 (0.182)	3,045	0.032 (0.177)	2,251
At risk[2]	0.042 (0.2)	5,296	0.046 (0.209)	3,045	0.036 (0.187)	2,251
Free/Reduced price lunch	0.242 (0.428)	5,296	0.305 (0.461)	3,045	0.155 (0.362)	2,251
English proficient	0.996 (0.066)	5,296	0.993 (0.083)	3,045	0.999 (0.03)	2,251
Gifted and talented	0.438 (0.496)	5,296	0.423 (0.494)	3,045	0.458 (0.498)	2,251
Cost of attendance	26868 (4009)	5,296	27039 (3850)	3,045	26635 (4204)	2,251
ACT score	25.3 (4.3)	5,296	24.9 (4.3)	3,045	25.8 (4.2)	2,251

Panel B: Select outcomes						
	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Switches major[3]	0.274 (0.446)	5,296	0.287 (0.453)	3,045	0.257 (0.437)	2,251
Switches from STEM to other majors[4]	0.19 (0.392)	3,628	0.193 (0.395)	2,141	0.185 (0.388)	1,487
Cummulative GPA - semester 1	2.982 (0.791)	5,104	2.955 (0.797)	2,926	3.019 (0.781)	2,178
Cummulative GPA - year 1	3.032 (0.675)	4,999	3.012 (0.675)	2,867	3.059 (0.673)	2,132
GPA below 2.0 - year 1	0.066 (0.248)	4,999	0.065 (0.246)	2,867	0.068 (0.251)	2,132
Cummulative loans - year 1[5]	8383 (5561)	3,233	7334 (4465)	1,846	9779 (6493)	1,387
Cummulative loans - year 2[5]	15425 (10697)	2,717	13165 (8593)	1,583	18579 (12414)	1,134
Cummulative loans - year 3[5]	22687 (15755)	1,964	19420 (12821)	1,157	27372 (18207)	807
Cummulative loans - year 4[5]	28401 (18974)	1,073	24759 (15482)	652	34040 (22247)	421

Panel C: TEXAS aid package						
	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Receives IY TEXAS grant	0.434 (0.496)	5,296	0.751 (0.432)	3,045	0.006 (0.079)	2,251
IY TEXAS award	5163 (1073)	2,421	5163 (1076)	2,407	5219 (423)	14
IY Pell award	2535 (1064)	3,113	2648 (997)	2,922	799 (191)	191
IY Pell award — receiving TEXAS	2712 (988)	2,300	2722 (981)	2,287	1004 (412)	13
IY Pell award — not receiving TEXAS	2033 (1112)	813	2383 (1007)	635	784 (156)	178
IY package award	8589 (4602)	4,588	10326 (4056)	2,946	5473 (3813)	1,642
IY package award — receiving TEXAS	11386 (3190)	2,301	11391 (3190)	2,287	10524 (3148)	14
IY package award — not receiving TEXAS	5775 (4057)	2,287	6628 (4544)	659	5430 (3790)	1,628
RY award (2nd year)[6]	0.777 (0.416)	1,454	0.779 (0.415)	1,447	0.429 (0.535)	7
RY award (3nd year)[6]	0.613 (0.487)	987	-		-	
RY award (4nd year)[6]	0.521 (0.5)	534	-		-	

[1] Standard deviation in parenthesis.
[2] Corresponds to a variable indicating if a student is at risk of being a high school dropout.
[3] Corresponds to a variable indicating if a student switches major.
[4] Corresponds to a variable indicating if a student switches away from STEM majors.
[5] Conditional on values greater than zero.
[6] Conditional on IY TEXAS receipt.
[7] Values not presented due to FERPA compliance.

Table A.15: Summary statistics: Emerging research institutions ($1,668 bandwidth)

Panel A: Covariates						
	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Eligible	0.559 (0.497)	5,369	-		-	
Female	0.536 (0.499)	5,369	0.55 (0.498)	3,000	0.518 (0.5)	2,369
Asian	0.104 (0.305)	5,369	0.099 (0.299)	3,000	0.11 (0.313)	2,369
Black	0.115 (0.319)	5,369	0.12 (0.325)	3,000	0.109 (0.312)	2,369
Hispanic	0.458 (0.498)	5,369	0.483 (0.5)	3,000	0.426 (0.495)	2,369
White	0.283 (0.45)	5,369	0.26 (0.439)	3,000	0.312 (0.464)	2,369
Other race/ethnicity	0.04 (0.197)	5,369	0.039 (0.193)	3,000	0.043 (0.202)	2,369
At risk[2]	0.113 (0.317)	5,369	0.122 (0.327)	3,000	0.103 (0.304)	2,369
Free/Reduced price lunch	0.277 (0.448)	5,369	0.327 (0.469)	3,000	0.214 (0.411)	2,369
English proficient	0.995 (0.073)	5,369	0.995 (0.068)	3,000	0.994 (0.079)	2,369
Gifted and talented	0.227 (0.419)	5,369	0.218 (0.413)	3,000	0.238 (0.426)	2,369
Cost of attendance	24180 (4872)	5,369	24208 (4800)	3,000	24146 (4963)	2,369
ACT score	21.9 (4)	5,369	21.7 (3.9)	3,000	22.1 (4.2)	2,369

Panel B: Select outcomes						
	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Switches major[3]	0.274 (0.446)	4,541	0.283 (0.451)	2,553	0.263 (0.44)	1,988
Switches from STEM to other majors[4]	0.089 (0.284)	4,431	0.088 (0.284)	2,474	0.089 (0.285)	1,957
Cummulative GPA - semester 1	2.771 (0.966)	5,248	2.761 (0.963)	2,928	2.784 (0.969)	2,320
Cummulative GPA - year 1	2.784 (0.873)	4,966	2.78 (0.873)	2,773	2.79 (0.873)	2,193
GPA below 2.0 - year 1	0.156 (0.363)	4,966	0.154 (0.361)	2,773	0.159 (0.365)	2,193
Cummulative loans - year 1[5]	7442 (4651)	3,453	6682 (3729)	1,840	8309 (5389)	1,613
Cummulative loans - year 2[5]	13391 (8630)	2,515	12017 (7274)	1,400	15117 (9812)	1,115
Cummulative loans - year 3[5]	20494 (13672)	1,543	18397 (11583)	844	23026 (15464)	699
Cummulative loans - year 4[5]	26458 (17495)	633	23842 (14729)	348	29652 (19936)	285

Panel C: TEXAS aid package						
	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Receives IY TEXAS grant	0.401 (0.49)	5,369	0.701 (0.458)	3,000	0.021 (0.144)	2,369
IY TEXAS award	5917 (1782)	2,228	5892 (1777)	2,178	6991 (1687)	50
IY Pell award	1704 (623)	3,072	1802 (577)	2,759	841 (221)	313
IY Pell award — receiving TEXAS	1832 (564)	2,150	1849 (558)	2,101	1099 (297)	49
IY Pell award — not receiving TEXAS	1407 (652)	922	1653 (611)	658	793 (164)	264
IY package award	6767 (4017)	4,499	8300 (3759)	2,846	4128 (2931)	1,653
IY package award — receiving TEXAS	9817 (2397)	2,154	9803 (2384)	2,104	10394 (2847)	50
IY package award — not receiving TEXAS	3965 (3048)	2,345	4035 (3675)	742	3933 (2711)	1,603
RY award (2nd year)[6]	0.611 (0.488)	1,111	0.615 (0.487)	1,087	0.417 (0.504)	24
RY award (3nd year)[6]	0.4 (0.49)	665	-		-	
RY award (4nd year)[6]	0.328 (0.47)	256	-		-	

[1] Standard deviation in parenthesis.
[2] Corresponds to a variable indicating if a student is at risk of being a high school dropout.
[3] Corresponds to a variable indicating if a student switches major.
[4] Corresponds to a variable indicating if a student switches away from STEM majors.
[5] Conditional on values greater than zero.
[6] Conditional on IY TEXAS receipt.
[7] Values not presented due to FERPA compliance.

Table A.16: Summary statistics: Other institutions ($1,654 bandwidth)

Panel A: Covariates						
	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Eligible	0.55 (0.498)	5,271	-		-	
Female	0.588 (0.492)	5,271	0.593 (0.491)	2,897	0.581 (0.493)	2,374
Asian	0.031 (0.172)	5,271	0.031 (0.173)	2,897	0.03 (0.172)	2,374
Black	0.155 (0.362)	5,271	0.159 (0.366)	2,897	0.149 (0.356)	2,374
Hispanic	0.411 (0.492)	5,271	0.437 (0.496)	2,897	0.38 (0.485)	2,374
White	0.358 (0.48)	5,271	0.328 (0.469)	2,897	0.396 (0.489)	2,374
Other race/ethnicity	0.046 (0.208)	5,271	0.046 (0.209)	2,897	0.045 (0.208)	2,374
At risk[2]	0.152 (0.359)	5,271	0.151 (0.358)	2,897	0.154 (0.361)	2,374
Free/Reduced price lunch	0.304 (0.46)	5,271	0.352 (0.478)	2,897	0.245 (0.43)	2,374
English proficient	0.994 (0.08)	5,271	0.992 (0.091)	2,897	0.996 (0.065)	2,374
Gifted and talented	0.17 (0.376)	5,271	0.171 (0.377)	2,897	0.168 (0.374)	2,374
Cost of attendance	22366 (4265)	5,271	22313 (4309)	2,897	22431 (4209)	2,374
ACT score	20.3 (3.7)	5,271	20.2 (3.8)	2,897	20.5 (3.7)	2,374

Panel B: Select outcomes						
	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Switches major[3]	0.219 (0.413)	4,981	0.218 (0.413)	2,754	0.22 (0.414)	2,227
STEM to other[4]	0.072 (0.258)	4,334	0.074 (0.262)	2,371	0.069 (0.254)	1,963
Cummulative GPA - semester 1	2.745 (0.971)	5,125	2.726 (0.98)	2,821	2.769 (0.961)	2,304
Cummulative GPA - year 1	2.759 (0.872)	4,811	2.737 (0.882)	2,648	2.786 (0.858)	2,163
GPA below 2.0 - year 1	0.157 (0.364)	4,811	0.164 (0.371)	2,648	0.149 (0.356)	2,163
Cummulative loans - year 1[5]	7734 (4766)	3,523	6980 (3892)	1,809	8531 (5430)	1,714
Cummulative loans - year 2[5]	13854 (8785)	2,703	12154 (7510)	1,442	15799 (9691)	1,261
Cummulative loans - year 3[5]	20523 (13106)	1,706	18132 (11719)	929	23382 (14077)	777
Cummulative loans - year 4[5]	27291 (16864)	796	24538 (15834)	432	30558 (17478)	364

Panel C: TEXAS aid package						
	All students		Below EFC cap		Above EFC cap	
	Mean	Observations	Mean	Observations	Mean	Observations
Receives IY TEXAS grant	0.405 (0.491)	5,271	0.722 (0.448)	2,897	0.019 (0.136)	2,374
IY TEXAS award	5382 (1188)	2,231	5381 (1189)	2,186	5446 (1125)	45
IY Pell award	1689 (617)	3,066	1790 (569)	2,743	834 (207)	323
IY Pell award — receiving TEXAS	1823 (563)	2,124	1838 (557)	2,084	1016 (198)	40
IY Pell award — not receiving TEXAS	1389 (627)	942	1638 (582)	659	808 (195)	283
IY package award	6094 (3779)	4,494	7576 (3543)	2,804	3635 (2731)	1,690
IY package award — receiving TEXAS	8862 (2342)	2,137	8890 (2343)	2,092	7595 (1898)	45
IY package award — not receiving TEXAS	3584 (3002)	2,357	3718 (3655)	712	3526 (2670)	1,645
RY award (2nd year)[6]	0.653 (0.476)	1,192	0.651 (0.477)	1,176	0.75 (0.447)	16
RY award (3nd year)[6]	0.424 (0.494)	734	-		-	
RY award (4nd year)[6]	0.398 (0.49)	332	-		-	

[1] Standard deviation in parenthesis.
[2] Corresponds to a variable indicating if a student is at risk of being a high school dropout.
[3] Corresponds to a variable indicating if a student switches major.
[4] Corresponds to a variable indicating if a student switches away from STEM majors.
[5] Conditional on values greater than zero.
[6] Conditional on IY TEXAS receipt.
[7] Values not presented due to FERPA compliance.

Table A.17: Effects of eligibility on control variables (local randomization assumption)

	All	Emerging research	Flagship	Other
Female	0.024	0.002	0.002	0.051*
	(0.019)	(0.025)	(0.026)	(0.026)
Asian	-0.001	-0.004	-0.024	-0.002
	(0.011)	(0.020)	(0.020)	(0.011)
Black	0.000	-0.004	-0.000	0.004
	(0.013)	(0.017)	(0.015)	(0.019)
White	0.022	0.032	-0.024	0.013
	(0.020)	(0.031)	(0.027)	(0.030)
Hispanic	-0.023	-0.029	0.023	-0.017
	(0.020)	(0.029)	(0.030)	(0.028)
At risk	-0.023*	-0.001	0.005	-0.040**
	(0.012)	(0.016)	(0.010)	(0.020)
Free/reduced price lunch	0.023	0.038	0.007	0.028
	(0.018)	(0.024)	(0.020)	(0.025)
English proficient	0.002	0.006	0.001	-0.002
	(0.002)	(0.004)	(0.002)	(0.004)
Gifted and talented	-0.022	-0.042*	-0.014	-0.005
	(0.017)	(0.022)	(0.028)	(0.025)
ACT	0.224	0.243	-0.090	0.110
	(0.175)	(0.201)	(0.245)	(0.220)
Cost of attendance	148.706	130.218	-193.485	-22.304
	(189.545)	(294.398)	(205.638)	(243.945)
χ^2	14.61	17.77	12.81	12.65
p-value	0.201	0.0870	0.306	0.317
Observations	11,424	5,369	5,296	5,271

[1] Standard errors in parentheses are clustered at values of EFC. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A.18: Effects of eligibility on other forms of aid (exclusion assumption)

	All	Flagship	Emerging research	Other
Pell Grant (receipt)	0.176***	0.367***	0.237***	0.186***
	(0.026)	(0.034)	(0.034)	(0.037)
Pell Grant	179***	418***	216***	225***
	(27)	(37)	(38)	(39)
Other federal/state (receipt)	0.045	0.075	0.001	0.058
	(0.029)	(0.049)	(0.043)	(0.043)
Other federal/state	-223	67	-147	-473
	(164)	(321)	(203)	(412)
Institutional aid (receipt)	0.021	-0.030	0.045	0.035
	(0.022)	(0.033)	(0.030)	(0.034)
Institutional aid	15	-236	101	128
	(119)	(152)	(202)	(170)
Observations	10,685	4,994	4,984	5,290

[1] Standard errors in parentheses are clustered at values of EFC. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

[2] Other forms of aid includes work-study, Federal Supplemental Educational Opportunity Grant (FSEOG), Texas Public Educational Grant (TPEG) , Tuition Equalization Grant Program (TEG), appropriations from HB 3015, merit aid, The top 10% scholarship, and other smaller programs.

Table A.19: Manipulation tests on EFC (non-manipulability)

	All		Flagship		Emerging research		Other	
	McCrary	CJM	McCrary	CJM	McCrary	CJM	McCrary	CJM
t-statistic	-0.154	-0.054	-0.981	-1.522	0.187	0.035	-0.832	-0.626
p-value	0.878	0.957	0.326	0.128	0.852	0.972	0.406	0.531
Bandwidth	1,428		3,130		1,668		1,654	
Observations	11,424		5,296		5,369		5,271	

[1] The tests correspond to those proposed by McCrary (2008) and Cattaneo et al. (2019) which test the null hypothesis of continuity at the cut-off.

Table A.20: Other outcomes: All institutions

	LATE		ITT	
Business (I)	-0.014	-0.039	-0.008	-0.018
[0.095]	(0.019)	(0.035)	(0.011)	(0.017)
STEM (I)	0.053*	0.054	0.03*	0.026
[0.279]	(0.031)	(0.054)	(0.017)	(0.025)
Liberal Arts (I)	-0.005	0.009	-0.003	0.004
[0.18]	(0.027)	(0.049)	(0.015)	(0.023)
STEM (F)	0.025	-0.004	0.014	-0.002
[0.241]	(0.029)	(0.053)	(0.017)	(0.025)
Business (F)	-0.01	-0.01	-0.006	-0.005
[0.121]	(0.022)	(0.04)	(0.013)	(0.019)
Liberal Arts (F)	-0.006	0.028	-0.003	0.013
[0.188]	(0.027)	(0.051)	(0.016)	(0.024)
Transfer	-0.012	0.03	-0.007	0.014
[0.08]	(0.018)	(0.032)	(0.01)	(0.015)
Continuous enrollment - next year	0.011	-0.023	0.006	-0.01
[0.923]	(0.021)	(0.04)	(0.012)	(0.018)
Continuous enrollment - next 2 years	0.047	0.02	0.026	0.009
[0.764]	(0.046)	(0.087)	(0.026)	(0.038)
Graduation (4 year)	0.089	-0.079	0.052	-0.038
[0.322]	(0.067)	(0.115)	(0.04)	(0.056)
Worker	-0.005	0.033	-0.003	0.016
[0.341]	(0.031)	(0.055)	(0.018)	(0.026)
Cum GPA - year 2	0.001	-0.023	0.001	-0.012
[2.981]	(0.05)	(0.085)	(0.031)	(0.045)
Cum GPA - year 3	0.024	-0.01	0.015	-0.005
[3.016]	(0.063)	(0.106)	(0.039)	(0.055)
Cum GPA - year 4	-0.154	-0.152	-0.1	-0.081
[3.029]	(0.094)	(0.167)	(0.061)	(0.09)
Credit hours attempted - year 1	0.397	0.158	0.236	0.08
[27]	(0.321)	(0.543)	(0.192)	(0.274)
Credit hours attempted - year 2	0.197	-0.039	0.123	-0.02
[56]	(0.7)	(1.229)	(0.437)	(0.642)
Credit hours attempted - year 3	0.566	-0.722	0.35	-0.373
[85]	(1.211)	(2.159)	(0.748)	(1.114)
Credit hours attempted - year 4	0.177	3.272	0.115	1.749
[111]	(2.19)	(4.242)	(1.421)	(2.267)
Covariates	No	Yes	No	Yes

[1] Standard errors in parentheses are clustered at values of EFC. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[2] Counterfactual mean in square brackets.
[3] The set of covariates includes gender, race/ethnicity, at risk of dropping out from high school, free/reduced price lunch, English proficiency, gifted and talented status, ACT scores, and cost of attendance.
[4] Optimal bandwidths is $1,428 dollars.

Table A.21: Other outcomes: Flagship institutions

	LATE		ITT	
Business (I)	-0.055**	-0.114***	-0.036**	-0.074***
[0.095]	(0.025)	(0.037)	(0.016)	(0.024)
STEM (I)	-0.016	0.131**	-0.01	0.085**
[0.462]	(0.044)	(0.064)	(0.029)	(0.041)
Liberal Arts (I)	0.095***	0.1*	0.062***	0.065*
[0.198]	(0.036)	(0.054)	(0.023)	(0.035)
STEM (F)	-0.052	0.05	-0.034	0.032
[0.367]	(0.042)	(0.061)	(0.027)	(0.04)
Business (F)	-0.03	-0.107***	-0.019	-0.07***
[0.113]	(0.027)	(0.041)	(0.018)	(0.026)
Liberal Arts (F)	0.01	0.012	0.006	0.008
[0.173]	(0.034)	(0.051)	(0.023)	(0.033)
Transfer	0.022	-0.001	0.015	-0.001
[0.043]	(0.018)	(0.027)	(0.012)	(0.017)
Continuous enrollment - next year	0.004	0.04	0.003	0.028
[0.954]	(0.02)	(0.031)	(0.015)	(0.022)
Continuous enrollment - next 2 years	0.022	0.083	0.015	0.055
[0.826]	(0.051)	(0.079)	(0.035)	(0.053)
Graduation (4 year)	-0.004	-0.01	-0.003	-0.008
[0.55]	(0.075)	(0.102)	(0.056)	(0.084)
Worker	-0.021	-0.054	-0.014	-0.035
[0.214]	(0.036)	(0.054)	(0.023)	(0.035)
Cum GPA - year 2	0.002	-0.053	0.002	-0.04
[3.148]	(0.048)	(0.068)	(0.036)	(0.051)
Cum GPA - year 3	-0.013	0.073	-0.009	0.053
[3.189]	(0.057)	(0.082)	(0.042)	(0.06)
Cum GPA - year 4	-0.099	0.005	-0.077	0.004
[3.147]	(0.083)	(0.115)	(0.065)	(0.099)
Credit hours attempted - year 1	0.062	-0.029	0.042	-0.019
[26]	(0.517)	(0.747)	(0.348)	(0.496)
Credit hours attempted - year 2	-1.158	-0.939	-0.872	-0.701
[54]	(0.927)	(1.335)	(0.697)	(0.995)
Credit hours attempted - year 3	-0.896	0.297	-0.663	0.218
[82]	(1.279)	(1.851)	(0.944)	(1.357)
Credit hours attempted - year 4	0.896	2.09	0.701	1.797
[107]	(2.104)	(2.809)	(1.648)	(2.422)
Covariates	No	Yes	No	Yes

[1] Standard errors in parentheses are clustered at values of EFC. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
[2] Counterfactual mean in square brackets.
[3] The set of covariates includes gender, race/ethnicity, at risk of dropping out from high school, free/reduced price lunch, English proficiency, gifted and talented status, ACT scores, and cost of attendance.
[4] Optimal bandwidths $3,130 dollars.

Table A.22: Other outcomes: Emerging research institutions

	LATE		ITT	
Business (I)	0.037	-0.034	0.021	-0.015
[0.086]	(0.027)	(0.052)	(0.016)	(0.023)
STEM (I)	0.089**	0.06	0.05**	0.027
[0.248]	(0.042)	(0.078)	(0.024)	(0.035)
Liberal Arts (I)	-0.085**	-0.162**	-0.049**	-0.073**
[0.171]	(0.039)	(0.077)	(0.022)	(0.034)
STEM (F)	0.049	-0.066	0.028	-0.03
[0.217]	(0.04)	(0.077)	(0.023)	(0.035)
Business (F)	0.044	0.048	0.025	0.022
[0.123]	(0.032)	(0.062)	(0.018)	(0.028)
Liberal Arts (F)	-0.048	0.024	-0.027	0.011
[0.177]	(0.039)	(0.075)	(0.022)	(0.034)
Transfer	-0.008	-0.012	-0.004	-0.005
[0.088]	(0.026)	(0.049)	(0.015)	(0.022)
Continuous enrollment - next year	-0.065**	-0.063	-0.037**	-0.027
[0.931]	(0.031)	(0.062)	(0.017)	(0.026)
Continuous enrollment - next 2 years	-0.042	-0.045	-0.023	-0.019
[0.754]	(0.069)	(0.137)	(0.038)	(0.058)
Graduation (4 year)	0.095	0.078	0.048	0.029
[0.235]	(0.108)	(0.221)	(0.055)	(0.083)
Worker	0.009	0.046	0.005	0.021
[0.379]	(0.048)	(0.091)	(0.027)	(0.041)
Cum GPA - year 2	0.044	-0.002	0.026	-0.001
[2.931]	(0.08)	(0.149)	(0.048)	(0.071)
Cum GPA - year 3	0.172*	0.092	0.103*	0.045
[2.946]	(0.098)	(0.175)	(0.058)	(0.084)
Cum GPA - year 4	-0.181	-0.257	-0.111	-0.133
[2.937]	(0.16)	(0.276)	(0.099)	(0.147)
Credit hours attempted - year 1	-0.19	-0.726	-0.114	-0.35
[28]	(0.426)	(0.734)	(0.255)	(0.349)
Credit hours attempted - year 2	-1.021	-1.561	-0.616	-0.749
[56]	(1.003)	(1.847)	(0.6)	(0.871)
Credit hours attempted - year 3	0.31	-2.238	0.186	-1.08
[85]	(2.019)	(3.818)	(1.211)	(1.829)
Credit hours attempted - year 4	-4.514	-4.637	-2.77	-2.4
[112]	(3.822)	(6.95)	(2.333)	(3.545)
Covariates	No	Yes	No	Yes

[1] Standard errors in parentheses are clustered at values of EFC. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[2] Counterfactual mean in square brackets.
[3] The set of covariates includes gender, race/ethnicity, at risk of dropping out from high school, free/reduced price lunch, English proficiency, gifted and talented status, ACT scores, and cost of attendance.
[4] Optimal bandwidths is $1,668 dollars.

Table A.23: Other outcomes: Other institutions

	LATE		ITT	
Business (I)	0.028	-0.008	0.016	-0.004
[0.106]	(0.031)	(0.059)	(0.017)	(0.027)
STEM (I)	-0.006	-0.051	-0.004	-0.023
[0.23]	(0.045)	(0.083)	(0.025)	(0.039)
Liberal Arts (I)	-0.006	0.052	-0.003	0.024
[0.168]	(0.038)	(0.071)	(0.021)	(0.033)
STEM (F)	0.008	0.021	0.004	0.01
[0.204]	(0.042)	(0.078)	(0.024)	(0.036)
Business (F)	0.029	-0.037	0.016	-0.017
[0.135]	(0.034)	(0.066)	(0.019)	(0.03)
Liberal Arts (F)	-0.04	-0.006	-0.023	-0.003
[0.191]	(0.039)	(0.073)	(0.022)	(0.034)
Transfer	-0.027	0.054	-0.015	0.025
[0.094]	(0.029)	(0.053)	(0.017)	(0.025)
Continuous enrollment - next year	0.051	0.039	0.029	0.016
[0.898]	(0.037)	(0.075)	(0.021)	(0.031)
Continuous enrollment - next 2 years	0.097	0.011	0.055	0.005
[0.736]	(0.067)	(0.142)	(0.038)	(0.056)
Graduation (4 year)	0.127	0	0.069	0
[0.268]	(0.098)	(0.166)	(0.054)	(0.081)
Worker	0.013	-0.005	0.007	-0.002
[0.368]	(0.048)	(0.088)	(0.027)	(0.041)
Cum GPA - year 2	0.004	-0.004	0.002	-0.002
[2.931]	(0.083)	(0.144)	(0.051)	(0.072)
Cum GPA - year 3	-0.079	-0.134	-0.049	-0.065
[2.97]	(0.108)	(0.193)	(0.066)	(0.093)
Cum GPA - year 4	-0.138	-0.525*	-0.084	-0.259*
[2.983]	(0.166)	(0.318)	(0.1)	(0.147)
Credit hours attempted - year 1	1.161***	1.897**	0.695***	0.945**
[28]	(0.442)	(0.754)	(0.265)	(0.373)
Credit hours attempted - year 2	3.096***	4.941***	1.901***	2.481***
[56]	(1.02)	(1.865)	(0.622)	(0.919)
Credit hours attempted - year 3	3.829**	3.073	2.353**	1.495
[86]	(1.925)	(3.66)	(1.183)	(1.788)
Credit hours attempted - year 4	4.67	-1.29	2.837	-0.637
[114]	(3.829)	(7.526)	(2.321)	(3.714)
Covariates	No	Yes	No	Yes

[1] Standard errors in parentheses are clustered at values of EFC. * p <0.1, ** p <0.05, *** p <0.01.
[2] Counterfactual mean in square brackets.
[3] The set of covariates includes gender, race/ethnicity, at risk of dropping out from high school, free/reduced price lunch, English proficiency, gifted and talented status, ACT scores, and cost of attendance.
[4] Optimal bandwidths is $1,654 dollars.

APPENDIX B

ADDITIONAL FIGURES

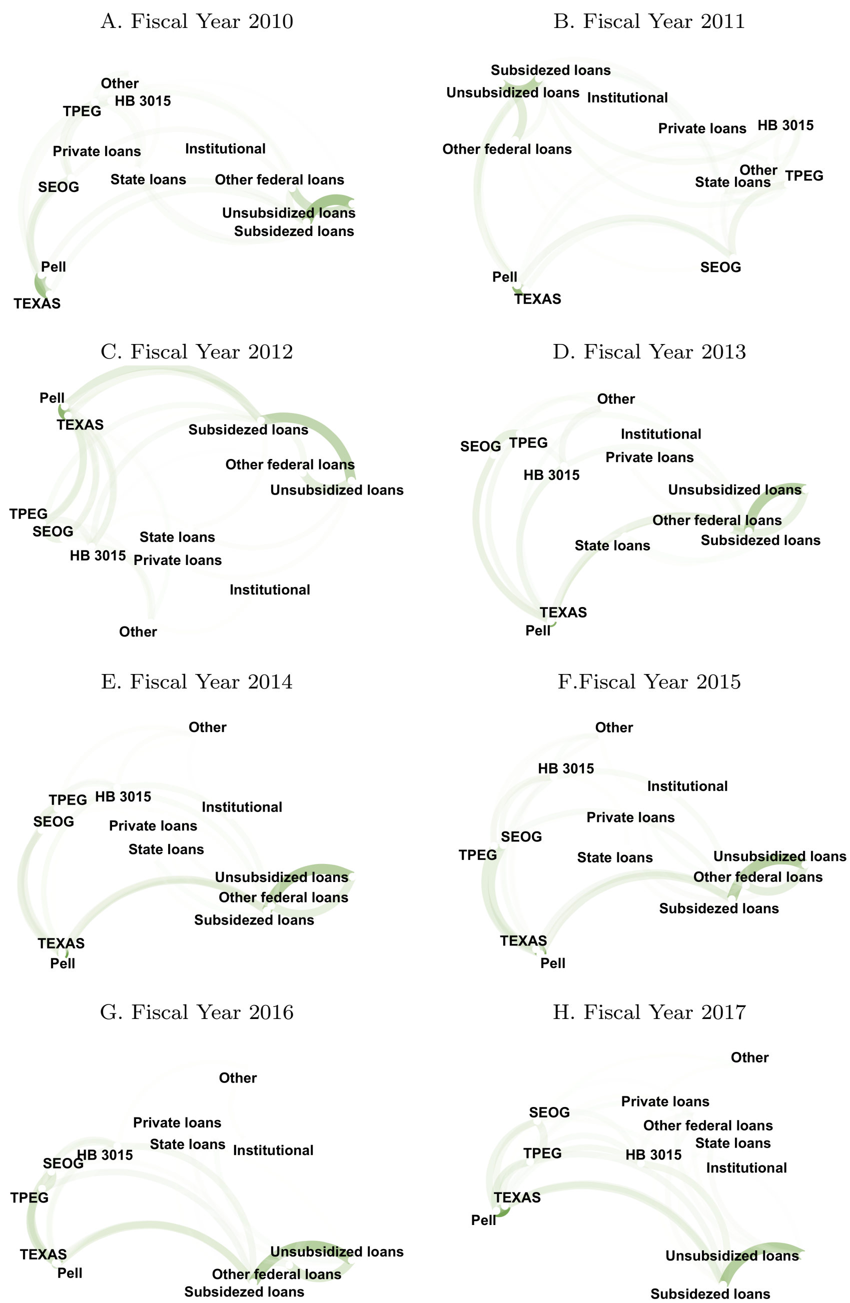


Figure B.1: Network plots for Spearman's correlation in financial aid programs

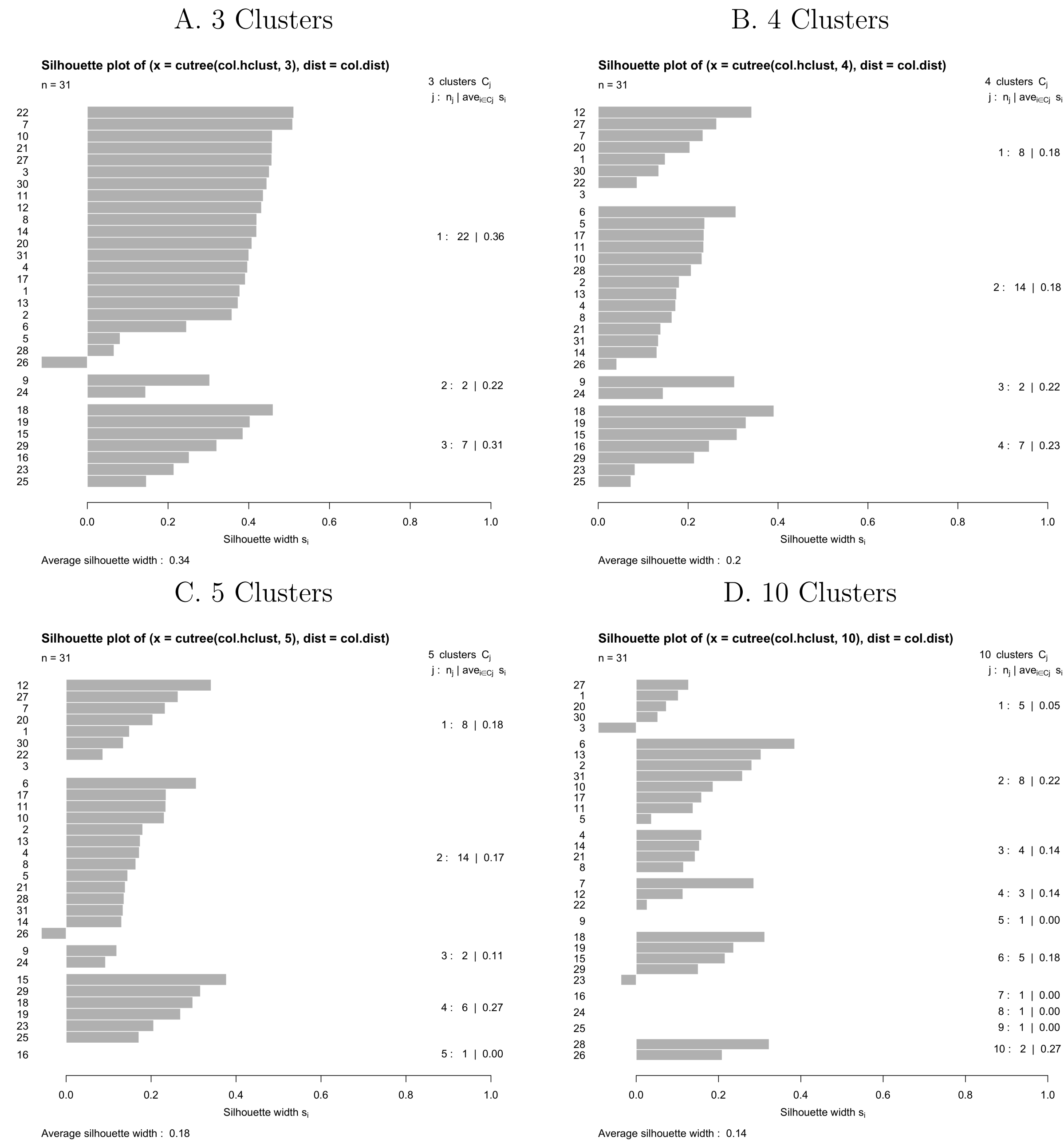


Figure B.2: Silhouette figures at different cluster levels

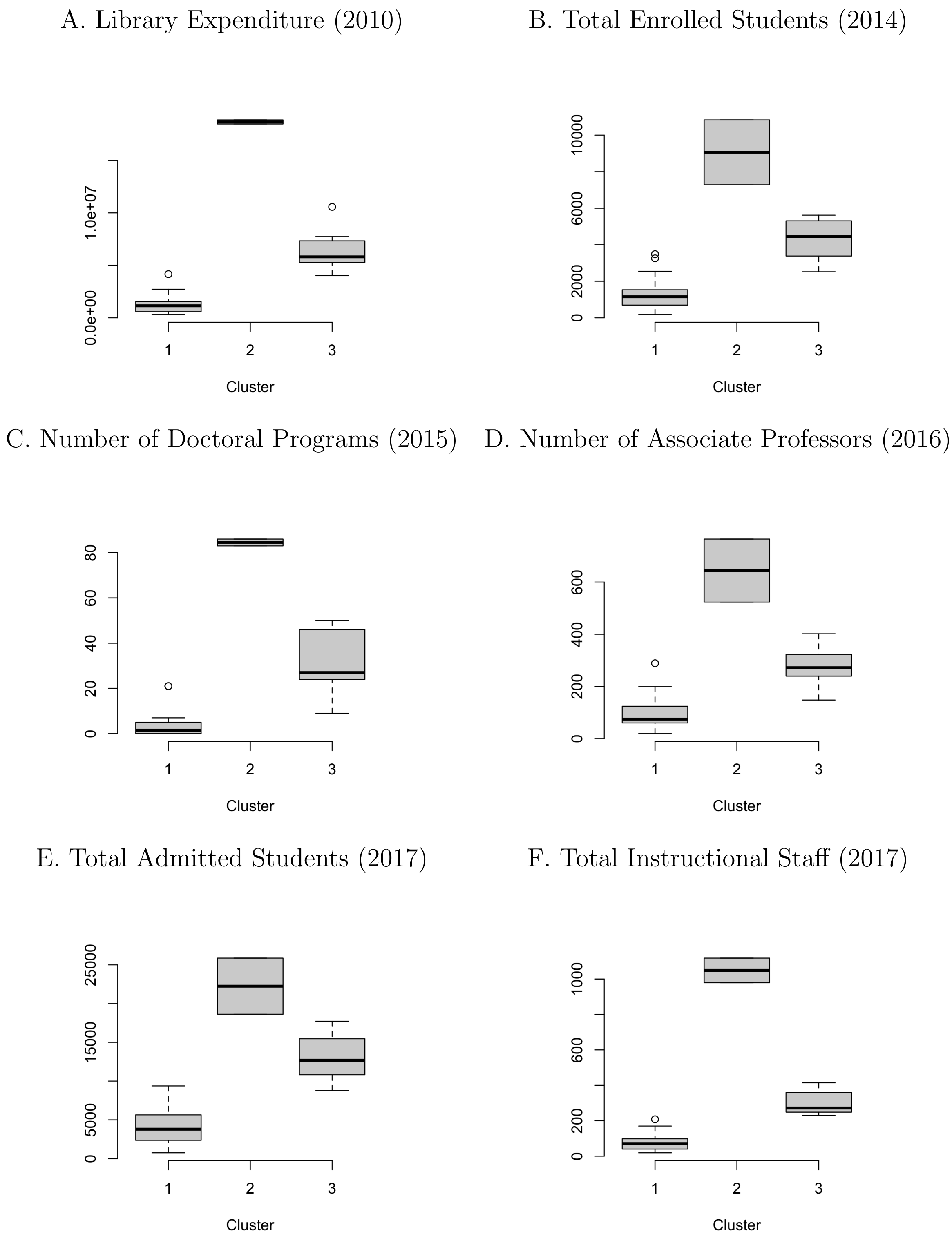


Figure B.3: Boxplots for select features: 3 clusters

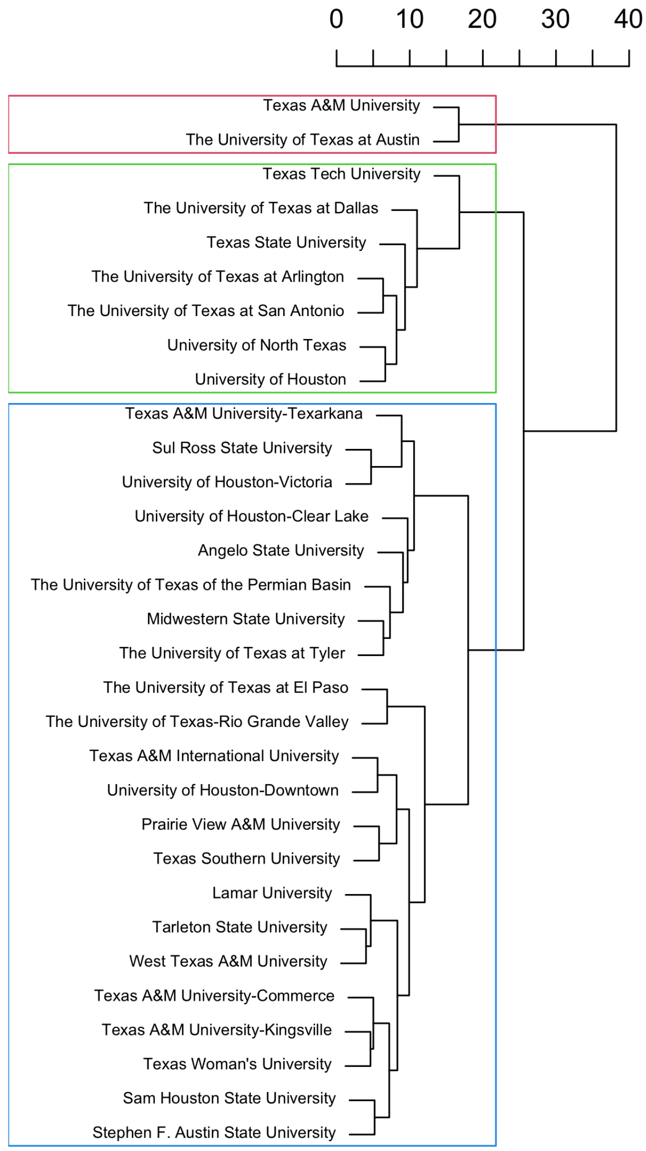
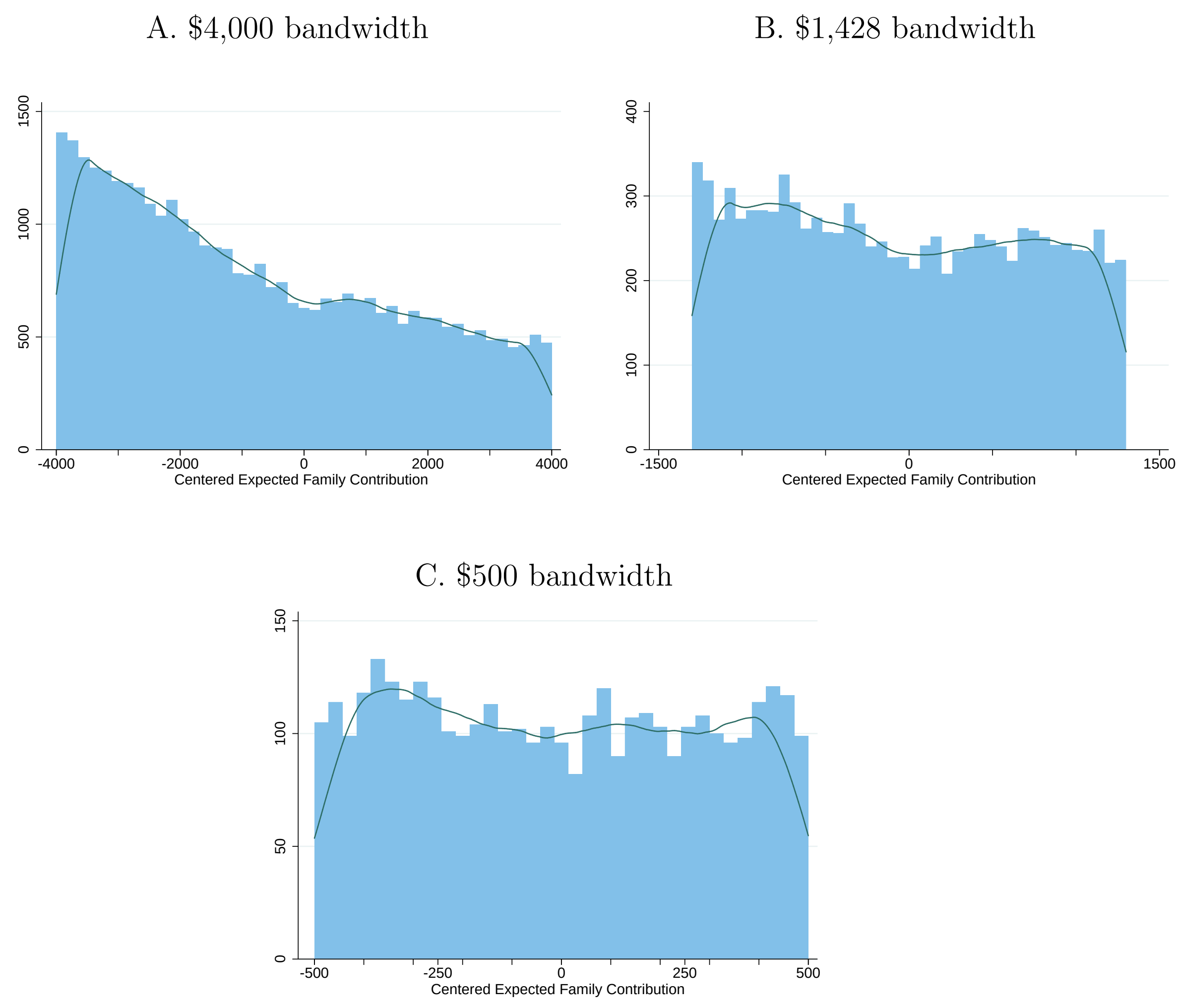


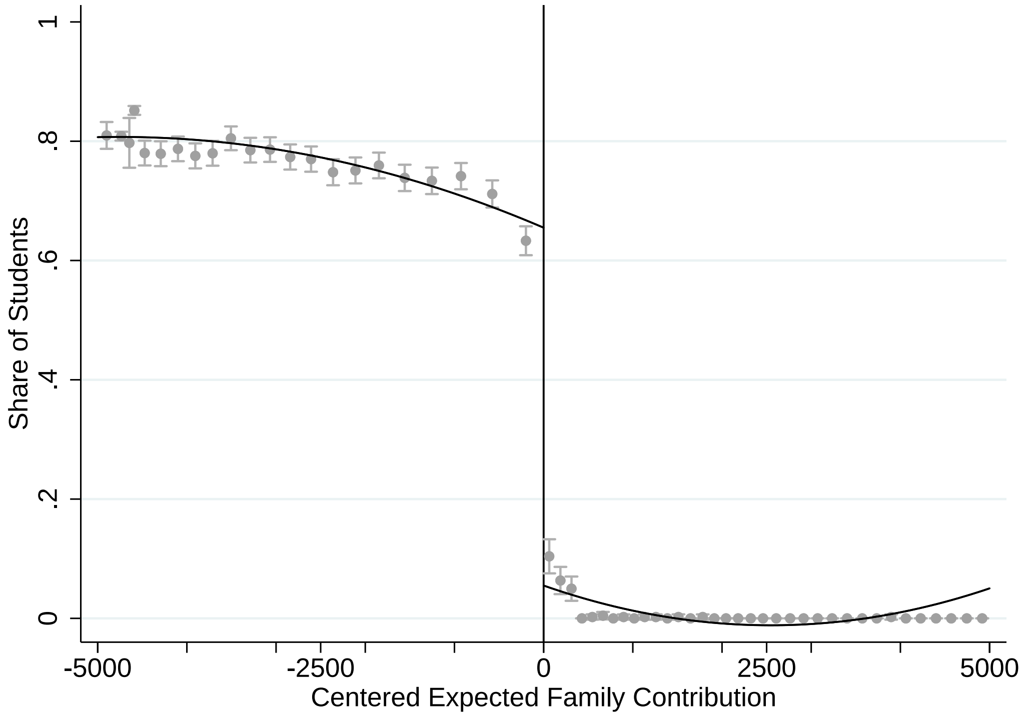
Figure B.4: Dendrogram for Texas public universities: 3 clusters



[1] Centered Expected Family Contribution (EFC) corresponds to the value of students' EFC minus the EFC threshold.

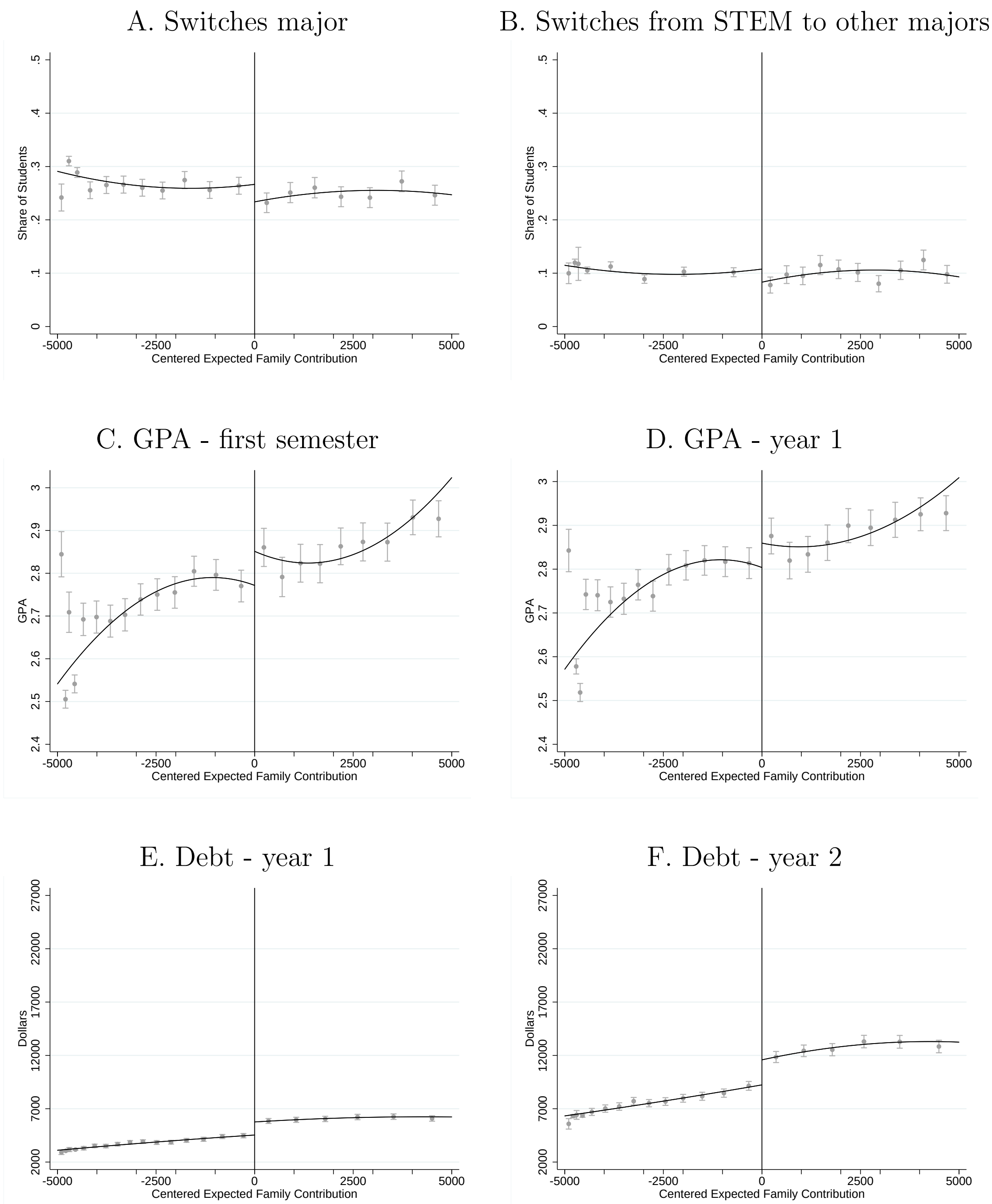
[2] Annual thresholds are: $4,000 for 2013, $4,620 for 2014, $4,800 for 2015, and $5,088 for 2016.

Figure B.5: Number of students by distance to the eligibility EFC threshold: All institutions



[1] Centered Expected Family Contribution (EFC) corresponds to the value of students' EFC minus the EFC threshold.
[2] Annual thresholds are: \$4,000 for 2013, \$4,620 for 2014, \$4,800 for 2015, and \$5,088 for 2016.

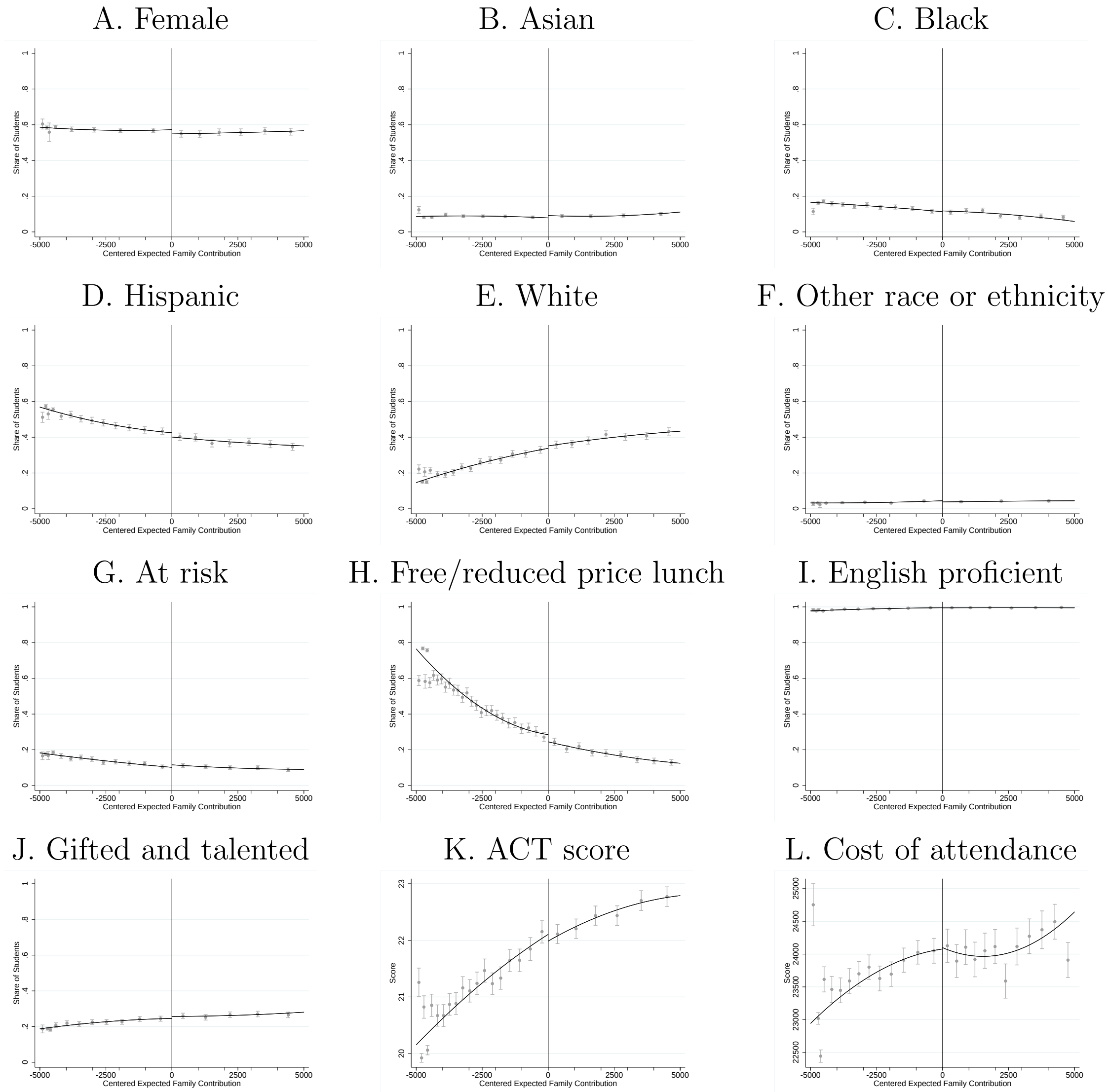
Figure B.6: TEXAS package receipt by distance to the eligibility EFC threshold



[1] Centered Expected Family Contribution (EFC) corresponds to the value of students' EFC minus the EFC threshold.

[2] Annual thresholds are: \$4,000 for 2013, \$4,620 for 2014, \$4,800 for 2015, and \$5,088 for 2016.

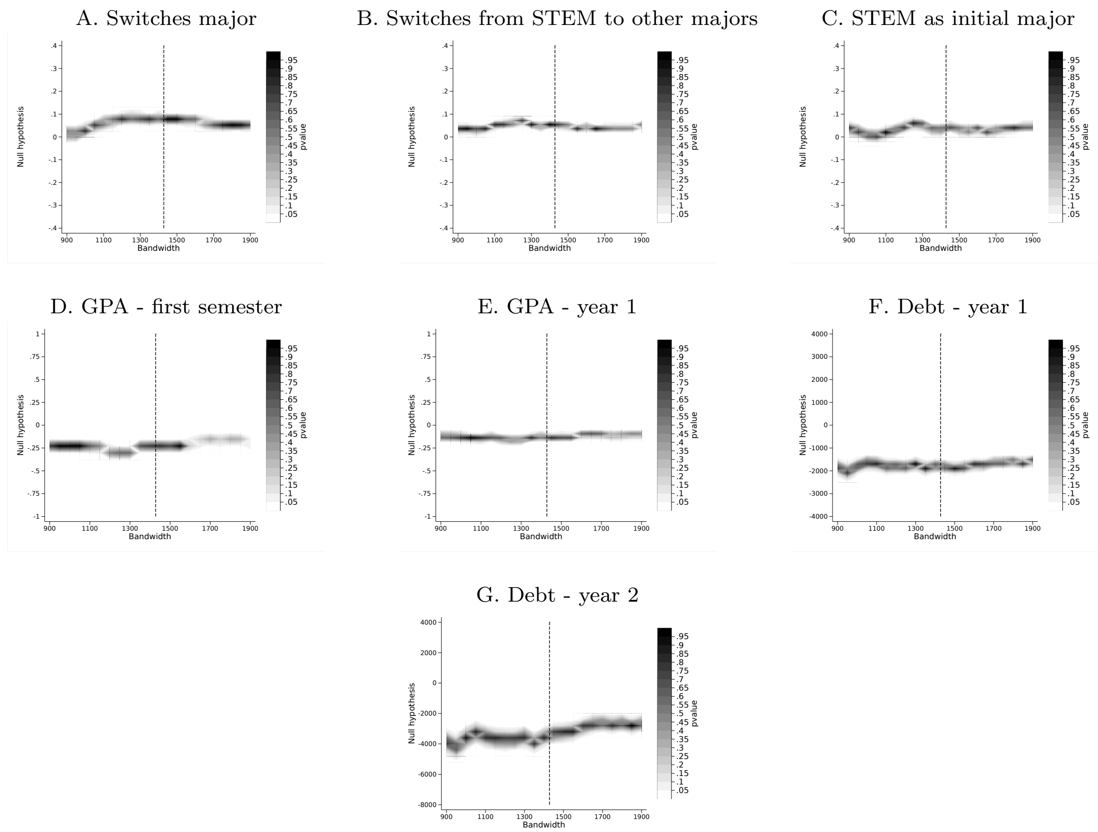
Figure B.7: Academic and financial outcomes by distance to the eligibility EFC threshold



[1] Centered Expected Family Contribution (EFC) corresponds to the value of students' EFC minus the EFC threshold.

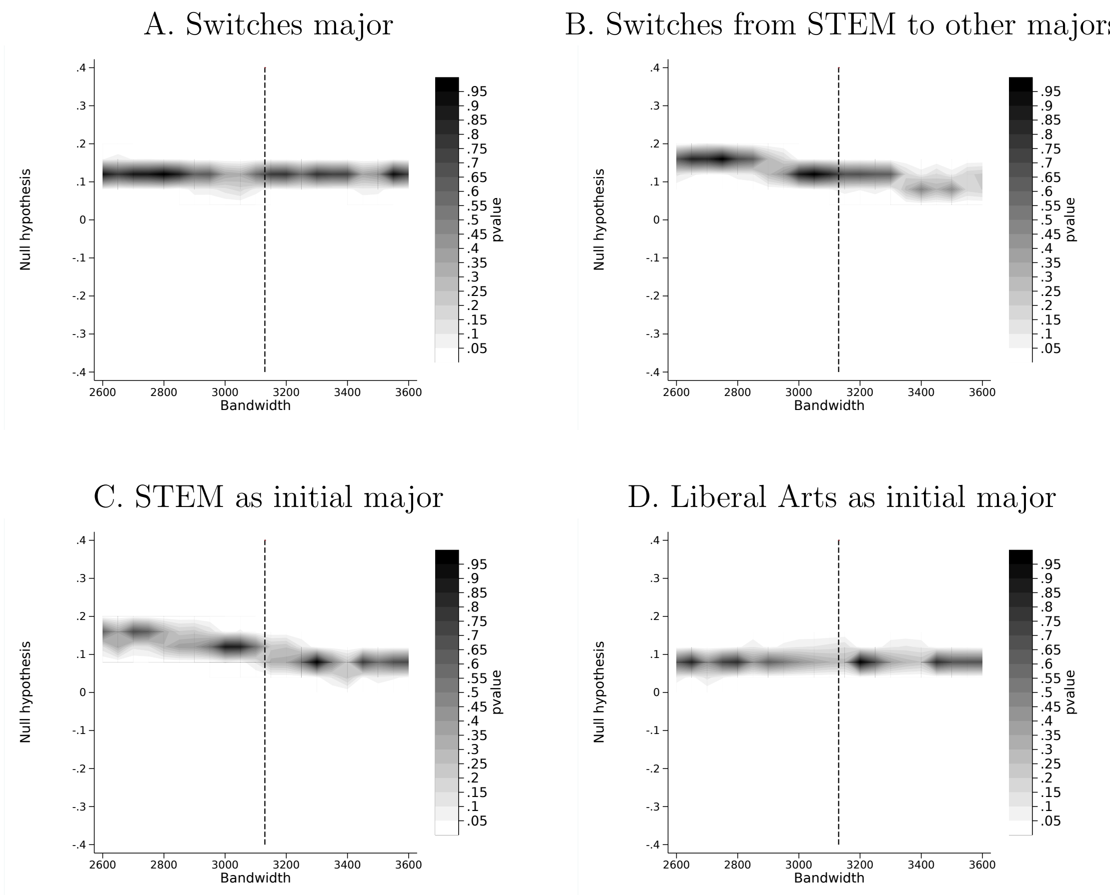
[2] Annual thresholds are: \$4,000 for 2013, \$4,620 for 2014, \$4,800 for 2015, and \$5,088 for 2016.

Figure B.8: Covariates by distance to the eligibility EFC threshold: All institutions



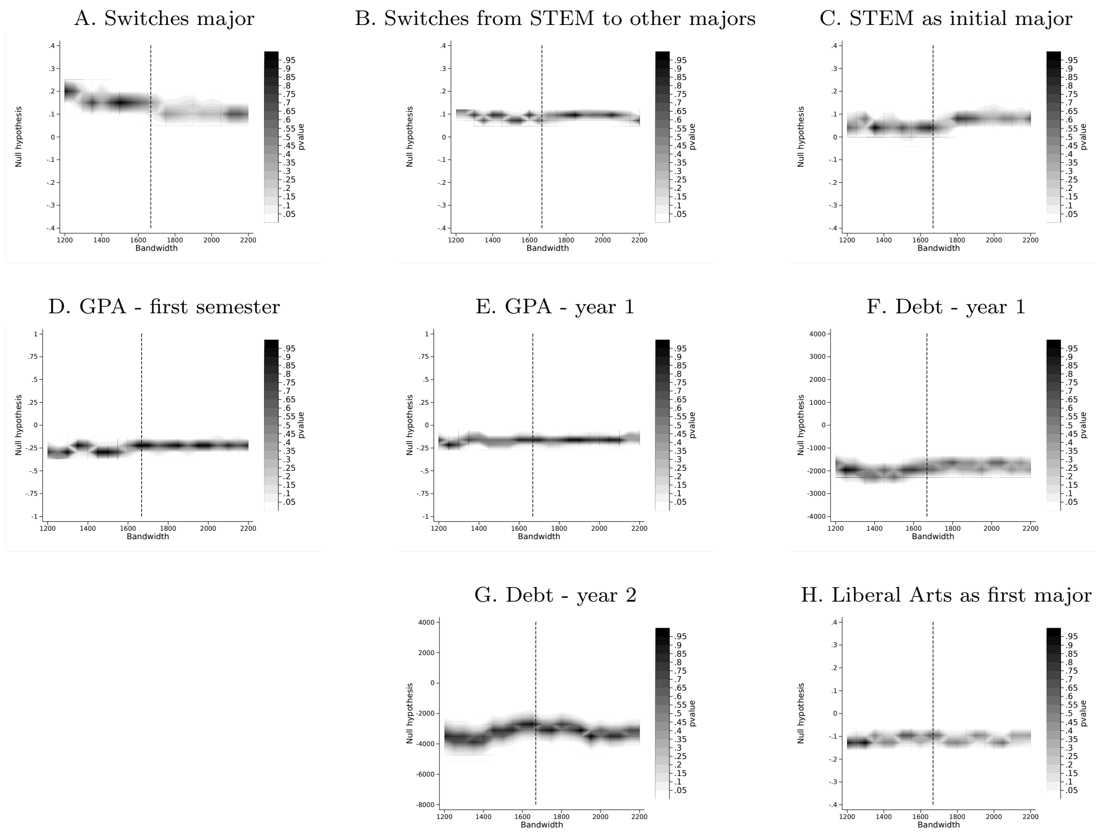
[1] Sensitivity to window length using constant additive treatment effect model.
[2] Randomized p-values are obtained using 1,000 permutations.
[3] Dashed line represents selected bandwidth.

Figure B.9: Sensitivity to bandwidth selection for select outcomes: All institutions



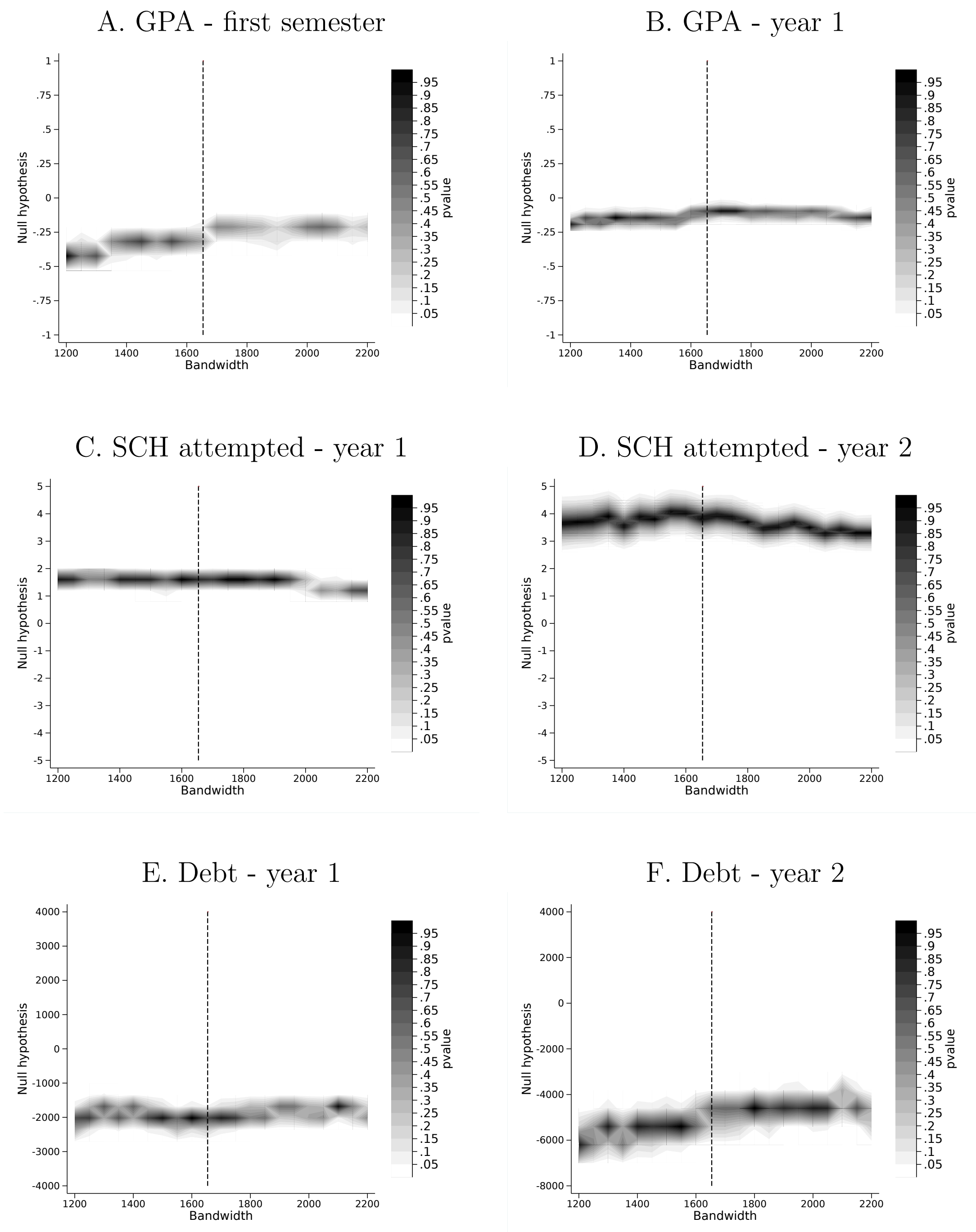
[1] Sensitivity to window length using constant additive treatment effect model.
[2] Randomized p-values are obtained using 1,000 permutations.
[3] Dashed line represents selected bandwidth.

Figure B.10: Sensitivity to bandwidth selection for select outcomes: Flagship institutions



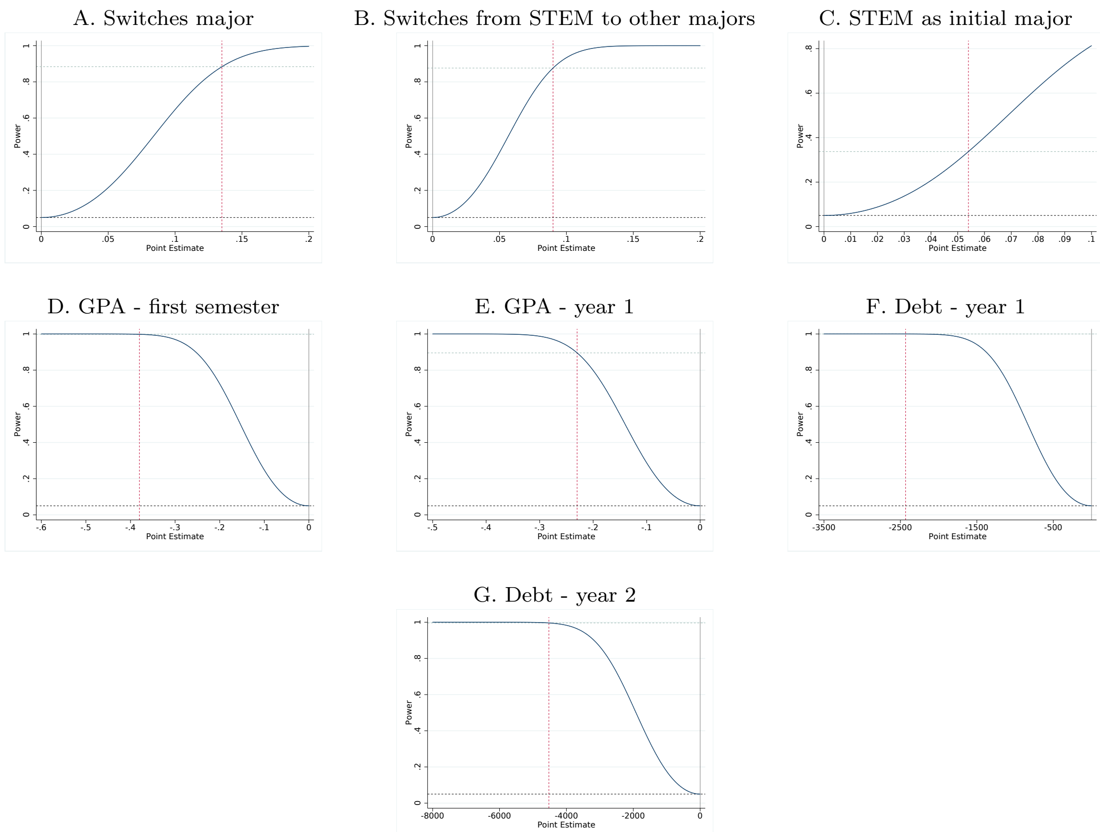
[1] Sensitivity to window length using constant additive treatment effect model.
[2] Randomized p-values are obtained using 1,000 permutations.
[3] Dashed line represents selected bandwidth.

Figure B.11: Sensitivity to bandwidth selection for select outcomes: Emerging research institutions



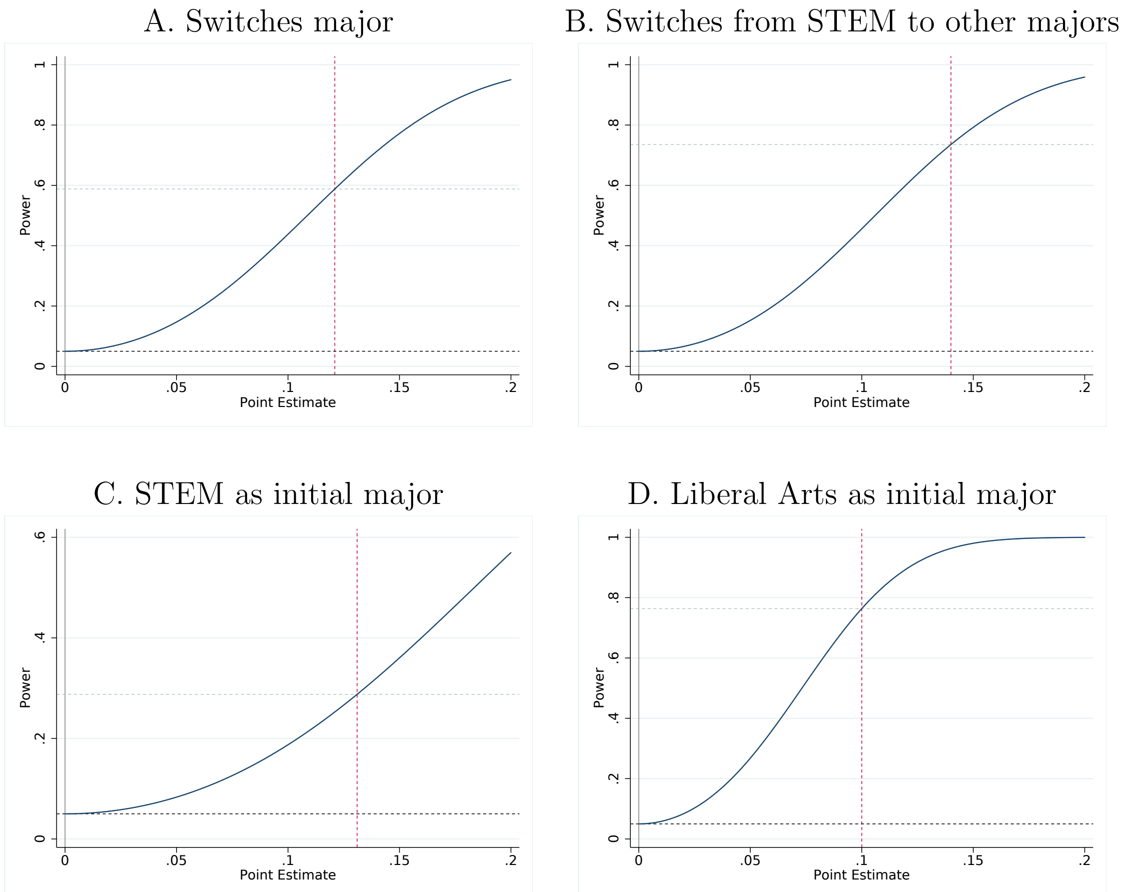
[1] Sensitivity to window length using constant additive treatment effect model.
[2] Randomized p-values are obtained using 1,000 permutations.
[3] Dashed line represents selected bandwidth.

Figure B.12: Sensitivity to bandwidth selection for select outcomes: Other institutions



[1] Estimated statistical power of point estimates.
[2] Dashed vertical line denotes the point estimate for the LATE and horizontal line depicts its power.

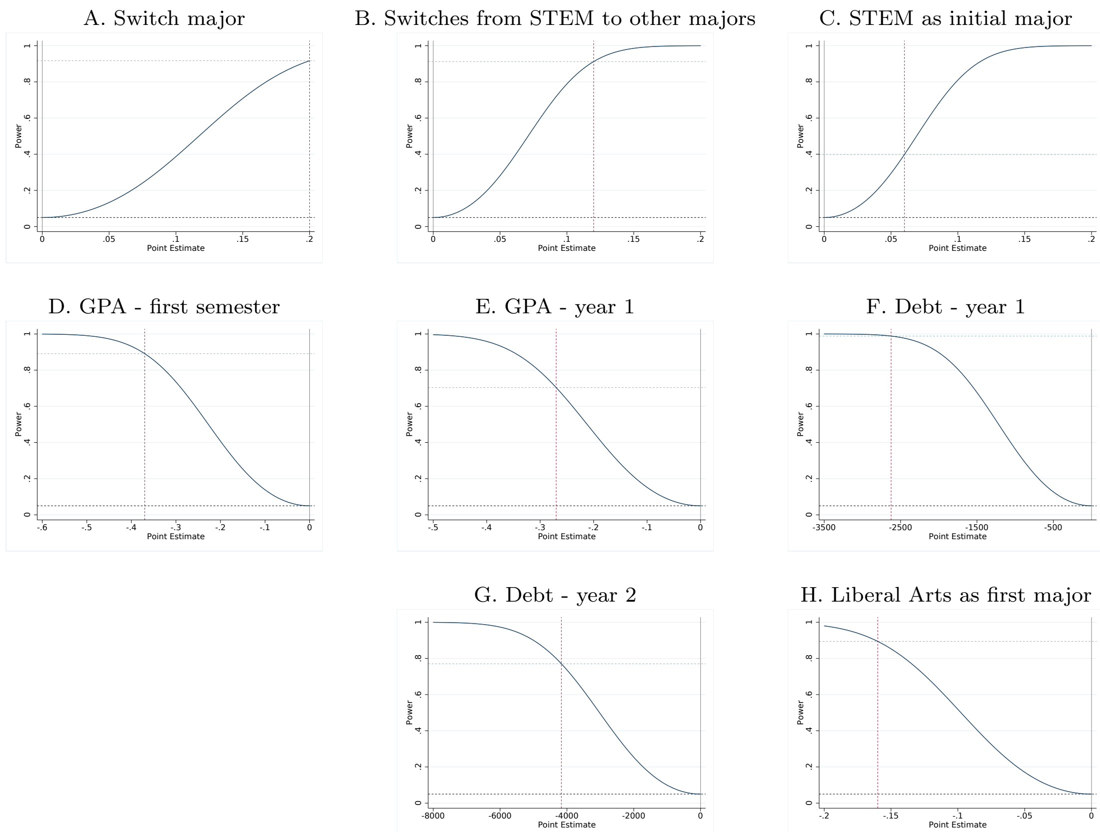
Figure B.13: Power test for select outcomes: All institutions



[1] Estimated statistical power of point estimates.

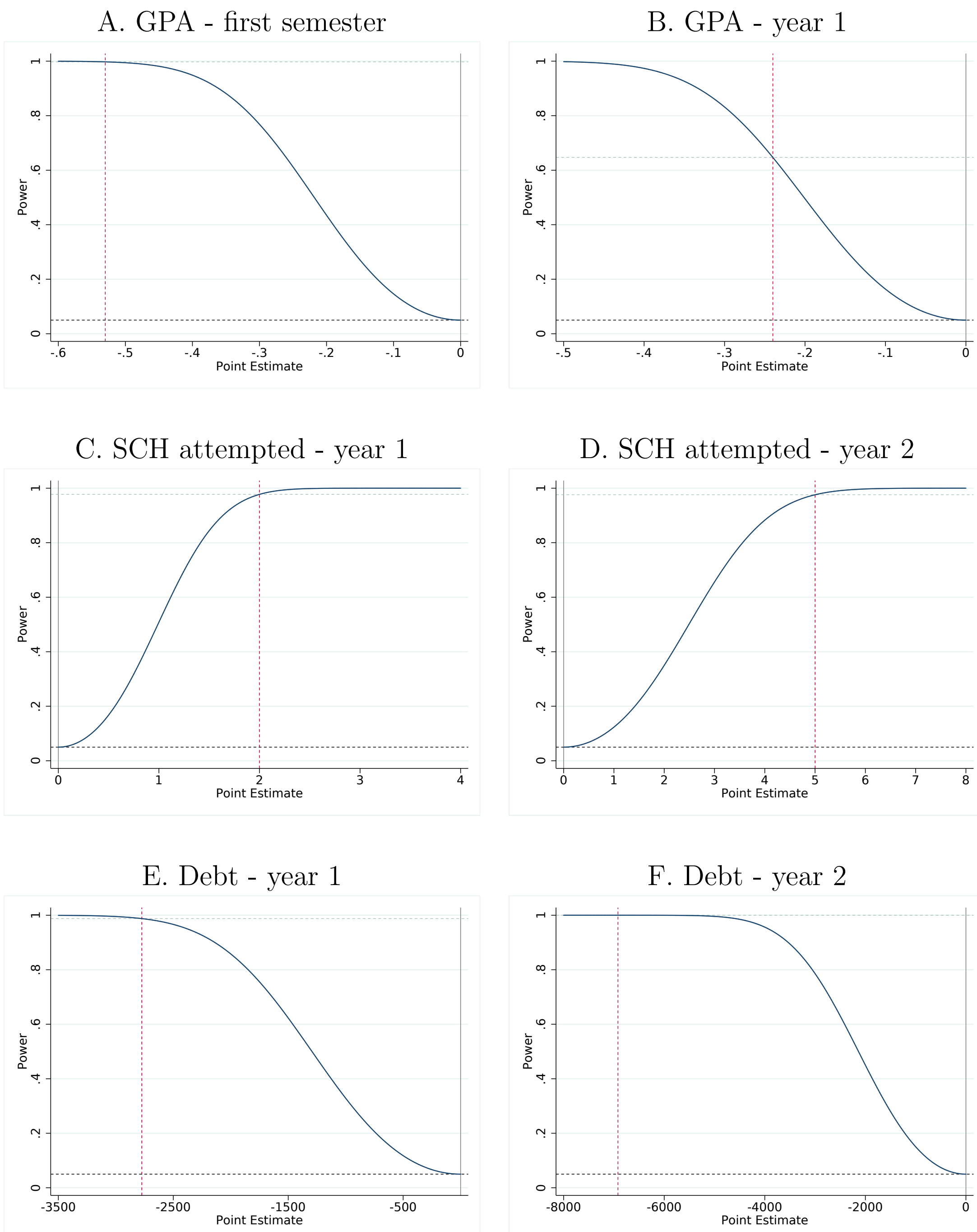
[2] Dashed vertical line denotes the point estimate for the LATE and horizontal line depicts its power.

Figure B.14: Power test for select outcomes: Flagship institutions



[1] Estimated statistical power of point estimates.
[2] Dashed vertical line denotes the point estimate for the LATE and horizontal line depicts its power.

Figure B.15: Power test for select outcomes: Flagship institutions



[1] Estimated statistical power of point estimates.
[2] Dashed vertical line denotes the point estimate for the LATE and horizontal line depicts its power.

Figure B.16: Power test for select outcomes: Other institutions

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BIOGRAPHICAL SKETCH

Sebastian Montenegro was born in Quito, Ecuador and raised in Cali, Colombia. In 2009 began his postsecondary education at ICESI University in Cali, Colombia. He joined the Master in Economics' fast-track program at the same institution and earned his BS in Economics and International Business in December 2013 and his MS in Economics in February 2015. In August 2016 he moved to Dallas, Texas to join the Doctoral program in Economics at The University of Texas at Dallas, where he earned a MS in Economics in 2018 and a PhD in Economics in 2020.

After completing his PhD, Dr. Montenegro joined the Fair Lending Analytics team at Citibank in Tampa, Florida. He remains engaged with the academic community: he participates in academic seminars and meetings and actively mentors prospective college freshman students.

CURRICULUM VITAE

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Educational History:

BS, Economics and International Business, ICESI University, 2013
MS, Economics, ICESI University, 2015
MS, Economics, The University of Texas at Dallas, 2018
PhD, Economics, The University of Texas at Dallas, 2020

Three Essays on the Economics of Financial Aid
Ph.D. Dissertation
Economics Department, The University of Texas at Dallas
Advisor: Dr. Rodney J. Andrews

Employment History:

Assistant Vice President of Fair Lending Analytics, Citibank, September 2020 – present
Teaching and Research Assistant, The University of Texas at Dallas, August 2016 – December 2020

Professional Recognitions and Honors:

School of Economic, Political and Policy Sciences, University of Texas at Dallas. UTD Graduate Studies Scholarship, Stipend and Full Tuition, Fall 2016 – Fall 2020
School of Economic, Political and Policy Sciences, University of Texas at Dallas. Charles C. McKinney Scholarship, Spring 2018, Spring 2019, & Spring 2020
School of Economic, Political and Policy Sciences, University of Texas at Dallas. Irving J. Hoch Scholarship, Spring 2020
Association for Education Finance & Policy (AEFP). Roe L. Johns Travel Grant, 2019
School of Administrative and Economic Sciences, ICESI University. Graduate Studies Scholarship, Stipend and Full Tuition, 2014 – 2015

Professional Memberships:

American Economic Association (AEA), 2019–present
Association for Education Finance & Policy (AEFP), 2018–present