Myopic Decisions of College Students: Major Choices and the Impacts of Merit Based Scholarships

by

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To Kelli and Lewis.

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ABSTRACT

In the last two decades there has been massive expansion in state-level merit based scholarship (MBS) programs. At the same time the US has experienced an expanding gap between the number of Science, Engineering, Technology, and Mathematics (STEM) jobs and STEM graduates needed to fill them. In this dissertation I examine the effects of various state funded MBS programs and how they impact a student's choice of college major, with a particular emphasis on how MBS programs impact STEM.

The first chapter of this dissertation uses the Beginning Postsecondary Student Longitudinal Study and regression discontinuity techniques to show that there is a causal link between merit based scholarship requirements and students leaving STEM majors. Merit based scholarships lead to an increase of roughly 35 percentage points in the probability of leaving STEM. I use these results to estimate the impact of MBS on the total number of STEM graduates and on long-term financial impacts for students.

The second chapter expands upon the results of the first. Continuing with the Beginning Postsecondary Student Longitudinal Study I focus on the impacts that MBS have on poorer students. Using instrumental variables techniques I am able to make use of much larger samples so that I can focus on students from different income groups and find that the negative impacts on STEM are concentrated almost exclusively among the lowest income tercile.

The third and final chapter focuses specifically on the Tennessee HOPE Scholarship. Again, I use a regression discontinuity approach to exploit arbitrary thresholds in initial eligibility and ongoing maintenance of the scholarship. Results suggest that for this particular sample students may initially shy away from STEM, but

this does not extend toward lower rates of graduation in STEM. Results on major also suggest large increases in nursing and education majors at the expense of business majors.

I extend the current understanding of the impacts of state merit based scholarship programs by providing causal links between college major decisions and the grade and test score requirements built into the programs. Each essay provides insight into student behavior that is important for future policy decisions.

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INTRODUCTION

A college education is increasingly becoming the largest and most important investment that an individual can make. This investment is becoming more than just a personal investment and is increasingly becoming an investment that our government makes in students through many different grant and scholarship programs. One such type of program that has gone through massive expansion over the previous two decades is state-funded merit scholarships.

In 1993 Georgia began its Helping Outstanding Pupils Educationally or HOPE scholarship program. Since then over half of all U.S. states offer some kind of merit scholarship with most of those states now offering the majority of their scholarship funds as some kind of merit scholarship.

While many people have studied the broader impacts of these programs like graduation, grades, and enrollment, one area that has been left relatively unexplored is how state merit programs impact the qualitative aspects of the college degree that students pursue or obtain.

Since these state merit scholarships come with scholastic measures that students must maintain, I hypothesize that these programs may carry with them some impacts on the type of degree a student chooses to pursue.

My first two studies utilize a nationally representative sample of college students that who are followed for six years. In the first chapter I present results centered around a regression discontinuity design. Results suggest that there is a causal link between the grade point averages required to maintain merit scholarships and leaving a science, technology, engineering, or mathematics (STEM) field. Additionally, students tend to take fewer STEM courses due to these merit scholarship programs. Some evidence is also presented that suggests that students from lower income groups may have stronger adverse effects.

The second chapter presents a more robust analysis of the disproportionate effects on low income students using an instrumental variables approach that allows me to make use of more observations and more delicately analyze different income groups. Results here confirm that students from the lowest income tercile start and graduate in STEM less often than the top two terciles as a result of the state merit scholarship programs.

The third and final chapter specifically looks at the Tennessee HOPE scholarship program using a fuzzy regression discontinuity approach. Results here show a reduction in the number of students attempting an initial STEM degree, but this does not translate to reduced numbers of students graduating with a STEM degree. This study also confirms some findings of previous studies with evidence of increased GPA and enrollment intensity.

CHAPTER I

UNINTENDED CONSEQUENCES STEM-ING FROM STATE MERIT BASED SCHOLARSHIPS

1 Introduction

Starting with Georgia's Helping Outstanding Pupils Educationally (HOPE) scholarship in 1993, there has been a steadily increasing movement toward offering state money in the form of merit-based scholarships (MBS). As of 2013, more than half of all states offer some form of MBS. Thirteen states now offer more than half of their scholarship funds through merit-based, rather than need-based, programs. The 42nd Annual Survey Report on State-Sponsored Financial Aid reports that in the 2010-2011 academic year about $3 billion in state funds were given to students in MBS programs, a number that constitutes 29% of all state scholarship funding.

During roughly the same period of time we have experienced a growing gap between the number of available STEM jobs and the supply of STEM graduates to fill them. While we have experienced overall growth in college graduates, the number graduating in STEM fields has remained stagnate. A special report to the President in 2012 detailed these problems and estimated that by 2018 we would need to produce an additional one million graduates with STEM degrees (Olsen and Riordan, 2012).

With all of the important policy decisions surrounding both MBS and STEM one would expect a more extensive research literature on the intersection of the two. Sjoquist and Winters (2013c) find that there is some evidence of MBS reducing the number of STEM graduates in a state; however, like other studies on MBS using American Community Survey data (Dynarski 2008, Hickman 2009, and Sjoquist and Winters 2012) the authors are unable to directly observe whether an individual student receives state merit funding. Despite this, these authors still find measurable effects.

Using a regression discontinuity approach, I find a causal impact of MBS on STEM with 2004:2009 Beginning Postsecondary Student Longitudinal Survey (BPS) data. I find that MBS cause students to change college major and switch into programs that are less rigorous as a result of having to maintain certain GPA standards set by the MBS. In addition changing away from STEM, I find that regardless of major students with MBS take significantly fewer math, science, and engineering courses. Overall, these results have significant implications on how MBS negatively impact the formation of STEM graduates and provide at least one connection between the rise of MBS and the decline of STEM graduates.

The adverse effects of MBS are not only in the aggregate, but also impact individual students. Students choosing less rigorous majors tends to produce students with lower future wages and higher rates of unemployment. A recent Georgetown Center for Education and the Workforce study shows that students graduating in STEM, regardless of their field of employment, earn about $500,000 more over their lifetime than non-STEM graduates.[1] STEM majors tend to have higher rates of pay and lower rates of unemployment after graduation. STEM majors "paying off" has been well researched. In a meta-analysis performed by Altonji, Blom, and Meghir (2012) STEM graduates have roughly 33% higher wages than non-STEM graduates. Table 1.1 shows some basic employment statistics for these graduates from the Baccalaureate and Beyond Longitudinal Study.[2] As evidence that STEM coursework is more rigorous, I compare GPA by major category in both STEM and non-STEM courses in Table 1.2. It can be seen that regardless of major, STEM classes have lower GPAs. It can also be seen that regardless of course type, STEM majors tend to outperform non-STEM majors.

The rest of the paper is organized as follows. Section 2 further motivates the analysis by looking at the literature on MBS, the benefits of STEM graduates, and demonstrates how this study adds to the literature. Section 3 describes the BPS data. Section 4 presents the empirical methodology used in identification. Section 5 presents the main results. Section 6 provides robustness tests that further reinforce these results. Section 7 provides back of the envelope calculations that further emphasize the significance of the results and their implications. Section 8 ends the study with concluding remarks.

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[1] https://cew.georgetown.edu/wp-content/uploads/2014/11/stem-complete.pdf

[2] Baccalaureate and Beyond participants are drawn from the same study as the Beginning Postsecondary Student Longitudinal Study. Statistics are from Baccalaureate and Beyond: A First Look at the Employment Experiences and Lives of College Graduates, 4 Years On. http://nces.ed.gov/pubs2014/2014141.pdf

2 Motivation & Previous Work

One of the most common arguments for MBS programs is that it decreases the probability that the best high school students from a given state will leave that state to pursue their college education. Stemming back this “brain drain" remains a large focus of most state education policy. To that end, many studies show MBS affects retention of high school students within the state. Dynarski (2000, 2002, 2004, 2008), Cornwell, Mustard, and Sridhar (2006), Hickman (2009), Zhang and Ness (2010), and Fitzpatrick and Jones (2012) all find evidence that MBS programs do have a positive impact on student retention through college enrollment. Additionally, Sjoquist and Winters (2014) find that in-state student retention is largely an effect of the amount of scholarship money that is given to students.

Studies examining the impacts of post-graduation retention and the stock of college graduates have shown many positive outcomes for both the state, college graduates, and those without a college education. Trostel (2010) estimates that government expenditure on college graduates is much lower over their lifetime, while future tax revenues from graduates are much higher with a conservative estimate on the returns on investment in college age at 10.3%. Moretti (2004) finds that due to the many spillover effects of an educated workforce a one percentage point increase in the number of college graduates increases the wages for dropouts, high school graduates, and college graduates by 1.9, 1.6, and 0.4 percentage points, respectively. Other positive externalities include; higher labor force participation rates, lower unemployment levels, resistance to economic shocks, and higher growth rates (Winters 2013, Glaeser and Saiz 2003).

In respect to the positive externalities generated by college graduates within a state, STEM graduates in particular are of even greater importance. Winters (2014) finds that while having a larger stock of college graduates generates positive wage impacts on all workers, a larger stock of STEM graduates results in even larger wage impacts. Because of the positive impacts of STEM and the decline of the US share of innovation-based industries, that are fueled by STEM graduates, policy makers have a particular interest in generating STEM degrees. Though it has been shown that they have been unable to design effective policies and programs even as new STEM job openings continue to outpace graduates (Atkinson and Mayo, 2010; Rothwell, 2014).

From the perspective of students, STEM degrees offer lower rates of unemployment and higher wages than non-STEM degrees. Carnevale, Cheah, and Strohl (2012) find lower unemployment rates for STEM graduates. The previously mentioned meta-analysis showed a roughly 33% increase in wages, and these wage premiums have been shown to impact the choice of major (Arcidiacono, 2004). Even with these larger payoffs the harsher grading distribution in STEM courses seem to play a large role in student choice. Arcidiacono, Aucejo, and Spenner (2012) show that harsher grade distributions are part of the reason that persistence in the sciences is lower among minority groups in spite of stronger initial preferences for those fields. Adding the potential loss of a MBS should strengthen this result by adding an even greater incentive to change major, beyond just the fear of a lower GPA.

Other research done on MBS programs does suggest that there may be some other positive results from a student's perspective. Student graduation rates, grades, time-use, and attainment gaps have been explored. Henry et al. (2004); Dynarski (2008); and

Sjoquist and Winters (2012) find evidence that graduation rates are higher for MBS recipients. While Sjoquist and Winters (2013) find no meaningful impact on degree completion for states with MBS programs. Hernandez-Julian (2010) shows that men have increased GPAs near the point of losing their MBS. Barrow and Rouse (2013) conduct a field experiment and show that when students are given a scholarship that is tied to performance they increase their time investment in educational attainment.

Merit aid and major choice are also important factors in many studies that examine minorities in education. Dynarski (2000; 2002) shows that the specific MBS program design impacts the income gap for racial and ethnic groups, in some situations widening the gap and in others shrinking it. Anderson and Kim (2006) have also shown that minorities are disproportionately graduating with fewer STEM degrees despite having a higher initial preference for STEM fields.

This study expands the literature by demonstrating the causal link between the GPA requirements built into state MBS programs and the propensity for STEM students to abandon STEM for a major that allows them to keep their scholarship. Where others have shown that grading and grade distribution matters for the choice of and persistence in the sciences, this study provides a direct link through which this behavior takes place.

3 Data on Postsecondary Students

My primary data source is the 2004:2009 Beginning Postsecondary Students Longitudinal Study (BPS). The BPS is a nationally representative sample of US students who began postsecondary education for the first time in the 2003-2004 academic year.

The BPS is longitudinal with participants being interviewed in their first, third, and sixth years since starting their postsecondary education. In addition, transcript data are available for classes taken. The initial cohort for BPS is drawn from the National Postsecondary Student Aid Study, a large nationally representative study that seeks to examine how students pay for college. The sample is a restricted-use dataset that is collected by the Institute of Education Sciences at the National Center for Education Statistics. Student interviews are combined with administrative records that include the previously mentioned student transcripts.

The BPS is ideally suited to answer questions regarding college major and course choice for several reasons. First, and most obviously, is the availability of student transcripts. This gives direct observation of courses taken by the student, although the order in which courses are taken is not available. Transcripts also allow accurate inferences to be made about what may be some of the causes of students changing majors. Additionally, observations can be made about student success in courses that deal directly with their major. For example, if we see a student who begins with a STEM major, but struggles (has a lower than average GPA) in STEM courses we might expect that to have a relatively large influence on their choice to switch away from STEM.

In addition to postsecondary and collegiate experience measures, there are numerous pre-college and family background variables available. Some high school performance information is also given. The high school variables most relevant to this analysis are “highest level of math," SAT/ACT scores, and high school GPA. Since the majority of students take either the ACT or SAT, and not both, official ETS concordance tables are used to convert all measures into ACT scores.[3] These variables serve two important purposes. First SAT/ACT scores act as a proxy for innate ability. Second, they act as a relative measure of college preparedness. Important family and other background characteristics are also available. Adjusted gross income (of parents in the case of dependent students) serves as a relative proxy for family wealth and for the availability of outside college funding options.

Table 1.3 provides descriptive statistics for the variables I use in the analysis. Statistics are for the full sample, just students receiving MBS, and for students with an initial choice of a STEM major.

The average student age at first enrollment is 21.22, but the distribution is skewed due to the nature of when people can conceivably start college. The median age at first enrollment in the sample is 19. The ratio of male to female students in the sample is relatively consistent with national averages. Ratios of white to minority students are also relatively consistent with national averages. Although in the BPS, whites are slightly underrepresented and all other minority groups (“Black" and “Hispanic") are slightly over represented.

“A-Student" and “B-Student" indicate the high school GPA range of the individual. Exact high school GPAs are not provided, but ranges that allow this classification are. As one might expect, students with MBS are much more prevalent in this range as compared with the sample as a whole. Initial STEM majors have slightly

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[3] Educational Testing Service concordance tables, http://www.ets.org/Media/Research/pdf/RR-99-02-Dorans.pdf

lower high school grades than all MBS students, however this likely the result of two things. First, qualification for MBS is largely based on high school GPA. Second, initial STEM majors have taken more difficult classes, like calculus, at higher levels.

It is also worth noting that despite having generally higher measures of pre-college ability (grades, SAT scores, math courses) the second year college GPA of STEM students is lower than that of both the full sample and the sub-sample of students with MBS. These GPAs appear in Table 1.4. I attribute this to having taken more difficult college courses as a result of being a STEM major.

MBS recipients have higher levels of major changing than both the full sample and just initial STEM students. Table 1.4 may shed some light on this. Within the sample of MBS recipients there are fewer students who did not initially declare majors. If a student does not declare a major initially they have more time to ultimately select into a major that not only fits her interests, but also allows her to choose a major that is less likely to jeopardize her scholarship. In addition, due to the correlation between high achievement, choosing STEM, and receiving a MBS, the MBS students are more likely to be in difficult majors that ultimately lead to switching.

The definition of STEM major varies slightly from source to source. For my analysis, STEM is defined as a major from any of the following condensed subsets of major in BPS: Life Sciences, Physical Sciences, Math, Computer/Information Sciences, and Engineering. Definition of STEM class by NCES is any course in physical, life, or computer sciences, mathematics, technology, engineering, critical foreign language, or what is considered a “qualified liberal arts course." Because this differs slightly from what many consider STEM, I separate course designations for science (physical, life, and computer), engineering, and math courses. In addition to these I use the NCES definition for STEM course.

4 Evidence for STEM Major Switching

4.1 Empirical Methodology

My identification strategy utilizes the arbitrary GPA threshold needed to maintain an MBS. In particular I estimate the causal impact of MBS on students' choice of major using a regression discontinuity (RD) design. The RD approach therefor uses the exogenous variation in GPA around the MBS threshold. As Lee and Lemieux (2010) show, even if the forcing variable is endogenous, as GPA is here, the RD approach is still valid if the individual cannot perfectly determine the value of the forcing variable. This is certainly the case with GPA. While GPA is endogenous to student effort and ability, idiosyncratic shocks such as an especially difficult instructor, illness, or time commitments outside of class mean that GPA cannot be perfectly determined by the student. It is therefore this exogenous variation in GPA that allows me to identify the causal effects of MBS. Lee (2008) shows that in this case as long as there are no discontinuities in the control variables that treatment in the neighborhood of the cutpoint is statistically randomized.

I estimate the RD model using OLS with up to second degree polynomials. The basic model is as follows.

$$Y = \alpha + \tau T + \beta f(X) \quad (1)$$

Where *Y* is whether or not a student switched major. *T* is the treatment variable, defined as a GPA above the scholarship loss threshold. The forcing variable, *T*, is GPA. A smooth non-linear function of *X* is represented by *f(X)*. An expanded model follows:

$$Y = \alpha + \tau T + \sum_{p=1}^{P} \beta_{0p} X^p + \sum_{p=1}^{P} \beta_{1p} X^p T + \gamma Z + \eta \quad (2)$$

In Equation 2 *P* represents the order of the polynomials of the forcing variable. One set of polynomials is interacted with the treatment, allowing for different non-linear functions on each side of the cut point. A vector of controls is represented by γZ and η is the error term. My analysis considers the model where *P = 1* and *P = 2*.[4]

For the main analysis of this section the samples are restricted to only those students who have chosen an initial STEM major, start college with a MBS, who have not transferred between institutions, and who otherwise meet all criteria for their MBS at the time of major changing behavior. Because of this, all results should be interpreted as changes in the behavior of STEM majors with MBS.

Since the cutpoint of MBS requirements varies across states, I normalize GPAs such that the cutpoint is zero. The varying thresholds do raise one issue. Due to the nature of the GPA calculation, the impact of the differing state cutpoints would likely change based on where the GPA limit is set. Consider two students, Student A and

[4] Gelman and Imbens (2014) provide a guide to and a caution against using higher order polynomials in RD designs.

Student B. Student A has to maintain a 3.75, while Student B must maintain a 3.00. If each student is currently .25 GPA points under what they must maintain (3.50 and 2.75, respectively) Student A will likely have to switch to an even less difficult major than Student B since in the next period Student A will have to achieve a 4.0, while Student B will only need a 3.25.[5] All else equal, this is more difficult. As you get higher in the GPA range, it is relatively more difficult to increase your GPA because of the limited upside of a maximum grade. Student A must increase or maintain his grades in each class, while Student B could potentially do worse in some classes as long as there is a larger offset from performing better in others. Similarly, as students complete more credit-hours, it becomes more difficult for them to influence their GPA. I assume that the effect is the same for students no matter where the specific student's cutpoint is and regardless of how many credit-hours they have completed. Despite differing scholarship cutpoints, the normalization ensures the internal validity of the RD design remains intact. Since most MBS at this time had relatively similar cutpoints it is unlikely that the assumption of similar treatment effects biases the analysis.[6]

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[5] Here I define a “period" as the length of time to earn the same amount of credit-hours as the students' current GPA is based on.

[6] In the sample 65.3% of students must maintain a 3.0 and 17.8% must maintain a 2.5. Louisiana has the lowest requirement of 2.0, while Kentucky has the highest requirement at 3.3, making up 6.1 and 8.7% of the sample respectively.

4.2 Results

Table 1.5 presents results from a wide GPA bandwidth of 1.25 points on either side of the cutpoint. Because of the relatively large bandwidth, the covariates described in section 3.1 are used. Results of the linear model show that there is a positive and significant impact of roughly 35 percentage points on the probability of STEM majors with a MBS changing to a non-STEM major.

Two falsification tests are provided in Table 1.5. First, the model of changing majors is estimated with non-STEM majors. If there are only two major choices, STEM and non-STEM, and that STEM courses produce lower GPAs (Table 1.2), then there is no easier, alternative major for non-STEM people to switch to. Thus as expected, there is no statistically discernible effect from MBS on non-STEM majors. It is specifically students with STEM majors, that tend to be more difficult academically, who exhibit the major changing behavior.

The second falsification test looks at STEM majors without a MBS. These are students that would be given MBS, but are either in states where they are not offered or they didn't meet the high school eligibility requirements. Again, at the cutpoint we see no significant effect for students without a MBS. This is consistent with the idea that MBS GPA requirements are the causal link in the decision to change majors.

Further falsification tests of the RD results are presented in Table 1.6. The first column is the same as the linear and quadratic results from Table 1.5. False cutpoints of ±.20 GPA points, where there is no expectation of a jump in probability of changing majors, are tested above and below the real cutpoint. All regressions presented in Table

1.6 are from the initial subset of students with MBS and who have initial STEM majors. At the false cutpoints there is no evidence of the major switching behavior. This again supports the idea that it is indeed the GPA cutoff in the MBS that is the causal force behind the decision to switch away from a STEM major.

Local linear RD specifications are presented in Table 1.7 with representative graphs in Figure 1.1. Figure 1.1 represents the first local linear regression presented in Table 1.7 along with the two falsification tests for those without MBS and those who were not initial STEM majors. The bandwidth chosen is ±.500 GPA points on both sides of the cutpoint. While smaller bandwidths may increase the internal validity of the model, sample size restrictions make it difficult to shrink the bandwidth too narrowly. The local linear specifications are presented both with (first column, Table 1.7) and without (second column, Table 1.7) other control variables included. With controls, I find a 45% increase in the probability of switching from a STEM major to a non-STEM major as a student approaches the GPA cutpoint. Without controls, a 47% increase is observed.

Again, I present falsification tests for non-STEM majors and STEM majors without a MBS. As with the wider bandwidth samples in Table 1.5, there are no significant impacts at the cutpoint for students who are not STEM majors or for students who are STEM majors, but do not have a MBS.

Checks for breaks in the control variables must also be explored since these breaks could be driving any results. An RD regression is estimated for each control variable for both the wide and the more restricted bandwidths with the results shown in

Table 1.8. No discontinuities are shown in the covariates and thus the results are not driven by any other observable measure.

One thing to note about the RD results is that at times the sample sizes become very small. Despite this, the results still show statistical significance. This is very telling of the line between the MBS threshold and major choice.

5 The Effects of MBS on Course Selection

5.1 Empirical Methodology

Again I employ an RD approach to estimate the causal impact of MBS on enrollment in STEM related courses. Specifically, STEM courses are defined as any course in physical, life, or computer sciences, mathematics, technology, engineering, critical foreign language, or what is considered a “qualified liberal arts course."[7] Separately, mathematics, engineering, and science (physical, life, and computer) courses attempted are analyzed.[8] The economic model takes the same form as that in Section 4.1. *Y* in

[7] Qualifications are based on definitions used in the National SMART Grant Program. http://ifap.ed.gov/fregisters/FR050109TEACHGrant.html

[8] It should be noted that due to the somewhat “open" nature of what is considered a STEM course under the National SMART Grant Program, the impacts of course selection in mathematics, engineering, and science will not necessarily sum to the impact in STEM courses.

Equations 1 and 2 take the form of credit-hours attempted in STEM, as defined by the National SMART Grant Program, and separately for mathematics, engineering, and science courses.

Samples are restricted to those students who start college with a MBS, who have not transferred between institutions, and who otherwise meet all criteria for their MBS at the time of the course selection. Again, since different states are used, the cutpoints have been normalized to zero.

One beneficial aspect of examining credit-hours attempted is that it does not restrict the sample size to the extent of the previous major choice analysis because all students, regardless of major, have the opportunity to take STEM courses. For this reason, the effects on women and men are able to be analyzed separately. Additionally, it allows for the analysis of the behavior of students from different income groups. This is important because the effects of MBS thresholds may be particularly acute for students from families with more difficulty affording college.

Because of the larger sample size, optimal bandwidths for this section are based on Imbens and Kalyanaraman (2009). Since the optimal bandwidth for each type of course varies slightly bandwidths from ±0.25 to ±0.35 are examined. This range of bandwidths encompasses all optimal bandwidths and has the added benefit of showing that results are not necessarily just a result of one individual specification.

Though students can manipulate GPA it cannot be perfectly manipulated. Because there is still a chance for manipulation, I test for densities around the cutpoint following McCrary (2008). The results of this test are presented in Figure 1.5 and show no problematic manipulation of treatment.

5.2 Results

I now discuss the effects of MBS on the choice of courses. Table 1.10 presents the results of local linear RD models of varying bandwidths on either side of the cutpoint by course subcategory. Men show no statistically significant response in any course choice behavior at the cutpoint. However, the threat of losing a MBS has a significant impact of course choices for women. For women the impacts are a reduction in credit-hours attempted of 5.521-6.226 (depending on the specification) for STEM courses, 4.920-5.796 for engineering courses, and 5.418-6.028 for science courses. Graphical representations of the ±0.25 bandwidth are provided in Figures 1.2, 1.3, and 1.4. In these figures the circles represent weighted averages of credit-hours attempted at each GPA. The lines represent regression fit lines with the cutpoint represented as a vertical line.

Tests to check the effects at false cutpoints are also run. Tables 1.11 and 1.12 present the results of the same regressions represented in Table 1.10 with false cutpoints 0.15 GPA points higher and lower of the true cutpoint, respectively. The overall lack of significance in these two tables reinforces the idea that the true cutpoint is correct and that the MBS GPA requirements are a causal force in the reduction in attempted STEM-related courses.

6 Robustness Tests

To further show the causal link between the potential loss of a MBS and enrollment choices, I also test the difference between students that may be more reliant on their MBS than others. I separate students that come from households that are above and below the median household adjusted gross income in the sample. Students in the ”low income" group are likely to be more reliant on their MBS than the “high income" group because their families likely have fewer resources to pay for college. As a basic test of this Table 1.13 shows student responses to the whether or not their parents helped pay for their tuition or housing and whether their parents give them a monthly allowance. As expected students from the "high income" group have much higher rates of financial help from their parents.

Regressions run for the “high income" and “low income" groups are presented in Table 1.14. Students from the “low income" show large significant responses. These students show statistically significant reductions in science courses between 6.016-8.630 credit-hours, engineering courses between 6.664-8.347 credit-hours, and STEM courses between 7.141-7.863 credit-hours. These results represent larger and more significant estimates than the non-separated regressions presented previously in Table 1.10. These results further reinforce the idea that the financial incentives are what is driving the behavior.

7 Discussion & Concluding Remarks

Back of the envelope calculations using NCES numbers for graduates by college major and the results presented here suggest roughly 27,000-35,000 fewer STEM graduates over the 6-year span of the 2003-2009 academic years or roughly 3-4% of the STEM graduates produced during that time.[9] With increasing adoption of MBS, and overall growth of the current MBS programs, this number is likely to increase over time. Policy makers have shown that they are concerned with creating more STEM graduates, even suggesting freezing tuition rates in STEM fields.[10] Since it has been shown here that the choice of a STEM major is altered by some of the conditions of MBS, this is an opportunity for policy makers to tailor policy to the current needs of the job market within their respective states.

From the perspective of a student, the opportunity to reduce tuition costs is very attractive, but the conditions I show that come with this opportunity alter the behavior of students in a way that will impact their job prospects and wages in the future. While Arcidiacono, Kang, and Hotz (2012) find that students do have a general idea about the earnings differences of different fields, switching from high earning majors to low earning majors suggests that students do not fully internalize the long-term impact that a major change may have. Using National Center for Education Statistics estimates for persistence in STEM, Census estimates for median earnings by degree, and the results presented in this study the median expected yearly earnings of a student who chooses an

[9] http://nces.ed.gov/programs/digest/d12/tables/dt12_313.asp

[10] http://www.nytimes.com/2012/12/10/education/florida-may-reduce-tuition-for-select-majors.html?pagewanted=all

initial STEM major drops from roughly $70,000 to $66,000 a year as a result of having a MBS.[11]

Another area that these results shed light on is the growing debate about the gap between and return to various college degrees. Consider a student choosing between a 2-year and 4-year degree. If this student who would have been in a relatively difficult 2-year STEM program decides to now enroll in a 4-year STEM program they are less likely to now finish with a 4-year STEM degree. Considering that the median person with a STEM associate's degree earns more than the median person with bachelor's degree in all non-STEM, health, and business fields, it stands to reason that MBS could be impacting these college wage gaps through the choice of major.[12]

[11] http://www.census.gov/prod/2012pubs/acsbr11-10.pdf, http://nces.ed.gov/pubs2014/2014001rev.pdf

[12] According to a recent report from the State Higher Education Executive Officers Association, http://www.sheeo.org/sites/default/files/publications/Econ\%20Benefit\%20of\%20Degrees\%20Report\%20with\%20Appendices.pdf

REFERENCES

1. Altonji, J. G., Blom, E., and Meghir, C. Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers. Annual Review of Economics 4, 1 (07 2012), 185 - 223.

2. Anderson, E. L., and Kim, D. Increasing the Success of Minority Students in Science and Technology. No. 4. American Council on Education Washington, DC, 2006.

3. Arcidiacono, P. Ability Sorting and the Returns to College Major. Journal of Econometrics 121, 1-2 (2004), 343-375.

4. Arcidiacono, P., Aucejo, E. M., and Spenner, K. What Happens After Enrollment? An Analysis of the Time Path of Racial Differences in GPA and Major Choice. IZA Journal of Labor Economics 1, 1 (2012), 1-24.

5. Arcidiacono, P., Hotz, V. J., and Kang, S. Modeling College Major Choices Using Elicited Measures of Expectations and Counterfactuals. Journal of Econometrics 166, 1 (2012), 3 - 16. Annals Issue on "Identification and Decisions", in Honor of Chuck Manski's 60th Birthday.

6. Atkinson, R. D., and Mayo, M. J. Refueling the US Innovation Economy: Fresh Approaches to Science, Technology, Engineering and Mathematics (STEM) Education. The Information Technology & Innovation Foundation, Forthcoming (2010).

7. Carnevale, A. P., Cheah, B., and Strohl, J. Hard Times: College Majors, Unemployment and Earnings: Not All College Degrees Are Created Equal.

8. Cornwell, C., Mustard, D. B., and Sridhar, D. J. The Enrollment Effects of Merit-Based Financial Aid: Evidence from Georgia's HOPE Program. Journal of Labor Economics 24, 4 (October 2006), 761-786.

9. Dynarski, S. Hope for Whom? Financial Aid for the Middle Class and Its Impact on College Attendance. NBER Working Papers 7756, National Bureau of Economic Research, Inc, June 2000.

10. Dynarski, S. The Consequences of Merit Aid. NBER Working Papers 9400, National Bureau of Economic Research, Inc, Dec. 2002.

11. Dynarski, S. The New Merit Aid. Working Paper Series rwp04-009, Harvard University, John F. Kennedy School of Government, Feb. 2004.

12. Dynarski, S. Building the Stock of College-Educated Labor. Journal of Human Resources 43, 3 (2008), 576-610.

13. Fitzpatrick, M. D., and Jones, D. Higher Education, Merit-Based Scholarships and Post-Baccalaureate Migration. NBER Working Papers 18530, National Bureau of Economic Research, Inc, Nov. 2012.

14. Gelman, A., and Imbens, G. Why High-order Polynomials Should Not be Used in Regression Discontinuity Designs. NBER Working Papers 20405, National Bureau of Economic Research, Inc, Aug. 2014.

15. Glaeser, E. L., and Saiz, A. The Rise of the Skilled City. NBER Working Papers 10191, National Bureau of Economic Research, Inc, Dec. 2003.

16. Henry, G. T., Rubenstein, R., and Bugler, D. T. Is HOPE Enough? Impacts of Receiving and Losing Merit-Based Financial Aid. Educational Policy 18, 5 (2004), 686-709.

17. Hernandez-Julian, R. Merit-Based Scholarships and Student Effort. Education Finance and Policy 5, 1 (2010), 14-35.

18. Hickman, D. C. The Effects of Higher Education Policy on the Location Decision of Individuals: Evidence from Florida's Bright Futures Scholarship Program. Regional Science and Urban Economics 39, 5 (2009), 553-562.

19. Imbens, G., and Kalyanaraman, K. Optimal Bandwidth Choice for the Regression Discontinuity Estimator. Review of Economic Studies 79, 3 (2012), 933-959.

20. Imbens, G. W., and Lemieux, T. Regression Discontinuity Designs: A Guide to Practice. Journal of Econometrics 142, 2 (February 2008), 615-635.

21. Lee, D. S. Randomized Experiments from Non-random Selection in US House Elections. Journal of Econometrics 142, 2 (2008), 675 - 697. The regression discontinuity design: Theory and applications.

22. Lee, D. S., and Lemieux, T. Regression Discontinuity Designs in Economics. Journal of Economic Literature 48, 2 (June 2010), 281-355.

23. McCrary, J. Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test. Journal of Econometrics 142, 2 (February 2008), 698-714.

24. Moretti, E. Estimating the Social Return to Higher Education: Evidence from Longitudinal and Repeated Cross-sectional Data. Journal of Econometrics 121, 1-2 (2004), 175 - 212. Higher education (Annals issue).

25. National Association of Student Grant and Aid Programs. 42nd Annual Survey Report on State-Sponsored Student Financial Aid, 2010-2011 Academic Year. National Association of State Student Grant and Aid Programs, 2011.

26. Olson, S., and Riordan, D. G. Engage to Excel: Producing One Million Additional College Graduates with Degrees in Science, Technology, Engineering, and Mathematics. Report to the President. Executive Office of the President (2012).

27. Rothwell, J. Still Searching: Job Vacancies and STEM Skills. Metropolitan Policy Program, Brookings Institution (2014).

28. Sjoquist, D. L., and Winters, J. V. Building the Stock of College- Educated Labor Revisited. Journal of Human Resources 47, 1 (2012), 270-285.

29. Sjoquist, D. L., and Winters, J. V. State Merit-based Financial Aid Programs and College Attainment. IZA Discussion Papers 6801, Institute for the Study of Labor (IZA), Aug. 2012.

30. Trostel, P. The Fiscal Impacts of College Attainment. Research in Higher Education 51, 3 (2010), 220-247.

31. Winters, J. V. Human Capital Externalities and Employment Differences Across Metropolitan Areas of the USA. Journal of Economic Geography 13, 5 (2013), 799 - 822.

32. Winters, J. V. STEM Graduates, Human Capital Externalities, and Wages in the U.S. Regional Science and Urban Economics 48, C (2014), 190-198.

33. Zhang, L., and Ness, E. C. Does State Merit-based Aid Stem Brain Drain? Educational Evaluation and Policy Analysis 32, 2 (2010), 143-165.

APPENDIX A

Table 1.1. Employment Measures of STEM vs. Non-STEM Graduates

	Median Salary	Unemployed	# of Jobs Since Degree
STEM	\$60,000	5.0%	1.9
Non-STEM	\$44,000	7.1%	2.1

Baccalaureate and Beyond: A First Look at the Employment Experiences and Lives of College Graduates, 4 Years On. http://nces.ed.gov/pubs2014/2014141.pdf

Table 1.2. GPA by Major and Class Type

	GPA in STEM Classes	GPA in Non-STEM Classes
STEM Majors	2.741	3.032
	(0.816)	(0.743)
Non-STEM Majors	2.716	2.945
	(0.851)	(0.775)
All Majors	2.720	2.956
	(0.846)	(0.771)

Standard deviations in parenthesis.

Table 1.3. Descriptive Statistics

	Merit Based Scholarship Recipients		Initial STEM Majors		Full Sample			
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Min	Max
Age	20.03	5.63	20.174	5.759	21.218	6.959	15	79
Female	.580	.494	.326	.469	.589	.492	0	1
Black	.175	.380	.145	.352	.151	.357	0	1
Hispanic	.051	.219	.116	.321	.127	.333	0	1
SAT Math	522.845	110.769	547.626	111.318	504.282	122.378	200	800
Calculus	.234	.423	.310	.462	.162	.368	0	1
Precalc	.203	.403	.195	.396	.179	.383	0	1
Private HS	.089	.285	.100	.300	.101	.301	0	1
A - Student	.440	.497	.398	.489	.292	.454	0	1
B - Student	.404	.491	.349	.476	.375	.484	0	1
'06 GPA	316.344	56.596	308.974	58.132	315.068	57.388	0	400
Changed Major	.427	.495	.382	.486	.332	.471	0	1
Cost of Attendance	13838.42	7795.97	16687.49	9835.35	15020.028	9788.764	1337	56740
AGI	58054.31	44909.24	58291.04	50836.17	54360.48	49712.63	0	497686
Any MBS	-	-	.079	.269	.061	.241	0	1
MBS Amount	1954.09	1381.99	1734.298	7224.234	1205.198	5819.635	0	10000
Initial STEM Major	.166	.372	-	-	.129	.336	0	1
Observations	1030		2170		16690			

Observations rounded to the nearest 10 per data use restrictions.

Table 1.4. GPA in First Two Years

	STEM Majors	MBS Recipients	All Students
First Year GPA	2.952	3.027	2.959
	(0.796)	(0.757)	(0.806)
GPA After 2 Years	3.090	3.163	3.151
	(0.581)	(0.566)	(0.574)

Standard deviations in parenthesis.

Table 1.5. Linear and Quadratic RD Models w/ Falsification Tests (Wide Bandwidth)

	Linear	Quadratic	Falsification Non-STEM	Falsification Non-MBS
Effect at Cutpoint	0.3497***	0.6120***	0.0897	-0.0328
	(0.1218)	(0.0984)	(0.0787)	(0.0517)
Bandwidth	$\pm.1.25$	$\pm.1.25$	$\pm.1.25$	$\pm.1.25$
MBS	√	√	√	
STEM	√	√		√
Observations	150	150	620	1300

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.
Variables included in control groups are described in section 3.1 above.
Robust standard errors in parenthesis.
Observations rounded to the nearest 10 per data use restrictions.

Table 1.6. RD Results with False Cutpoints

	Real Cutpoint	-0.20	+0.20
Linear w/ Controls	0.3497***	0.0620	0.0272
	(0.1218)	(0.2068)	(0.1641)
Quadratic w/ Controls	0.6120***	0.0521	0.0424
	(0.984)	(0.2976)	(0.2247)
Bandwidth	±1.25	±1.25	±1.25
Observations	150	150	150

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.
Variables included in control groups are described in section 3.1 above.
Robust standard errors in parenthesis.
Observations rounded to the nearest 10 per data use restrictions.

Table 1.7. Local Linear RD Specifications

	Linear	Linear	Falsification Non-STEM	Falsification Non-MBS
Effect at Cutpoint	0.4543**	0.4728**	0.1438	-0.0039
	(0.1971)	(0.1922)	(0.1199)	(0.0760)
Bandwidth	+/-0.500	+/-0.500	+/-0.500	+/-0.500
Controls		√	√	√
MBS	√	√	√	
STEM	√	√		√
Observations	70	70	280	690

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.
Variables included in control groups are described in section 3.1 above.
Robust standard errors in parenthesis.
Observations rounded to the nearest 10 per data use restrictions.

Table 1.8. Covariate Checks

	±1.25	±0.50
Age	-0.364	-0.839
	(1.038)	(1.713)
Female	-0.232	0.159
	(0.144)	(0.201)
Black	-0.027	0.123
	(0.107)	(0.171)
SAT Math	21.719	45.702
	(30.756)	(41.787)
Calculus	0.203	0.140
	(0.144)	(0.216)
Pre-Calc	-0.122	-0.142
	(0.131)	(0.222)
Private HS	0.059	0.092
	(0.069)	(0.117)
A-Student	0.125	0.271
	(0.152)	(0.226)
B-Student	-0.113	-0.280
	(0.149)	(0.218)
Cost ($1000)	-2.376	-1.868
	(2.663)	(3.763)
AGI ($1000)	-24.853	-35.776
	(19.173)	29.595
Observations	.150	.80

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.
Variables included in control groups are described in section 3.1 above.
Robust standard errors in parenthesis.

Table 1.9. Covariate Robustness

	Full	Male Only	No Calculus
Wide Bandwidth	0.349***	0.426***	0.414**
	(0.122)	(0.126)	(0.175)
Observations	150	100	80
Restricted Bandwidth	0.453**	0.838***	-0.172
	(0.192)	(0.143)	(0.521)
Observations	70	50	40

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.
Variables included in control groups are described in section 3.1 above.
Robust standard errors in parenthesis.
Observations is rounded to the nearest 10 per data use restrictions.

Table 1.10. Local Linear Regressions for Course Selection

	Both Sexes				Females				Males			
Bandwidth	STEM	Engineering	Math	Science	STEM	Engineering	Math	Science	STEM	Engineering	Math	Science
±0.25	4.761	4.896**	-0.384	2.845*	6.226*	5.796*	-0.218	6.028*	1.246	3.228	-0.492	0.723
	(2.962)	(2.404)	(0.325)	(1.584)	(3.698)	(3.268)	(0.600)	(3.254)	(4.519)	(3.634)	(0.387)	(1.775)
Observations	260	260	260	260	150	150	150	150	120	120	120	120
±0.30	4.532*	4.677**	-0.201	2.922**	5.977*	5.381*	0.237	6.437**	1.240	3.458	-0.533	0.495
	(2.730)	(2.183)	(0.295)	(1.446)	(3.446)	(2.943)	(0.538)	(2.805)	(4.216)	(3.359)	(0.357)	(1.678)
Observations	300	300	300	300	170	170	170	170	130	130	130	130
±0.35	2.366	2.761	-0.0906	1.719	5.521*	4.920**	0.421	5.418**	-3.215	-0.384	-0.504	-1.161
	(2.441)	(1.957)	(0.263)	(1.337)	(2.817)	(2.461)	(0.465)	(2.367)	(3.982)	(3.167)	(0.329)	(1.716)
Observations	360	360	360	360	200	200	200	200	160	160	160	160

Marginal effects; Standard errors in parentheses.

Observations rounded to nearest 10 per data use restrictions.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.11. Local Linear Regressions for Course Selection - False Cutpoint +0.15

	Both Sexes				Females				Males			
Bandwidth	STEM	Engineering	Math	Science	STEM	Engineering	Math	Science	STEM	Engineering	Math	Science
±0.25	-1.658	-2.008	0.130	-2.505	-5.289	-4.860	-0.146	-5.021*	3.416	1.797	0.434	0.0202
	(3.011)	(2.518)	(0.372)	(1.865)	(3.578)	(3.222)	(0.530)	(2.888)	(5.080)	(4.107)	(0.506)	(2.222)
Observations	260	260	260	260	150	150	150	150	120	120	120	120
±0.30	0.623	0.0763	0.319	-0.671	-1.568	-1.859	0.0519	-2.643	4.140	2.851	0.628	1.547
	(2.559)	(2.114)	(0.338)	(1.554)	(2.998)	(2.630)	(0.451)	(2.404)	(4.274)	(3.435)	(0.519)	(1.781)
Observations	310	310	310	310	180	180	180	180	140	140	140	140
±0.35	1.659	1.168	0.157	-0.191	0.0126	-0.344	-0.0593	-1.397	3.533	2.804	0.420	0.758
	(2.421)	(1.980)	(0.329)	(1.434)	(2.633)	(2.304)	(0.471)	(2.124)	(4.160)	(3.355)	(0.432)	(1.898)
Observations	340	340	340	340	190	190	190	190	150	150	150	150

Marginal effects; Standard errors in parentheses.

Observations rounded to nearest 10 per data use restrictions.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.12. Local Linear Regressions for Course Selection - False Cutpoint -0.15

	Both Sexes				Females				Males			
Bandwidth	STEM	Engineering	Math	Science	STEM	Engineering	Math	Science	STEM	Engineering	Math	Science
±0.25	-1.298	-2.088	1.009	-0.196	0.551	0.831	0.363	0.751	-2.011	-4.589	1.924*	-0.553
	(3.755)	(3.161)	(0.611)	(2.541)	(3.648)	(3.381)	(0.621)	(3.380)	(6.619)	(5.699)	(1.155)	(3.962)
Observations	220	220	220	220	130	130	130	130	100	100	100	100
±0.30	-3.355	-3.663	0.768	-1.966	-4.897	-4.740	0.273	-4.839	-0.572	-2.101	1.418	1.248
	(3.261)	(2.740)	(0.477)	(2.168)	(3.294)	(3.131)	(0.535)	(3.126)	(5.814)	(4.897)	(0.856)	(3.211)
Observations	270	270	270	270	150	150	150	150	120	120	120	120
±0.35	-2.969	-3.363	0.630	-1.422	-4.696*	-4.253*	0.194	-3.843	-0.302	-2.058	1.263	1.776
	(2.975)	(2.465)	(0.417)	(1.816)	(2.735)	(2.486)	(0.457)	(2.393)	(5.554)	(4.654)	(0.774)	(2.811)
Observations	300	300	300	300	160	160	160	160	140	140	140	140

Marginal effects; Standard errors in parentheses.

Observations rounded to nearest 10 per data use restrictions.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.13. Course Selection for Low and High Income Group Students

	Parents Help Pay Tuition	Parents Help Pay Housing	Parents Give Monthly Allowance
Low Income	0.3049	0.2311	0.1127
	(0.4608)	(0.4218)	(0.3165)
High Income	0.6393	0.5553	0.8221
	(0.4807)	(0.4974)	(0.3825)

Standard deviations in parenthesis.

Table 1.14. Course Selection by Income Group

	Low Income				High Income			
Bandwidth	STEM	Engineering	Math	Science	STEM	Engineering	Math	Science
±0.25	7.863*	8.347**	-0.0179	8.630**	1.497	2.053	-0.562	-0.185
	(4.324)	(3.763)	(0.655)	(3.658)	(4.024)	(3.223)	(0.394)	(1.629)
Observations	120	120	120	120	140	140	140	140
±0.30	7.143*	7.091**	0.425	7.511**	1.833	2.530	-0.510	0.108
	(3.925)	(3.267)	(0.561)	(3.006)	(3.791)	(3.019)	(0.383)	(1.586)
Observations	140	140	140	140	160	160	160	160
±0.35	7.141**	6.664**	0.338	6.016**	-1.388	-0.139	-0.327	-0.779
	(3.286)	(2.771)	(0.503)	(2.537)	(3.450)	(2.752)	(0.333)	(1.644)
Observations	160	160	160	160	200	200	200	200

Marginal effects; Standard errors in parentheses.

Observations rounded to nearest 10 per data use restrictions.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

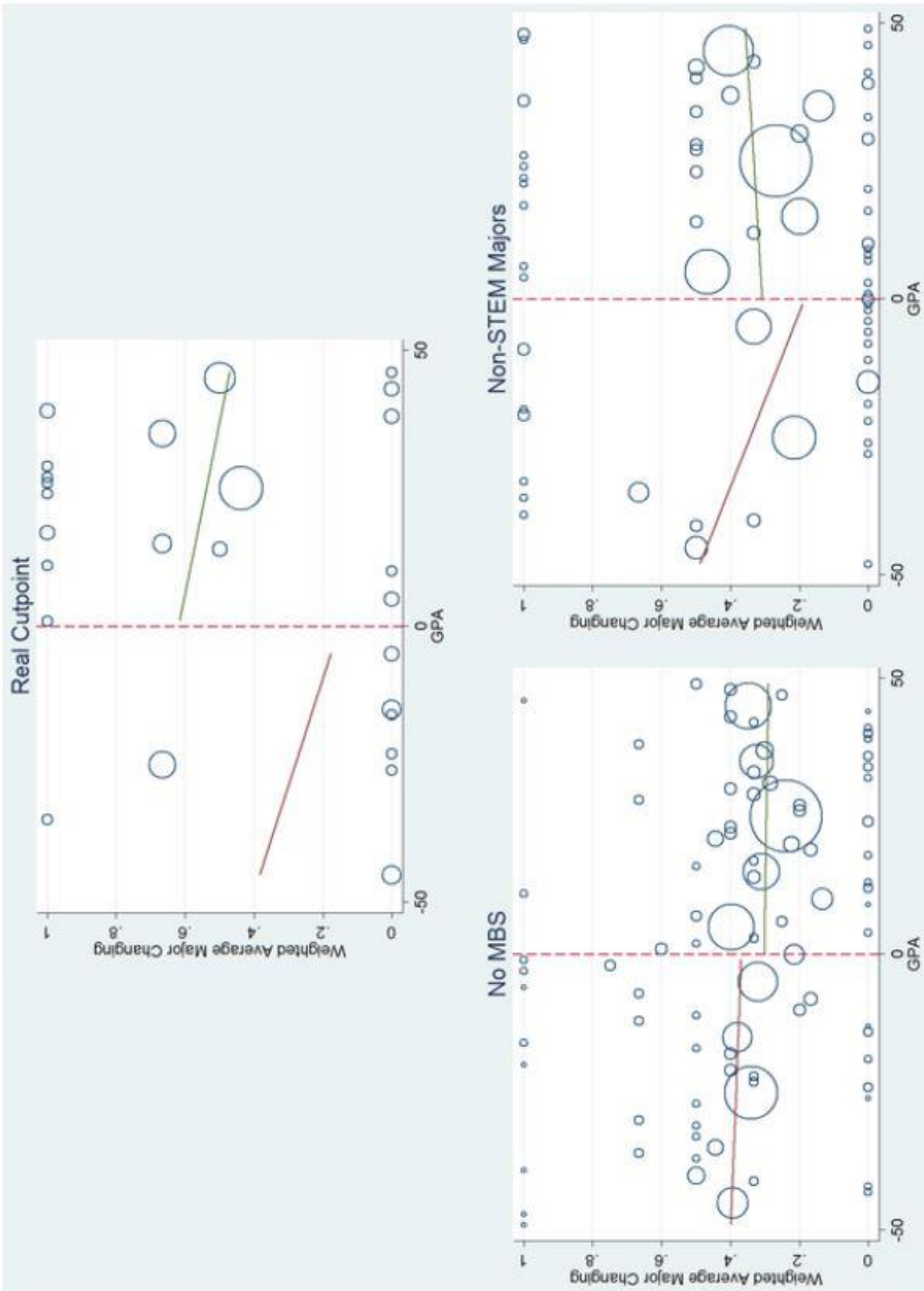

Figure 1.1: RD Graphs of Table 1.7

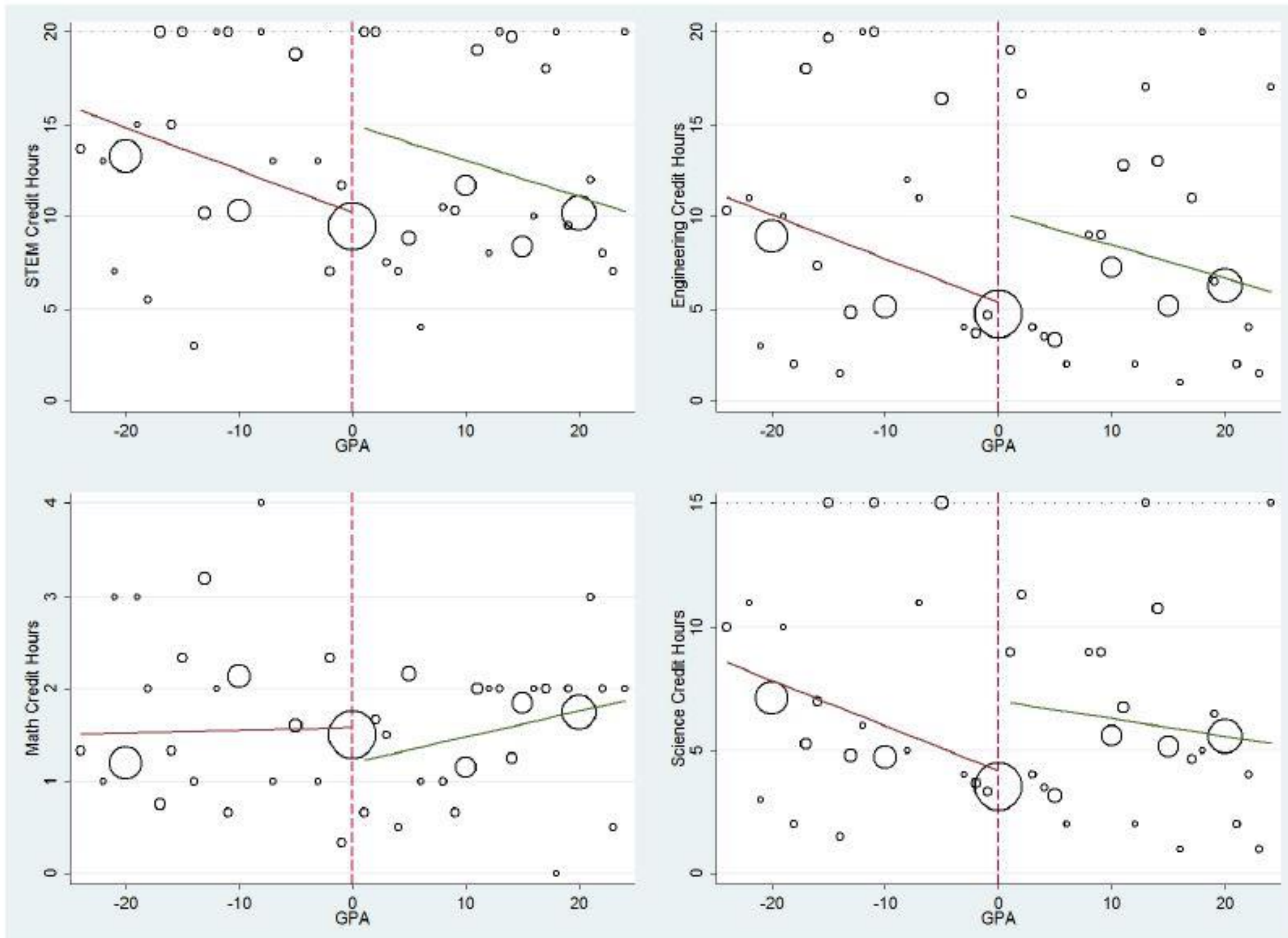

Figure 1.2: RD Graphs of Table 1.10

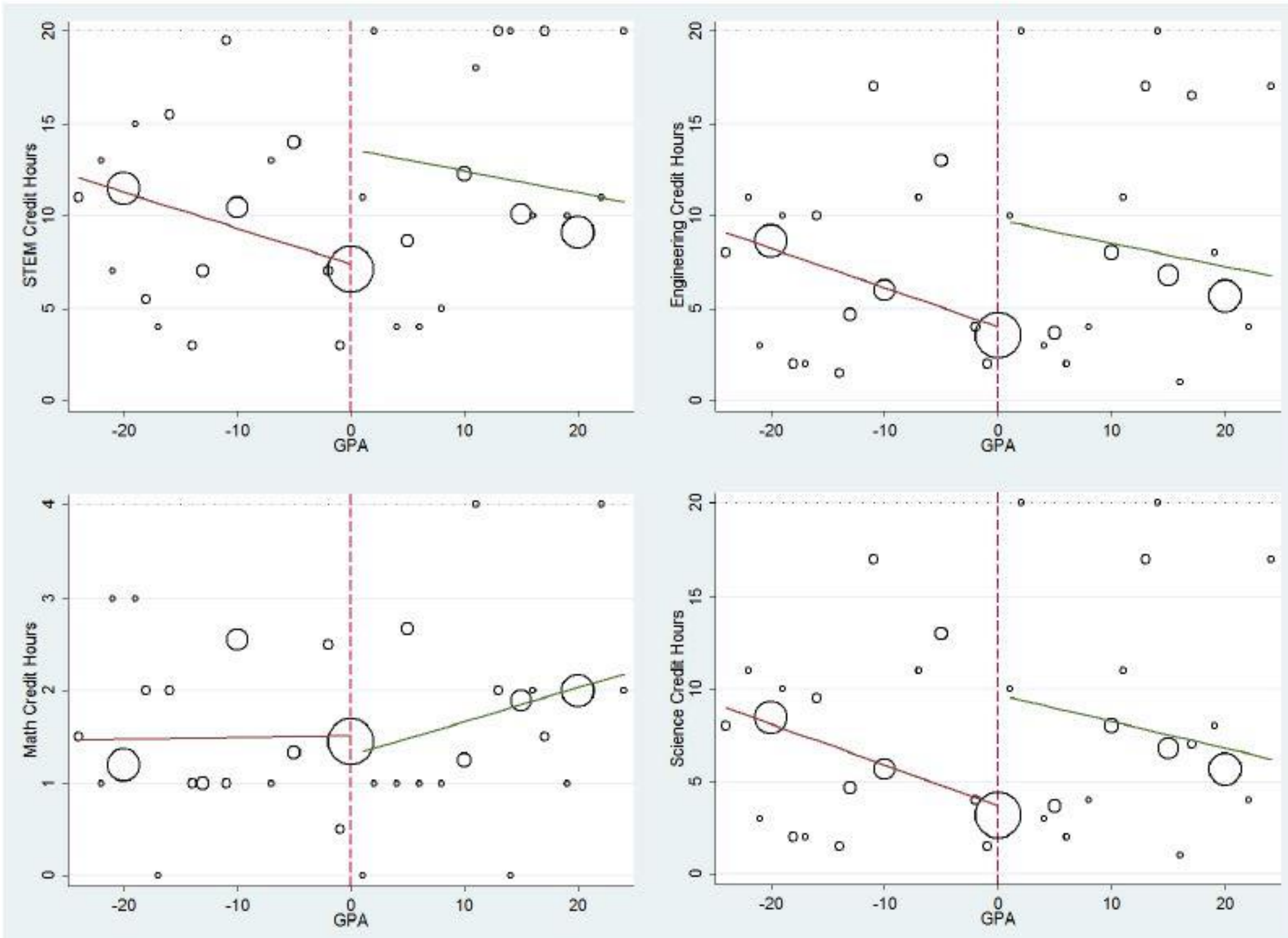

Figure 1.3: RD Graphs of Table 1.10 - Female

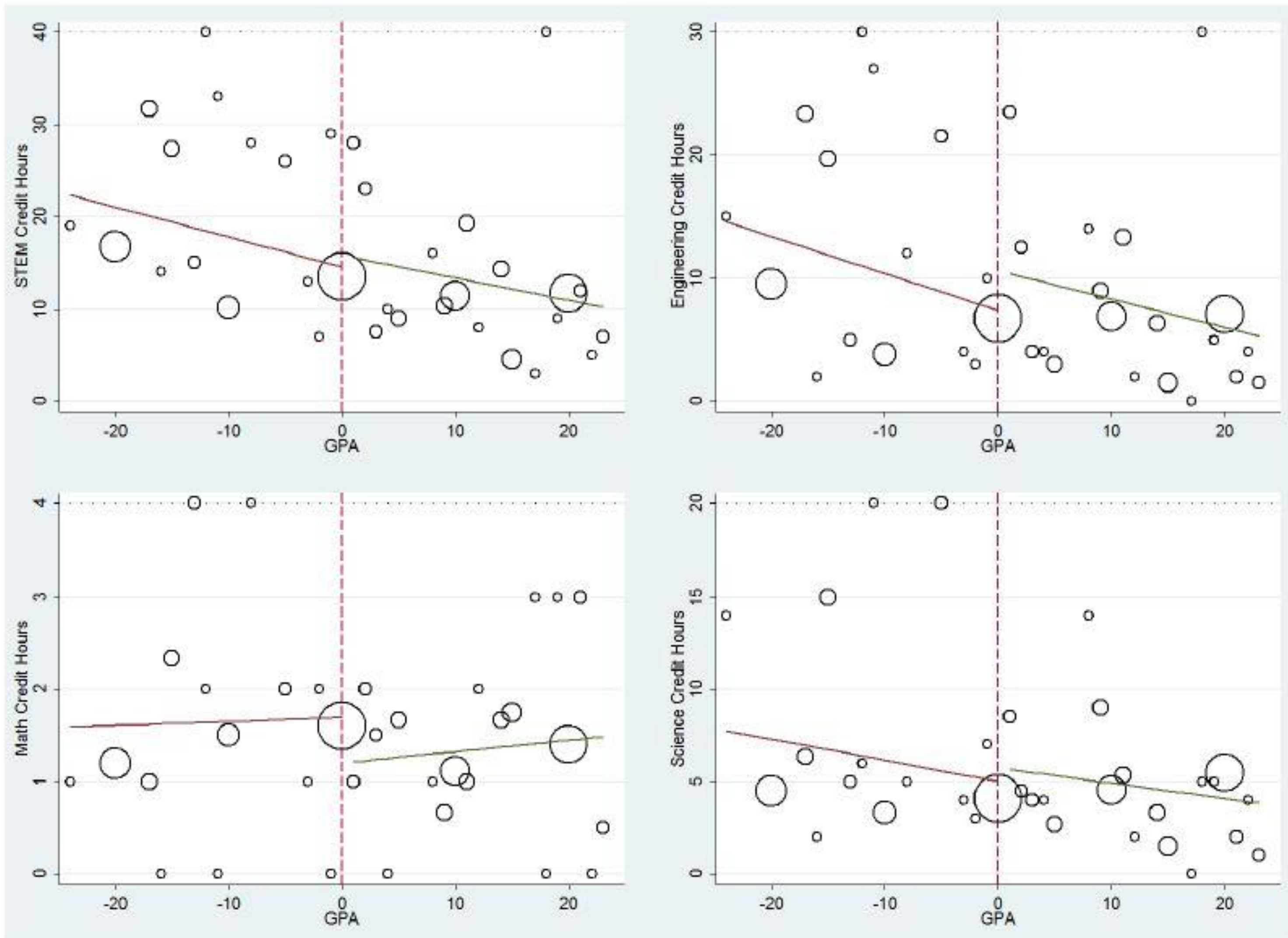

Figure 1.4: RD Graphs of Table 1.10 - Male

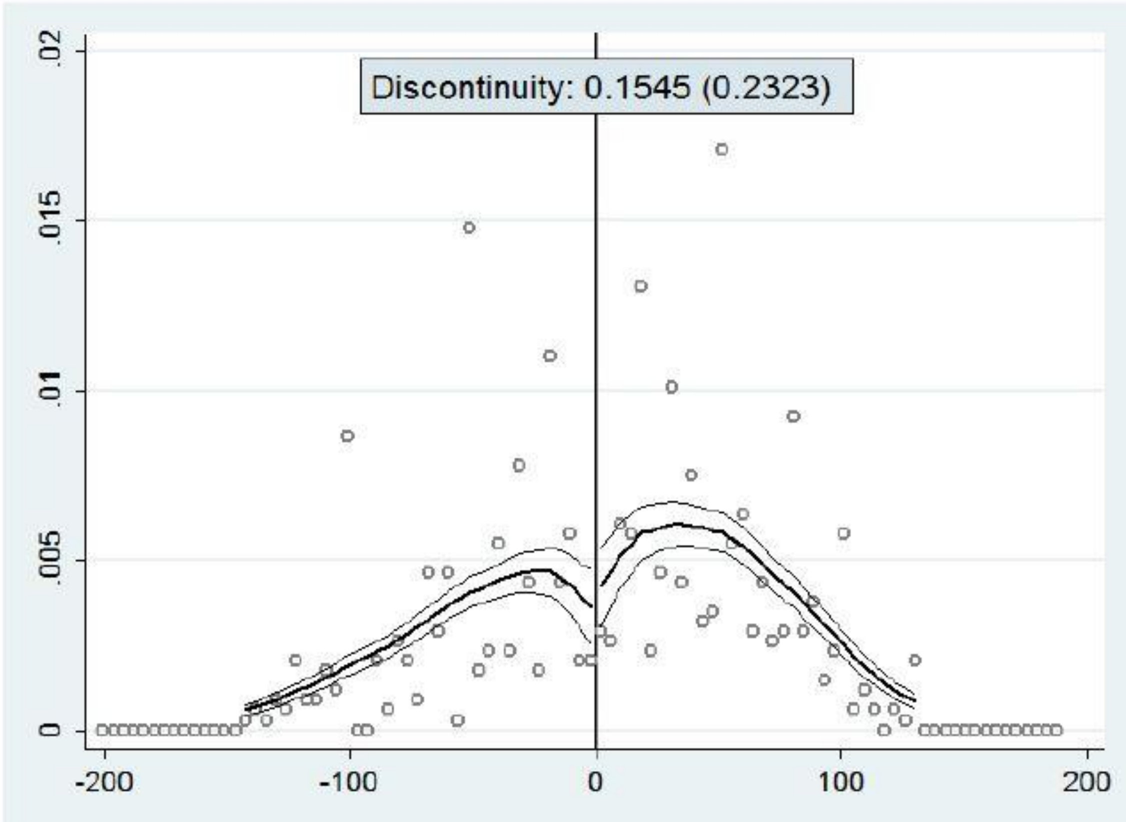

Figure 1.5: Density Test for Selection into Treatment

Chapter II

STEM & STATE MERIT SCHOLARHIPS: PUSHING OUT THE POOR

1 Introduction

The growth in state merit scholarship programs has been on a steady rise since the early 1990s. These programs offer awards to students that decide to pursue a college degree at an in-state school provided they meet specific academic benchmarks. As of 2013, more than half of all states offer some form of merit scholarship program. Thirteen states offer more than half of their scholarship funds through merit based, rather than need based, programs. The 42nd Annual Survey Report on State-Sponsored Financial Aid reports that in the 2010-2011 academic year about $3 billion in state funds were given to students in MBS programs, a number that constitutes 29% of all state scholarship funding.

During roughly the same period of time we have experienced a growing gap between the number of available science, technology, engineering, and mathematics (STEM) jobs and the supply of STEM graduates to fill them. While we have experienced overall growth in college graduates, the number graduating in STEM fields has remained stagnate. A special report to the President in 2012 detailed these problems and estimated that by 2018 we would need to produce an additional one million graduates with STEM degrees (Olsen and Riordan, 2012).

While the body of literature surrounding state merit scholarships is large one area that has only been lightly explored is the intersection of state merit scholarships and STEM. With all of the important policy decisions surrounding both topics this leaves researchers with important questions that still need to be answered. Sjoquist and Winters (2015) find using American Community Survey data that exposure to a state merit scholarship program leads to a 6.5-9.1% reduction in the number of STEM graduates. Sjoquist and Winters (2015b) find similar results for the Georgia HOPE scholarship using data from the University System of Georgia. In these studies the specific channel through which merit scholarships cause students to not enter or leave STEM is not identified. However, examining the robust literature around college major choice may provide insight into the channels that the causal links flow.

Arcidiacono, Aucejo, and Spenner (2012) show that harsher grade distributions are part of the reason that persistence in the sciences is lower among minority groups in spite of stronger initial preferences for those fields. Stinebrickner and Stinebrickner (2014) find that students leave science majors due to expectations of future lower grade performance.[13] Cornwell, Lee, and Mustard (2005) provide a link between grade point average fears and state merit scholarships by showing that students with the Georgia

[13]Table 2.22 shows grade point averages for courses taken by students with different majors in the Beginning Postsecondary Students Longitudinal Study, explained in Section 2. Students tend to score lower in STEM courses regardless of their major confirming the fears of students in Stinebrickner and Stinebrickner (2014).

HOPE scholarship strategically choose less difficult courses and majors as a result of the grade-based retention requirements of the scholarship

Carruthers and Ozek (2013) find that students who lose the Tennessee HOPE scholarship are more likely to leave college altogether and that this effect is larger for students from lower income backgrounds. Additionally, students were shown to work more after the loss of the scholarship. This suggests that students are bound by an underlying financial constraint that is unequal between students from different financial backgrounds.

Using Beginning Postsecondary Students Longitudinal data and an instrumental variables approach I examine the relationship that state merit scholarships have with majoring in STEM. Using family income characteristics along with survey questions that explore how students fund their college education I provide evidence that students from poorer backgrounds are more reliant on state merit scholarships than other students. Bivariate probit estimates provide clear evidence that not only do state merit scholarships have a negative impact on STEM attainment, but also that those impacts are borne almost entirely by poor students.

Previewing my results, I show that students with state merit scholarships coming from the lowest income terciles are 13 percentage points less likely to choose an initial STEM major, 17 percentage points less likely to ever major in STEM, and 7 percentage points less likely to graduate with a STEM degree as a result of the scholarship.

2 Data on Postsecondary Students

To investigate the effects of state merit scholarships I use the Beginning Postsecondary Students Longitudinal Study (BPS). Specifically, the BPS:96/2001 and BPS:04/09 waves are used. BPS in a restricted-use dataset that is collected by the Institute of Education Sciences at the National Center for Education Statistics. BPS draws its initial cohorts from the National Postsecondary Student Aid Study (NPSAS), which examines how students pay for college using a large nationally representative sample. Administrative data is combined with student surveys that are completed in at the end of their first, third, and sixth academic years. BPS is ideally suited to answer questions regarding the impacts of different methods of postsecondary funding because it gives an account of the sources of many of the funding sources that students use.

With the administrative and survey data available I am able to observe a student's major at their initial enrollment, at every survey time, and upon graduation. While major during each semester is not observed the students are asked whether they ever had a STEM major while they were enrolled. The combination of this with the administrative information allows me to accurately infer whether or not a particular student was ever in a STEM major.

In addition to information on college experiences and funding sources, BPS has numerous pre-college and family background indicators. The availability of family income data from the year prior to the students' enrollment allows inferences about the students' financial background. Some measures of high school outcomes are also used in the analysis. High school grade point average and ACT/SAT scores serve as proxies for innate ability as well as a general measure of college preparedness.[14]

Merit scholarships for the purposes of this study are any state-based scholarships that are based only on student academic merit and not other demographic characteristics; such as, minority status, underrepresented areas, or level of poverty. Because of the timing of the introduction and cancellation of some state merit programs some states are excluded from the analysis. Table 2.1 lists these exclusions along with the reason for exclusion. Table 2.2 lists the state merit programs covered in this analysis along with the sample that they are present in. Merit programs are classified into strong or weak categories based on the criteria set up by Sjoquist \& Winters (2014). Strong merit states tend to have larger enrollment and a higher average awards as compared to weak merit states. Based on the current sample 30.62% of students from strong merit states received some merit money versus just 9.55% for weak merit states. Additionally, students from strong merit states earned an average of about $1000 more in merit money.

The sample used for this study is restricted to only students who initially pursue a 4-year degree. Income terciles are generated using adjusted gross income (AGI) the year that the student applies to their first institution with all dollar amounts adjusted to 2003 dollars. To show that state merit scholarship money is more important to students from

[14] Since the majority of students take either the ACT or SAT, and not both, official ETS concordance tables are used to convert all measures into SAT scores http://www.ets.org/Media/Research/pdf/RR-99-02-Dorans.pdf.

lower income terciles Table 2.3 presents basic statistics on how students with merit scholarships pay the costs of college by income tercile. “Costs" represent the yearly cost of attendance for a student less any need-based aid, federal grants, institutional grants, work benefits, and veterans benefits. Students from the lowest income tercile are much more dependent on merit scholarships than those from the highest with merit money making up 37.2% of their total costs and 87.1% of their costs not covered by student loans compared to 21% and 31.3% for students in the highest tercile.

Another example of the financial constraint that is faced by those in the lowest income tercile is presented in Table 2.4. Parental assistance is commonplace when it comes to students' funding of a college education, but certainly those from relatively poorer backgrounds have less access to family help. Students were given several follow-up questions about their families' support while they were in college. As expected there are clear differences between income terciles. 53% of students from the first income tercile reported any financial support from their parents compared to 69% and 85% for the second and third terciles. The discrepancy is even higher when students were asked whether their parents helped pay tuition and fees, 38.97%, 66.77%, and 82.88% of students from the first, second, and third terciles answered affirmatively. This enforces the idea that the state merit scholarships are disproportionately impactful for students coming from lower income families. Not only do state merit scholarships make up a large portion of their funding, but they have less access to one of the largest sources of outside funding, their parents.

Summary statistics are separately reported in Table 2.5 for the combined sample, the sample of female students, the students who are STEM majors at any point in their university education, and those who have state merit scholarships. The full sample contains 11180 students 8.13% of which begin their college career with a state merit scholarship and 16.9% of which choose an initial STEM major.

The definition of STEM major varies slightly from source to source. For my analysis, STEM is defined as a major from any of the following condensed subsets of major in BPS: Life Sciences, Physical Sciences, Math, Computer/Information Sciences, and Engineering. This definition is consistent with National Center for Education Statistics publications based on Classification of Instructional Programs (CIP) criteria.[15]

3 Methodology

I consider the effects of state merit aid programs on several STEM major outcomes. My interest is to find whether students receiving state merit funding alter their major choice behavior specifically focusing on STEM majors. First, I estimate the impact of having a merit scholarship using a probit model. Then an instrumental variables regression strategy is implemented using bivariate probit regressions instrumenting for the endogenous presence of merit aid with a student's residence in a strong or weak merit state.

As suggested in Nichols (2011) the results are presented alongside traditional linear IV. Angrist and Pischke (2008:148-152) using support from Angrist and Evans (1998) and Angrist (2001), show that comparing the results of the typical linear IV model

[15] For more information on CIP see http://nces.ed.gov/pubs2002/cip2000/ciplist.asp

to the bivariate probit with continuous covariates may produce more biased estimates and that both estimates should be featured. In another comparison of linear IV to bivariate probit Chiburis, Das, and Lokshin (2012) show that bivariate probit outperforms linear IV in situations with sample sizes below 5,000, when treatment probabilities are close to zero or one, and when there are covariates in the model. Additional work by Bhattacharya, Goldman, and McCaffrey (2006) suggests that bivariate probit estimates are robust to model misspecification and that they produce less biased results than linear IV in some specifications.

An additional reason to present the results of linear IV along with bivariate probit is due to the lack of tests for IV strength in the non-linear bivariate probit setting. Weak instruments have been studied at length with the main concern being biased estimates making the cure worse than the disease, (Bound, Jaegar, and Baker, 1993). The tests proposed by Stock and Yogo (2005) while effective for linear IV are unproven for use in non-linear settings. The standard of an *F*-statistic of at least 16 for a sufficiently strong estimate (Stock and Yogo, 2005) is shown to be inappropriate by Nichols (2011) and in simulations produce no reliable critical first stage *F* values for the bivariate probit case. Since there is no standard measurement for instrument strength in the bivariate probit case I use the traditional tests and argue that there is sufficient evidence that the instruments are strong.

A statistical test of the endogeneity of merit based scholarships and a joint test of overidentification and validity of the excluded instruments are included in Table 2.6. The first test of endogeneity is a Hausman test of exogeneity. The null hypothesis of exogeneity is rejected in each case. The results of these tests are unsurprising from a common sense perspective. Being awarded a merit scholarship is likely correlated with unobserved ability as well as interest in the sciences. For this reason ordinary probit estimates are likely to be biased upward. Hansen *J* statistics with the null hypothesis of the joint validity of the instruments and correct exclusion from the regression equation is shown and not rejected in each instance. Validity and correct exclusion of instruments is also believable in this instance. We would not expect state of residence to be correlated with the error in the main equation. Tests of instrument strength, identification, correct exclusion, and redundancy are presented in Table 2.7. The first stage results for the combined and female samples show that being in a strong or weak merit state has a strong and significant influence on being the recipient of a state merit scholarship. The Keibergen-Paap Wald rank test with the null hypothesis of weak identification is clearly rejected for both first stage regressions used consistent with the strength of the significance of the instruments. The Sanderson-Windmeijer *F*-test of underidentification rejects the null that the first stage is underidentified in both instances. To demonstrate that strong and weak merit states should used as separate instruments an IV redundancy test is run following the recommendations in Baum et al. (2007).[16] Additionally, the results of the first stage suggest that the impact on whether you have a merit scholarship is different if you come from a strong or weak merit state.

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[16] Statistical tests are implemented using the ivreg2 package written by Baum, Schaffer, & Stillman (2002)

4 Results

Tables 2.8-2.11 present endogenous marginal effects of probit estimates of the impact of receiving a merit scholarship on choosing an initial STEM major, ever becoming a STEM major, graduating with a STEM major, and graduating with a STEM major conditional on having ever been a STEM major. Regression 1 in each table is run with only age, gender, and racial characteristics. Regression 2 adds SAT scores and high school grade point average. Regression 3 adds any Pell grants the student receives and the students' cost of attendance less aid that does not require repayment excluding Pell grants and state merit scholarships. Regressions 4-6 mirror regressions 1-3 for just the sample of female students. The separate analysis for women is conducted because previous research (Griffith 2010; Ma 2011) shows that women behave differently than men in choosing, persisting, and graduating in STEM. All results are shown for the combined samples as well as income terciles.

Though the results of Tables 2.8-2.11 are biased upward due to unobserved heterogeneity it should be noted that the results follow a general pattern. Results are larger in magnitude and significance for the lowest income tercile and decrease as you move into the higher income groups. While the estimates are not to be trusted they do suggest that there are true disproportionate impacts among those in the lowest income tercile. The adding cost measures into the regression specifications shown in regressions 3 and 6 in Tables 2.8-2.11 does have significant impacts, shrinking the magnitude of the estimates as well as increasing the standard errors. For the remainder of the analysis I will use the specification in these regressions.

As mentioned previously bivariate probit estimation is the appropriate model specification in the case of a dichotomous endogenous variable and a dichotomous dependent variable; however, since the traditional tests for instrument strength and identification have not been proven for use in bivariate probit models it is suggested that linear two stage least squares (2SLS) results be presented along with bivariate probit results as a means of both a means of statistical testing and for comparison.

Tables 2.12 and 2.13 present the impact of a state merit scholarship on the choice of an initial STEM major for the combined sample and female sample, respectively, of the endogenous probit regression alongside the first and second stage of the 2SLS model. The result show that for the combined income sample state merit recipients are 6 percentage points less likely to choose an initial STEM major and women are 6.95 percentage points less likely to choose an initial STEM major. Tables 2.14 and 2.15 estimate the state merit money's impact on whether a student ever chooses to major in STEM. Again, there are negative results suggesting that students are roughly 8.8 percentage points less likely to ever major in STEM and women are slightly more than 9 percentage points less likely. Tables 2.16 and 2.17 show statistically significant and negative results for graduating with a STEM major of 8.1 and 6.9 percentage points for the combined sample and females, respectively.

Tables 2.18 and 2.19 consider the impact of state merit money on graduating with a STEM major for those who have ever declared a major in STEM. Another way to think of this is persistence in STEM. The 2SLS results suggest a large significant impact from state merit scholarships that leads to a 21 percentage point drop in STEM persistence with an even larger 23 percentage point drop for women.

Table 2.20 presents the results of the correctly specified bivariate probit models for all previously considered dependent variables by income tercile along with the 2SLS results and probit results as points of comparison. Comparing the 2SLS and bivariate probit results we see that they are very similar with the bivariate probit results being slightly smaller in magnitude. When examining the bivariate probit results by income tercile the disproportionate impacts felt by the lowest income tercile become clear. Students belonging to this lowest income group are 13 percentage points less likely to start out majoring in STEM and 17.6 percentage points less likely to ever major in STEM compared to no significant effects for those with families in the top two income terciles. The bivariate probit results for graduating with a STEM major show negative and significant values for students in the lowest two income terciles with a 7.2 and 8.6 percentage point drop for the first and second terciles, respectively. The results of persistence in STEM should be interpreted with caution. It would seem that the lowest income tercile experiences a smaller magnitude drop in persistence, but it should be noted that significantly fewer students even from the lowest income group even attempt a STEM major. It is likely that the students who never attempted STEM would be the first to leave a STEM major if they had not already been pushed out, an effect partially reflected in the observation sizes. Despite nearly equal observation sizes initially, there are over 20% fewer students left in the first tercile to persist in STEM.

Table 2.21 presents the bivariate probit as well as the 2SLS and probit results for just the female sample of students. Similar results of lower magnitude estimates for the bivariate probit model are shown for the female sample. Smaller negative effects on initial STEM choice and ever attempting a STEM major are shown in the first tercile for female students as compared to the combined sample with an almost 12 percentage point drop in females choosing initial STEM majors and a 17 percentage point drop in ever attempting a STEM major. Effects in the second and third terciles are statistically insignificant. The impact on graduating with a STEM major is significant only for the first tercile in the female sample versus the first two terciles for the combined sample. Women in the first tercile with state merit scholarships are 8 percentage points less likely to graduate with a STEM major. Persistence in STEM for females in the first tercile decreases by 25 percentage points due to state merit scholarships. It should be noted that sample sizes for STEM persistence are getting relatively small with fewer than 500 observations present.

5 Discussion & Concluding Remarks

The bivariate probit results by income tercile demonstrate that students from families in lower income groups are more sensitive to the effects of merit scholarships than those from higher income groups. Not considering the financial constraints a student faces ignores what may be the most important result, that it is the poorer students that bear almost the entire burden of the negative effects of state merit scholarships.

The existence of negative STEM impacts is not entirely novel, Sjoquist & Winters (2013; 2015) find negative effects of similar magnitudes among students receiving the Georgia HOPE Scholarship and students in the ACS. However, the discovery of strong disproportionate effects among students from lower income families is not only novel but incredibly important. If the goal of state merit scholarships is to increase graduation rates, increase GPA, there are studies that support successes in these areas (Henry et al., 2004; Dynarski, 2008; Sjoquist & Winters, 2012; Hernandez-Julian, 2010). If a concern of policy makers is to address the increasing gap in STEM graduates there is a growing literature that supports the idea that merit scholarship policies are doing harm.

Additionally, the results of this study suggest that the existence of state merit scholarship programs is keeping the poor out of STEM while having no impact on those who are less bound by state merit scholarships to finance their education. This has major implications on long-term earnings and employment trajectories. Carnevale, Cheah, and Strohl (2012) find that STEM graduates have lower unemployment rates than their non-STEM counterparts. Arcidiacono (2004) provides evidence that STEM graduates show a roughly 33\% wage premium over non-STEM.

Arcidiacono, Kang, and Hotz (2012) find that even when students are generally aware of the earnings differentials between fields that they fail to accurately forecast the impacts that these differences may have. Though out of the scope of the current study, this could have significant impacts on income mobility within poor communities.

This study demonstrates that future research into the impacts of state merit scholarships must account for income or borrowing constraints faced by students. Even if the goal of merit scholarship policies are not to help the poor raise up out of poverty these costs have to be accounted for when we are evaluating merit scholarship programs.

REFERENCES

1. Angrist, J. D. Estimation of Limited Dependent Variable Models with Dummy Endogenous Regressors. Journal of business & economic statistics 19, 1 (2001).

2. Angrist, J. D., and Evans, W. N. Children and Their Parents' Labor Supply: Evidence from Exogenous Variation in Family Size. American Economic Review 88, 3 (June 1998), 450–77.

3. Angrist, J. D., and Pischke, J.-S. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press, 2008.

4. Arcidiacono, P. Ability Sorting and the Returns to College Major. Journal of Econometrics 121, 1-2 (2004), 343–375.

5. Arcidiacono, P., Aucejo, E. M., and Spenner, K. What Happens After Enrollment? An Analysis of the Time Path of Racial Differences in GPA and Major Choice. IZA Journal of Labor Economics 1, 1 (2012), 1–24.

6. Arcidiacono, P., Hotz, V. J., and Kang, S. Modeling College Major Choices Using Elicited Measures of Expectations and Counterfactuals. Journal of Econometrics 166, 1 (2012), 3 – 16. Annals Issue on "Identification and Decisions", in Honor of Chuck Manski's 60th Birthday.

7. Baum, C. F., Schaffer, M. E., and Stillman, S. IVREG2: Stata Module for Extended Instrumental Variables/2SLS and GMM Estimation. Statistical Software Components, Boston College Department of Economics, Apr. 2002.

8. Baum, C. F., Schaffer, M. E., and Stillman, S. Enhanced Routines for Instrumental Variables/Generalized Method of Moments Estimation and Testing. Stata Journal 7, 4 (December 2007), 465–506.

9. Bound, J., Jaeger, D. A., and Baker, R. The Cure Can Be Worse than the Disease: A Cautionary Tale Regarding Instrumental Variables. NBER Technical Working Papers 0137, National Bureau of Economic Research, Inc, June 1993.

10. Carnevale, A. P., Cheah, B., and Strohl, J. Hard Times: College Majors, Unemployment and Earnings: Not All College Degrees are Created Equal. Center on Education and the Workforce, January 2012.

11. Carruthers, C. K., and Ozek, U. Losing HOPE: Financial Aid and the Line Between College and Work. National Center for Analysis of Longitudinal Data in Education Research, Working Paper 91, September 2013.

12. Chiburis, R. C., Das, J., and Lokshin, M. A Practical Comparison of the Bivariate Probit and Linear {IV} Estimators. Economics Letters 117, 3 (2012), 762 – 766.

13. Cornwell, C. M., Lee, K. H., and Mustard, D. B. Student Responses to Merit Scholarship Retention Rules. Journal of Human Resources 40, 4 (2005), 895–917.

14. Dynarski, S. The New Merit Aid. Working Paper Series rwp04-009, Harvard University, John F. Kennedy School of Government, Feb. 2004.

15. Dynarski, S. Building the Stock of College-Educated Labor. Journal of Human Resources 43, 3 (2008), 576–610.

16. Griffith, A. L. Persistence of Women and Minorities in STEM Field Majors: Is It the School that Matters?. Economics of Education Review 29, 6 (2010), 911 – 922.

17. Hausman, J. A. Specification Tests in Econometrics. Econometrica: Journal of the Econometric Society 46, 6 (1978), 1251–1271.

18. Heller, D. E., and Marin, P. State Merit Scholarship Programs and Racial Inequality. Civil Rights Project at Harvard University (The) (2004).

19. Henry, G. T., Rubenstein, R., and Bugler, D. T. Is HOPE Enough? Impacts of Receiving and Losing Merit-based Financial Aid. Educational Policy 18, 5 (2004), 686–709.

20. Hernández-Julián, R. Merit-based Scholarships and Student Effort. Education Finance and Policy 5, 1 (2010), 14–35.

21. Ma, Y. Gender Differences in the Paths Leading to a STEM Baccalaureate. Social Science Quarterly 92 (2011), 1169 – 1190.

22. Nichols, A. Causal Inference for Binary Regression with Observational Data. CHI11 Stata Conference 6, Stata Users Group, July 2011.

23. National Association of State Student Grant and Aid Programs. 42nd Annual Survey Report on State-Sponsored Student Financial Aid, 2010-2011 Academic Year. National Association of State Student Grant and Aid Programs, 2011.

24. Olson, S., and Riordan, D. G. Engage to Excel: Producing One Million Additional College Graduates with Degrees in Science, Technology, Engineering, and Mathematics. Report to the President. Executive Office of the President (2012).

25. Sjoquist, D., and Winters, J. The Effect of Georgia's HOPE Scholarship on College Major: A Focus on STEM. IZA Journal of Labor Economics 4, 1 (December 2015), 1–29.

26. Sjoquist, D. L., and Winters, J. V. Building the Stock of College-Educated Labor Revisited. Journal of Human Resources 47, 1 (2012), 270–285.

27. Sjoquist, D. L., and Winters, J. V. State Merit-Aid Programs and College Major: A Focus on STEM. IZA Discussion Papers 7381, Institute for the Study of Labor (IZA), May 2013.

28. Sjoquist, D. L., and Winters, J. V. Merit Aid and Post-college Retention in the State. Journal of Urban Economics 80, 0 (2014), 39 – 50.

29. Sjoquist, D. L., and Winters, J. V. State Merit Aid Programs and College Major: A Focus on STEM. Journal of Labor Economics 33, 4 (2015), pp. 973–1006.

30. Stinebrickner, R., and Stinebrickner, T. R. A Major in Science? Initial Beliefs and Final Outcomes for College Major and Dropout. Review of Economic Studies 81, 1 (2014), 426–472.

31. Stock, J., and Yogo, M. Testing for Weak Instruments in Linear IV Regression. Cambridge University Press, New York, 2005, pp. 80–108.

APPENDIX B

Table 2.1. Merit States Excluded from Analysis

State	Program Name	Reason for Exclusion
California	Competitive Cal Grant Program	Included a need-based element at the time of the survey.
Idaho	Robert R. Lee Promise Scholarship	Only initial high school requirements needed for scholarship.
New York	NY Scholarships for Academic Excellence	No set scholarship criteria. Took top students by rank.
Illinois	Illinois Merit Recognition Scholarship	Program ended during sample period.
Maryland	Maryland HOPE Scholarship	Program ended during sample period
Washington	Washington Promise Scholarship	Requirements for keeping the scholarship are unclear

Note: Merit recipients accounted for only 1.7% of students from these states versus 30.6% for strong merit states and 9.5% for weak merit states.

Table 2.2. Merit Scholarship Programs Present in Sample

	BPS:96/2001	BPS:04/09		Program Name
Strong Merit States				
Florida		X		Florida Bright Futures Scholarship
Georgia	X	X		Georgia HOPE Scholarship
Kentucky		X		Kentucky Educational Excellence Scholarship
Louisiana		X		Louisiana TOPS Scholarship
Nevada		X		Nevada Millenium Scholarship
New Mexico		X		New Mexico Lottery Success Scholarship
South Carolina		X		South Carolina LIFE Scholarship
Tennessee		X		Tennessee HOPE Scholarship
West Virginia		X		West Virginia PROMISE Scholarship
Percentage of Students Receiving State Merit Aid			30.62	
Average Merit Award			$2,275.59	
Weak Merit States				
Alaska		X		Alaska Scholars
Arkansas	X	X		Arkansas Academic Challange Scholarship
Mississippi		X		Mississippi TAG Scholorship
Missouri		X		Missouri Bright Flight Scholarship
New Jersey		X		New Jersey Outstanding Scholar Recruitment Program
Oklahoma	X	X		Oklahoma PROMISE Scholarship
Utah		X		New Century Scholarship
Michigan		X		Michigan Merit & Promise Scholarship*
North Dakota		X		North Dakota Scholars Program**
Percentage of Students Receiving State Merit Aid			9.55	
Average Merit Award			$1,265.67	

Sources: Dynarski (2004), Heller & Marin (2004), Sjoquist & Winters (2014), and state websites.

Students receiving aid, and award averages are from the analyzed sample.

*Program was discontinued during survey period, but eligible students were not impacted.

**Merit program was in effect during BPS:96/2001, however no students merit recipients were present in the sample.

Table 2.3. Merit Scholarship and Student Costs

	Income Tercile		
	First	Second	Third
Costs	5272.34	7469.31	11779.44
Subsidized Loans	1378.34	1143.27	387.15
Unsubsidized Loans	1276.26	2392.77	2855.11
Private Loans	367.89	661.21	635.89
Costs Minus Loans	2249.85	3272.06	7901.29
Merit Scholarship	1959.15	2146.61	2475.33
% of Costs	37.2	28.7	21.0
% of Costs Not Covered by Loans	87.1	65.6	31.3

"Costs" is the cost of attendance less all non-state merit aid.
Amounts in 2003 dollars.

Table 2.4. Student Responses to Financial Support Questions

	Income Tercile		
	First	Second	Third
Parents Gave Financial Support (%)	53.31	69.72	85.21
	(0.49)	(0.46)	(0.36)
Parents Helped Pay Tuition & Fees (%)	38.97	66.77	82.88
	(0.49)	(0.47)	(0.38)
Family Helping to Repay Loans (%)	12.80	18.70	25.11
	(0.33)	(0.39)	(0.43)

Student responses to questions on last follow-up survey.
Standard deviations in parenthesis.

Table 2.5. Summary Statistics

	Combined		Females		Ever STEM Majors		Merit Scholarship	
	mean	sd	mean	sd	mean	sd	mean	sd
Merit Scholarship	.0813	.273	.0805	.272	.096	.295	–	–
Merit ($1000)	.179	.704	.173	.684	.223	.799	2.196	1.292
STEM	.169	.375	.109	.313	.650	.477	.220	.414
Age	18.466	.789	18.419	.773	18.406	.711	18.410	.694
Female	.565	.496	–	–	.408	.492	.559	.497
Black	.112	.315	.123	.329	.102	.302	.152	.359
Hispanic	.073	.260	.074	.262	.069	.255	.049	.217
Asian	.035	.183	.032	.178	.059	.235	.046	.210
SAT Score	1001.039	209.073	984.364	204.651	1070.052	211.919	1046.733	200.231
High School GPA	3.633	.482	3.673	.457	3.733	.431	3.775	.346
Cost ($1000)	15.988	9.220	15.909	9.183	17.153	9.458	14.320	7.282
Pell Grant	594.451	1198.402	651.881	1239.344	498.055	1102.166	614.777	1242.211
Strong Merit State	.149	.356	.153	.359	.133	.340	.696	.460
Weak Merit State	.110	.313	.109	.312	.109	.312	.158	.365
Observations	11180		6310		2900		910	

Table 2.6. IV Specification Tests

	Initial STEM Major Choice	Graduating w/ STEM Major	Ever Having STEM Major
Hausman Test			
$\chi^2(1)$	11.166	15.185	12.237
p-value	0.001	0.000	0.001
Hansen J Statistic			
$\chi^2(2)$	0.869	0.134	0.445
p-value	0.351	0.7148	0.505

Table 2.7. First Stage Tests

	Combined Sample	Female Sample
Strong Merit State	0.368***	0.366***
	(0.0121)	(0.0159)
Weak Merit State	0.105***	0.0925***
	(0.00926)	(0.0117)
Age	-0.0132***	-0.0139***
	(0.00277)	(0.00372)
Female	-0.00654	–
	(0.00463)	–
Black	0.0134	0.0198*
	(0.00915)	(0.0120)
Hispanic	-0.0186**	-0.0288***
	(0.00822)	(0.0104)
Asian	0.0353***	0.0282*
	(0.0133)	(0.0162)
SAT Score	0.000108***	0.000102***
	(0.0000145)	(0.0000193)
HS GPA	0.0440***	0.0449***
	(0.00482)	(0.00643)
Cost	-0.00235***	-0.00201***
	(0.000262)	(0.000342)
Pell	-0.00000378*	-0.00000605**
	(0.00000211)	(0.00000271)
Observations	11180	6320
Sanderson-Windmeijer F-test of Underidentification		
$\chi^2(2)$	1027.68	577.56
p-value	0.000	0.000
Kleibergen-Paap Wald rk F Statistic		
F-Stat	513.24	288.23
Prob > F =	0.000	0.000
IV Redundancy Test		
$\chi^2(2)$	802.31	448.15
p-value	0.000	0.000

Regression results are from a linear probability model with standard errors in parenthesis.

Observations have been rounded to the nearest 10 per data use restrictions

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8. Impact of Merit Scholarship on Choosing an Initial STEM Major

	Combined Sample					Females Only
		Combined Sample		.	Females Only	
	(1)	(2)	(3)	.(4)	(5)	(6)
Combined	0.0496***	0.0334***	0.0274**	.0.0303***	0.0137	0.0109
	(0.0105)	(0.0117)	(0.0121)	.(0.0115)	(0.0132)	(0.0137)
	15460	11870	11180	.8810	6710	6320
				.		
First Tercile	0.0595***	0.0450**	0.0382*	.0.0309	0.0208	0.0120
	(0.0200)	(0.0205)	(0.0212)	.(0.0226)	(0.0232)	(0.0245)
	3630	3630	3410	.2210	2210	2070
				.		
Second Tercile	0.0482**	0.0270	0.0256	.0.0343	0.0225	0.0236
	(0.0199)	(0.0199)	(0.0205)	.(0.0215)	(0.0217)	(0.0222)
	3630	3630	3420	.2030	2030	1910
				.		
Third Tercile	0.0393*	0.0252	0.0131	.0.0159	-0.0104	-0.0156
	(0.0212)	(0.0214)	(0.0224)	.(0.0257)	(0.0251)	(0.0264)
	3630	3630	3390	.1930	1930	1790
				.		
Demographics	Yes	Yes	Yes	.Yes	Yes	Yes
High School Measures	No	Yes	Yes	.No	Yes	Yes
Tuition Costs	No	No	Yes	.No	No	Yes

Marginal effects; State clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9. Impact of Merit Scholarship on Ever Having a STEM Major

	Combined Sample			Females Only		
	(1)	(2)	(3)	(4)	(5)	(6)
Combined	0.0468***	0.0204	0.0193	0.0421***	0.0185	0.0210
	(0.0127)	(0.0140)	(0.0145)	(0.0146)	(0.0167)	(0.0172)
	15460	11870	11180	8810	6710	6320
First Tercile	0.0728***	0.0453*	0.0332	0.0604***	0.0421	0.0244
	(0.0237)	(0.0240)	(0.0250)	(0.0273)	(0.0275)	(0.0291)
	3630	3630	3410	2210	2210	2070
Second Tercile	0.0347	0.0121	0.0167	0.0282	0.0188	0.0272
	(0.0242)	(0.0243)	(0.0252)	(0.0289)	(0.0291)	(0.0297)
	3630	3630	3420	2030	2030	1910
Third Tercile	0.0297	0.00668	0.00727	0.0149	-0.0212	-0.00826
	(0.0259)	(0.0260)	(0.0269)	(0.0330)	(0.0327)	(0.0337)
	3630	3630	3390	1930	1930	1790
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
High School Measures	No	Yes	Yes	No	Yes	Yes
Tuition Costs	No	No	Yes	No	No	Yes

Marginal effects; State clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10. Impact of Merit Scholarship on Graduating with a STEM Major

	Combined Sample			Females Only		
	(1)	(2)	(3)	(4)	(5)	(6)
Combined	0.00917	-0.00958	-0.00555	0.0139	0.000189	0.00113
	(0.00826)	(0.00950)	(0.00989)	(0.00953)	(0.0111)	(0.0117)
	15460	11870	11180	8810	6710	6320
First Tercile	0.0393***	0.0285**	0.0258**	0.0446***	0.0325**	0.0260*
	(0.0129)	(0.0125)	(0.0129)	(0.0147)	(0.0144)	(0.0149)
	3630	3630	3410	2210	2210	2070
Second Tercile	-0.0185	-0.0352**	-0.0315*	-0.0211	-0.0252	-0.0255
	(0.0177)	(0.0179)	(0.0187)	(0.0211)	(0.0205)	(0.0216)
	3630	3630	3420	2030	2030	1910
Third Tercile	-0.0230	-0.0266	-0.0165	-0.00859	-0.0175	-0.00782
	(0.0195)	(0.0194)	(0.0204)	(0.0247)	(0.0246)	(0.0258)
	3630	3630	3390	1930	1930	1790
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
High School Measures	No	Yes	Yes	No	Yes	Yes
Tuition Costs	No	No	Yes	No	No	Yes

Marginal effects; State clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.11. Impact of Merit Scholarship on Graduating with a STEM Major Conditional on Ever Being a STEM Major

	Combined Sample			Females Only		
	(1)	(2)	(3)	(4)	(5)	(6)
Combined	0.0344	-0.0198	-0.0107	0.0355	-0.0275	-0.0386
	(0.0283)	(0.0278)	(0.0280)	(0.0439)	(0.0415)	(0.0420)
	3750	3070	2900	1470	1260	1190
First Tercile	0.129***	0.101**	0.0979**	0.162**	0.105	0.0845
	(0.0493)	(0.0455)	(0.0469)	(0.0696)	(0.0647)	(0.0676)
	820	820	780	370	370	350
Second Tercile	-0.0450	-0.102**	-0.0958*	-0.0851	-0.0986	-0.122
	(0.0528)	(0.0495)	(0.0500)	(0.0872)	(0.0810)	(0.0809)
	950	950	890	360	360	340
Third Tercile	-0.0684	-0.0633	-0.0457	-0.0672	-0.0900	-0.0902
	(0.0515)	(0.0481)	(0.0485)	(0.0791)	(0.0726)	(0.0726)
	1040	1040	980	430	430	400
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
High School Measures	No	Yes	Yes	No	Yes	Yes
Tuition Costs	No	No	Yes	No	No	Yes

Marginal effects; State clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.12. IV - Impact of Merit Scholarship on Choosing an Initial STEM Major

	Probit	First Stage	Second Stage
Merit Scholarship	0.0274*		-0.0600**
	(0.0121)		(0.0295)
Strong Merit State		0.368***	
		(0.0121)	
Weak Merit State		0.105***	
		(0.00926)	
Age	-0.00815*	-0.0132***	-0.00768*
	(0.00465)	(0.00277)	(0.00415)
Female	-0.133***	-0.00654	-0.133***
	(0.00735)	(0.00463)	(0.00731)
Black	0.106***	0.0134	0.0907***
	(0.0160)	(0.00915)	(0.0124)
Hispanic	0.0510***	-0.0186**	0.0425***
	(0.0158)	(0.00822)	(0.0141)
Asian	0.125***	0.0353***	0.127***
	(0.0239)	(0.0133)	(0.0231)
SAT Score	0.000250***	0.000108***	0.000271***
	(0.0000219)	(0.0000145)	(0.0000224)
HS GPA	0.0542***	0.0440***	0.0509***
	(0.00917)	(0.00482)	(0.00777)
Cost	-0.00234***		-0.00264***
	(0.000420)		(0.000437)
Pell	-0.00000347		-0.00000290
	(0.00000307)		(0.00000291)
Observations	11180	11180	11180

Marginal effects; Robust standard errors in parentheses.

Observations rounded to the nearest 10 per data restrictions.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.13. IV - Impact of Merit Scholarship on Choosing an Initial STEM Major (Female)

	Probit	First Stage	Second Stage
Merit Scholarship	0.0109		-0.0695**
	(0.0137)		(0.0341)
Strong Merit State		0.366***	
		(0.0159)	
Weak Merit State		0.0925***	
		(0.0117)	
Age	-0.0111*	-0.0139***	-0.0104**
	(0.00574)	(0.00372)	(0.00466)
Black	0.108***	0.0198*	0.0949***
	(0.0187)	(0.0120)	(0.0146)
Hispanic	0.0592***	-0.0288***	0.0511***
	(0.0187)	(0.0104)	(0.0165)
Asian	0.110***	0.0282*	0.109***
	(0.0299)	(0.0162)	(0.0286)
SAT Score	0.000180***	0.000102***	0.000207***
	(0.0000251)	(0.0000193)	(0.0000272)
HS GPA	0.0498***	0.0449***	0.0424***
	(0.0117)	(0.00643)	(0.00865)
Cost	-0.00139***	-0.00201***	-0.00160***
	(0.000462)	(0.000342)	(0.000500)
Pell	-0.00000509	-0.00000605**	-0.00000580*
	(0.00000329)	(0.00000271)	(0.00000319)
Observations	6320	6320	6320

Marginal effects; Robust standard errors in parentheses.

Observations rounded to the nearest 10 per data restrictions.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.14. IV - Impact of Merit Scholarship on Ever Choosing STEM Major

	Probit	First Stage	Second Stage
Merit Scholarship	0.0193		-0.0887***
	(0.0145)		(0.0339)
Strong Merit State		0.368***	
		(0.0121)	
Weak Merit State		0.105***	
		(0.00926)	
Age	-0.0175***	-0.0132***	-0.0151***
	(0.00578)	(0.00277)	(0.00484)
Female	-0.165***	-0.00654	-0.161***
	(0.00861)	(0.00463)	(0.00839)
Black	0.103***	0.0134	0.0931***
	(0.0173)	(0.00915)	(0.0141)
Hispanic	0.0410**	-0.0186**	0.0335**
	(0.0178)	(0.00822)	(0.0159)
Asian	0.166***	0.0353***	0.165***
	(0.0263)	(0.0133)	(0.0247)
SAT Score	0.000345***	0.000108***	0.000359***
	(0.0000265)	(0.0000145)	(0.0000256)
HS GPA	0.0739***	0.0440***	0.0674***
	(0.0109)	(0.00482)	(0.00913)
Cost	-0.000951*	-0.00235***	-0.00112**
	(0.000505)	(0.000262)	(0.000516)
Pell	-0.00000767**	-0.00000378*	-0.00000651*
	(0.00000373)	(0.00000211)	(0.00000336)
Observations	11180	11180	11180

Marginal effects; Robust standard errors in parentheses.
Observations rounded to the nearest 10 per data restrictions.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.15. IV - Impact of Merit Scholarship on Ever Choosing STEM Major (Female)

	Probit	First Stage	Second Stage
Merit Scholarship	0.0210		-0.0902**
	(0.0172)		(0.0409)
Strong Merit State		0.366***	
		(0.0159)	
Weak Merit State		0.0925***	
		(0.0117)	
Age	-0.0111*	-0.0139***	-0.0222***
	(0.00574)	(0.00372)	(0.00569)
Black	0.108***	0.0198*	0.105***
	(0.0187)	(0.0120)	(0.0168)
Hispanic	0.0592***	-0.0288***	0.0389**
	(0.0187)	(0.0104)	(0.0191)
Asian	0.110***	0.0282*	0.150***
	(0.0299)	(0.0162)	(0.0329)
SAT Score	0.000180***	0.000102***	0.000305***
	(0.0000251)	(0.0000193)	(0.0000321)
HS GPA	0.0498***	0.0449***	0.0600***
	(0.0117)	(0.00643)	(0.0107)
Cost	-0.00139***	-0.00201***	-0.0000645
	(0.000462)	(0.000342)	(0.000633)
Pell	-0.00000509	-0.00000605**	-0.00000703*
	(0.00000329)	(0.00000271)	(0.00000393)
Observations	6320	6320	6320

Marginal effects; Robust standard errors in parentheses.

Observations rounded to the nearest 10 per data restrictions.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.16. IV - Impact of Merit Scholarship on Graduating w/ STEM Major

	Probit	First Stage	Second Stage
Merit Scholarship	-0.00555		-0.0814***
	(0.00989)		(0.0234)
Strong Merit State		0.368***	
		(0.0121)	
Weak Merit State		0.105***	
		(0.00926)	
Age	-0.0154***	-0.0132***	-0.00940***
	(0.00429)	(0.00277)	(0.00311)
Female	-0.0616***	-0.00654	-0.0645***
	(0.00585)	(0.00463)	(0.00634)
Black	0.0363***	0.0134	0.0452***
	(0.0135)	(0.00915)	(0.00894)
Hispanic	-0.000929	-0.0186**	0.00249
	(0.0114)	(0.00822)	(0.0106)
Asian	0.0845***	0.0353***	0.111***
	(0.0192)	(0.0133)	(0.0215)
SAT Score	0.000242***	0.000108***	0.000305***
	(0.0000170)	(0.0000145)	(0.0000191)
HS GPA	0.0919***	0.0440***	0.0616***
	(0.00937)	(0.00482)	(0.00535)
Cost	0.00103***	-0.00235***	0.00156***
	(0.000297)	(0.000262)	(0.000413)
Pell	-0.00000740***	-0.00000378*	-0.00000700***
	(0.00000262)	(0.00000211)	(0.00000229)
Observations	11180	11180	11180

Marginal effects; Robust standard errors in parentheses.

Observations rounded to the nearest 10 per data restrictions.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.17. IV - Impact of Merit Scholarship on Graduating w/ STEM Major (Female)

	Probit	First Stage	Second Stage
Merit Scholarship	0.00113		-0.0695**
	(0.0117)		(0.0275)
Strong Merit State		0.366***	
		(0.0159)	
Weak Merit State		0.0925***	
		(0.0117)	
Age	-0.0111*	-0.0139***	-0.0109***
	(0.00574)	(0.00372)	(0.00357)
Black	0.108***	0.0198*	0.0512***
	(0.0187)	(0.0120)	(0.0107)
Hispanic	0.0592***	-0.0288***	0.0156
	(0.0187)	(0.0104)	(0.0129)
Asian	0.110***	0.0282*	0.0788***
	(0.0299)	(0.0162)	(0.0266)
SAT Score	0.000180***	0.000102***	0.000309***
	(0.0000251)	(0.0000193)	(0.0000239)
HS GPA	0.0498***	0.0449***	0.0355***
	(0.0117)	(0.00643)	(0.00592)
Cost	-0.00139***	-0.00201***	0.00108**
	(0.000462)	(0.000342)	(0.000500)
Pell	-0.00000509	-0.00000605**	-0.00000548**
	(0.00000329)	(0.00000271)	(0.00000264)
Observations	6320	6320	6320

Marginal effects; Robust standard errors in parentheses.

Observations rounded to the nearest 10 per data restrictions.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.18. IV - Impact of Merit Scholarship on Graduating w/ STEM Major Conditional on Ever Being a STEM Major

	Probit	First Stage	Second Stage
Merit Scholarship	-0.0107		-0.212***
	(0.0280)		(0.0609)
Strong Merit State		0.439***	
		(0.0255)	
Weak Merit State		0.147***	
		(0.0210)	
Age	-0.0342**	-0.0155***	-0.0256**
	(0.0157)	(0.00600)	(0.0117)
Female	0.0142	0.000841	0.0164
	(0.0205)	(0.00978)	(0.0178)
Black	-0.00328	0.0152	0.0113
	(0.0390)	(0.0193)	(0.0313)
Hispanic	-0.0566	-0.00971	-0.0446
	(0.0393)	(0.0182)	(0.0333)
Asian	0.0669	0.0327	0.0617*
	(0.0426)	(0.0215)	(0.0371)
SAT Score	0.000467***	0.000118***	0.000450***
	(0.0000610)	(0.0000293)	(0.0000518)
HS GPA	0.237***	0.0553***	0.188***
	(0.0304)	(0.0110)	(0.0201)
Cost	0.00895***	-0.00350***	0.00736***
	(0.00124)	(0.000554)	(0.00107)
Pell	-0.0000224**	0.00000242	-0.0000185**
	(0.00000978)	(0.00000526)	(0.00000831)
Observations	2900	2900	2900

Marginal effects; Robust standard errors in parentheses.
Observations rounded to the nearest 10 per data restrictions.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.19. IV - Impact of Merit Scholarship on Graduating w/ STEM Major Conditional on Ever Being a STEM Major (Female)

	Probit	First Stage	Second Stage
Merit Scholarship	-0.0386		-0.236***
	(0.0420)		(0.0878)
Strong Merit State		0.467***	
		(0.0407)	
Weak Merit State		0.116***	
		(0.0303)	
Age	-0.0374	-0.000784	-0.0240
	(0.0260)	(0.0105)	(0.0192)
Black	-0.0174	0.0102	0.00544
	(0.0548)	(0.0283)	(0.0449)
Hispanic	-0.0230	-0.0333	-0.0116
	(0.0585)	(0.0319)	(0.0492)
Asian	0.0110	0.0161	0.00563
	(0.0662)	(0.0306)	(0.0581)
SAT Score	0.000710***	0.0000838*	0.000649***
	(0.0000975)	(0.0000442)	(0.0000784)
HS GPA	0.196***	0.0685***	0.151***
	(0.0547)	(0.0192)	(0.0358)
Cost	0.00620***	-0.00260***	0.00491***
	(0.00196)	(0.000855)	(0.00167)
Pell	-0.0000139	0.00000188	-0.0000122
	(0.0000142)	(0.00000782)	(0.0000122)
Observations	1190	1190	1190

Marginal effects; Robust standard errors in parentheses.

Observations rounded to the nearest 10 per data restrictions.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.20. Bivariate Probit Results by Tercile

		Bivariate Probit by Income Tercile				Probit by Income Tercile			
	2SLS Result	Combined	First	Second	Third	Combined	First	Second	Third
Initial STEM Major	-0.0600**	-0.0527**	-0.130***	-0.0148	0.00837	0.0274**	0.0382*	0.0256	0.0131
	(0.0295)	(0.0243)	(0.0370)	(0.0466)	(0.0445)	(0.0121)	(0.0212)	(0.0205)	(0.0224)
	11180	11180	3410	3420	3390	11180	3410	3420	3390
Ever Choosing STEM Major	-0.0887***	-0.0740**	-0.176***	-0.00875	-0.00791	0.0193	0.0332	0.0167	0.00727
	(0.0339)	(0.0293)	(0.0439)	(0.0561)	(0.0527)	(0.0145)	(0.0250)	(0.0252)	(0.0269)
	11180	11180	3410	3420	3390	11180	3410	3420	3390
Graduating w/ STEM Major	-0.0814***	-0.0810***	-0.0723***	-0.0865**	-0.0621	-0.00555	0.0258**	-0.0315*	-0.0165
	(0.0234)	(0.0199)	(0.0224)	(0.0435)	(0.0385)	(0.00989)	(0.0129)	(0.0187)	(0.0204)
	11180	11180	3410	3420	3390	11180	3410	3420	3390
Graduating w/ STEM Major	-0.212***	-0.194***	-0.160*	-0.214**	-0.210**	-0.0107	0.0979**	-0.0958*	-0.0457
(Conditional on Initial STEM)	(0.0609)	(0.0512)	(0.0972)	(0.0949)	(0.0829)	(0.0280)	(0.0469)	(0.0500)	(0.0485)
	2900	2900	780	890	980	2900	780	890	980

Marginal effects; Robust standard errors in parentheses.

Observations rounded to the nearest 10 per data restrictions.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.21. Bivariate Probit Results by Tercile

		Bivariate Probit by Income Tercile					Probit by Income Tercile			
	2SLS Result	Combined	First	Second	Third	Combined	First	Second	Third
Initial STEM Major	-0.0695**	-0.0487*	-0.119***	0.00243	-0.00429	0.0109	0.0120	0.0236	-0.0156
	(0.0341)	(0.0278)	(0.0412)	(0.0535)	(0.0545)	(0.0137)	(0.0245)	(0.0222)	(0.0264)
	6320	6320	2070	1910	1790	6320	2070	1910	1790
Ever Choosing STEM Major	-0.0902**	-0.0694**	-0.170***	0.0220	-0.0252	0.0210	0.0244	0.0272	-0.00826
	(0.0409)	(0.0343)	(0.0478)	(0.0698)	(0.0657)	(0.0172)	(0.0291)	(0.0297)	(0.0337)
	6320	6320	2070	1910	1790	6320	2070	1910	1790
Graduating w/ STEM Major	-0.0695**	-0.0709***	-0.0814***	-0.0522	-0.0221	0.00113	0.0260*	-0.0255	-0.00782
	(0.0275)	(0.0233)	(0.0235)	(0.0655)	(0.0507)	(0.0117)	(0.0149)	(0.0216)	(0.0258)
	6320	6320	2070	1910	1790	6320	2070	1910	1790
Graduating w/ STEM Major	-0.236***	-0.213***	-0.251***	-0.148	-0.109	-0.0386	0.0845	-0.122	-0.0902
(Conditional on Initial STEM)	(0.0878)	(0.0734)	(0.0965)	(0.155)	(0.141)	(0.0420)	(0.0676)	(0.0809)	(0.0726)
	1190	1190	350	340	400	1190	350	340	400

Marginal effects; Robust standard errors in parentheses.

Observations rounded to the nearest 10 per data restrictions.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.22. GPA by Major and Course Type

	GPA in STEM Classes	GPA in Non-STEM Classes
STEM Majors	2.741	3.032
	(0.816)	(0.743)
Non-STEM Majors	2.716	2.945
	(0.851)	(0.775)
All Majors	2.720	2.956
	(0.846)	(0.771)

Standard deviations in parenthesis.

Chapter III

IMPACTS OF TENNESSEE HOPE: A REGRESSION DISCONTINUITY ANALYSIS

1 Introduction

Continually we have found that the *relative* value of a college degree has continued to rise over time. While the *real* value of a college degree has remained fairly consistent, the value of a high school diploma has continued to decline. Many studies have shown that federal and state programs that incentivize college through grants or scholarships can be effective instruments in guiding more students toward college enrollment (Deming and Dynarski, 2010, Dynarski, 2000, Kane, 2003). While the impact of state grants and scholarships on enrollment has become very clear, the impacts on the qualitative choices that students make in college is still murky.

One qualitative aspect that has been investigated involves the choice of overall institution quality. Cohodes and Goodman (2014) find that students are more likely to go to lower quality schools despite negative impacts to things like graduation rates and lifetime income. Additionally, Goodman (2008) finds that since the population of individuals receiving a state merit scholarship was already likely to go to college the scholarship only induced substitution away from private universities toward in-state public schools.

Another qualitative dimension that has been explored is whether merit scholarships motivate students to attempt four-year instead of two-year degree programs. Bruce and Carruthers (2014) suggest that students attempt four-year programs as a result of the Tennessee HOPE scholarship. Coupled with work from Reynolds (2012) students gain higher expected lifetime income from this even though their costs of attending a four-year program are explicitly higher and their lost wages from additional years of college are higher. Further work by Welch (2014) shows that for students who receive Tennessee HOPE there are no positive benefits to staying in a two-year program. Taken with the previous studies it seems that students are made better off by some of the effects of state merit scholarship programs.

One relatively unexplored aspect of state merit based scholarships is their impact on the type or quality of the degree students get while they are enrolled in a four-year degree program. Sjoquist and Winters (2015) find that states with merit scholarship programs have fewer science, technology, engineering, and mathematics (STEM) graduates, though no causal link can be demonstrated by their study. Some suggestive links can be found in other work not related specifically to state merit scholarships. Arcidiacono, Aucejo, and Spenner (2012) show that harsher grade distributions are part of the reason that persistence in the sciences is lower regardless of initial preference for the sciences. Stinebrickner and Stinebrickner (2014) find that students leave science majors due to expectations of future lower grade performance.

Using a quasi-experimental regression discontinuity approach I attempt to show a causal link between the Tennessee HOPE Scholarship and qualitative college degree measures, with a specific focus on STEM degrees. I find causal links between initial

Tennessee HOPE eligibility requirements and graduating with a four-year degree, starting with an initial STEM major, and graduating with a STEM degree for some students. I also find that student grade point averages, credit-hours taken, and number of semesters as a STEM major are impacted. Overall, these results expand the literature by exploring another dimension of degree quality that is impacted by state merit scholarship programs.

I pay special attention to different subgroups of students who may be of particular interest. Previous research has shown that state merit scholarship programs may contribute to the widening gap between the college attendance rates of students from low-income and high-income families. Results also suggest that these scholarship programs may have disproportionate positive impacts on white students. Overall, there is a concern that these programs may lead to a widening racial and income gap in college attendance (Dynarski, 2000). Women and minorities have also been a specific area of study in regards to STEM outcomes. Griffith (2010) finds differing impacts for the persistence of women and minorities in STEM and shows that many of the negative factors that impact these groups are due to differential levels of college preparedness versus men and whites. Focusing on specific thresholds where students can be thought of as relatively equal may shed some light on how these groups react differently.

2 Background

The Tennessee HOPE Scholarship is part of a larger group of Tennessee Education Lottery Scholarships that were started in 2004. During the 2014-2015 academic year over 70,000 HOPE scholarships were granted to students totaling over $275,000,000.[1]

Graduates of Tennessee high schools are eligible for the HOPE scholarship as long as they enroll in an institution in the state and they meet certain requirements. For initial eligibility students must either graduate with an overall weighted 3.0 grade point average or score a 21 on the ACT. Additionally, students must enroll within 16 months of high school graduation. Students attending a 4-year institution and meeting this criteria receive $2000 per semester for up to three semesters per year for a maximum of five years.

To maintain the HOPE scholarship students must also meet certain renewal criteria. In the semesters before a student attempts 48 credit hours a student must maintain a 2.75 cumulative GPA. In the semesters after that the student must maintain a 3.0 cumulative GPA. If a student fails to meet these academic goals they are able to regain their scholarship one time provided that they reattain the needed grade point averages.

Students who continue to maintain scholarship eligibility can freely transfer between universities within the state of Tennessee. For example a student could begin at

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[1] https://www.tn.gov/assets/entities/collegepays/attachments/TELS_Board_Report_-_2014-2015_AC_Year_Ending.pdf

one public state university then transfer to another private school within the state and as long as there are no gaps in enrollment they would continue to receive the HOPE scholarship.

3 Data

Data for the analysis come from student administrative records at a large public university in Tennessee. Student records come from students enrolling between 2007 and 2009, with students followed until 2015. GPA, credit hours, major, scholarships, grants, ACT scores and demographic data are collected along with FAFSA information that gives data on parent income. Summary statistics for all variables used in the analysis are presented in Table 3.1.

I break the data into four subsamples: the full sample, females, black students, and low income students. The low income subsample is composed of any student that was in the lowest income quartile based on parents reported FAFSA income. The full sample has 23,940 students. Sample means, while not exactly the same, are very similar to information published by the university. When comparing the different subsamples, graduation rates are proportionally higher for women and lower for black and low income students, with low income students graduating about thirteen percentage points less often than female students. Female students also have higher ACT Composite scores than the other two groups, with black students averaging about two and half points lower on average.

For the purpose of this study, the composite ACT score is recalculated using the four component test scores. When reporting composite ACT scores to students and universities ACT Incorporated rounds the average of the four component scores to the nearest whole number.[2] Without the recalculation to a decimal the ACT threshold is less clear. For example a student with component test scores of 21, 21, 21, and 22 receives a 21 as their composite score and a student with component test scores of 19, 19, 19, and 21 receives a composite score of 20. Testing on the rounded threshold leaves open the possibility that we are comparing these two students with total composite scores that are up to seven points different. Using the unrounded score calculated from the component scores allows a comparison between students that are one component score point away from the composite threshold needed for HOPE eligibility. A student with a 20.5 or higher average on the four component tests is eligible for the Tennessee HOPE Scholarship since that score will be rounded up to 21.

For the analysis using cumulative GPA as the running variable grade point averages are normalized to zero at the treatment threshold. The changing GPA threshold for eligibility varies for students who have attempted different numbers of credit hours. Before attempting 48 hours students only need a 2.75 to maintain their HOPE scholarship. After that point students must keep a cumulative GPA of 3.0. I subtract 2.75 from the first group's GPA and 3.0 from the second. The normalization I employ allows me to examine the common threshold of 0 as the normalized point in terms of ongoing HOPE eligibility. Regression discontinuity analysis is also restricted to students within 1

[2] http://www.act.org/content/dam/act/unsecured/documents/Student-Report-04-2016.pdf

GPA point from the threshold. Additionally, I drop students in their first semester of study since they have no cumulative GPA at that point.

4 Empirical Methodology

The fuzzy regression discontinuity (FRD) design utilizes a discontinuous jump in the probability of treatment at an arbitrary threshold. With the local linear regression approach to FRD Hahn, Todd, and Van der Klaauw (2001) show that the local average treatment effect is equivalent to the two-stage least squares estimator where passing the threshold in the first stage is used as an instrument in the second stage. In this case, as with standard instrumental variables, treatment effects are interpreted as local average treatment effects. Lee & Lemieux (2010) provide guidelines to implementing and interpreting FRD.

In the FRD the first stage, probability of treatment, can be written as

$$HOPE = \gamma + \delta Threshold + f(X - c) + \eta. \qquad (1)$$

where treatment is receiving an initial or the ongoing receipt of a HOPE scholarship, δ, estimates the jump in treatment at the policy threshold, and $f(X\text{-}c)$ is a functional form of the running variable and its distance from the policy threshold.

The second stage equation to be estimated is:

$$Y = \alpha + \tau HOPE + g(X - c) + \epsilon. \qquad (2)$$

Where Y is the outcome variable. The treatment effect, τ, is estimated by instrumenting *HOPE* with *Threshold*. A reduced form version is given by substituting the first stage into the second:

$$Y = \alpha + \tau_{red}Threshold + f_{red}(X - c) + \epsilon_{red}. \qquad (3)$$

In this reduced form equation τ_{red} is the intent to treat effect. The two stage least squares results, interpreted as a local average treatment effect, are the same as the intent to treat effect, τ_{red} , divided by the discontinuous jump in treatment at the threshold, δ, provided $f(X\text{-}c)$ and $g(X\text{-}c)$ are the same functional form. Standard errors are computed using robust standard errors clustered at each value along the running variable following the suggestions of Lee & Card (2007).

Two different running variables are used for different specifications. Since high school GPA is not available, composite ACT score is used as the running variable, X, in equation 1 for specifications involving initial HOPE eligibility.

The set of outcomes analyzed based on initial eligibility are whether a student graduates, graduates with a STEM major, chooses an initial STEM major, and how many semesters a student majors in a STEM field.[3] Results from the specification using a discontinuity in ACT score are used to analyze initial behavior and end results in college.

For specifications involving ongoing HOPE eligibility cumulative GPA is used as the running variable. This is a more appropriate measure to use when looking at in-college behavior since GPA is what determines treatment after a student is already enrolled. In-college outcomes analyzed are whether or not a student currently majors in a

[3] Majors considered STEM for this study are aerospace, animal science, biochemistry, biology, chemistry, computer science, engineering technology, environmental science, geological science, information systems, mathematics, mechatronics engineering, food science, physics, plant and soil science, and science.

STEM field, GPA for the current term, and number of credit hours taken in the current term. Observations are a pooled cross section of each student-semester presented in the data. Observations are restricted to those students who begin their college career with a HOPE scholarship. As such, the interpretation of the results should be taken as local average treatment effects on students receiving a HOPE scholarship.

While GPA is endogenous to student effort and ability, and thus open to manipulation, it is still impossible for a student to accurately manipulate GPA due to idiosyncratic shocks in the difficulty of a given class. A particularly difficult instructor, illness, or time constraints outside of class could all potentially impact the difficulty of a course. GPA can be thought of as two different components, effort and some exogenous unpredictable component that may reflect a particularly difficult exam, instructor, or even question. Even if students can endogenously manipulate GPA through effort localized random assignment can still occur as long as students cannot precisely sort around the threshold (Lee, 2008). Testing for GPA manipulation is still performed in Section 4.1.

4.1 Tests for Manipulation of the Running Variable

Though students cannot perfectly manipulate the results of the ACT they can retake tests until they reach the threshold. As before, even if ACT score is endogenous to student effort, there is some random component to the test that still provides local randomization.[4] As with ACT score there may be some ability for students to manipulate GPA. Again, as long as there is still a random component to GPA then localized random assignment around the threshold still exists.

To test whether there is randomization in assignment a test of the continuity in the density of each running variable is performed according to McCrary (2008), with the results shown in Figures 3.1 and 3.2. Neither figure shows a statistically significant break at the policy threshold suggesting no manipulation of the running variable by students.

4.2 Test for Discontinuities in Other Characteristics

Tests for discontinuities in related covariates and characteristics are performed according to suggestions from Lee (2008). Regression discontinuity assumes that characteristics are balanced on either side of the threshold with no discontinuities. Any discontinuity would indicate a violation of the local randomization around the threshold. Table 3.2 presents regression results using seemingly unrelated regressions where each equation represents a different covariate. This process is implemented again for each subsample used in the analysis.

[4] Test scores regularly fluctuate over time with variation over year and by test within a particular year. https://nces.ed.gov/programs/digest/d10/tables/dt10_155.asp

5 Results

5.1 Initial HOPE Eligibility

I estimate the first stage, represented by Equation 1, to assess the impact of passing the threshold on receiving a HOPE Scholarship. Linear functions of the running variable are used for this analysis.

Graphical representations of HOPE eligibility are presented in Figure 3.3 for each subsample. Visually, a clear discontinuity can be seen at the threshold in each subsample. Equation 1 regression results that correspond with Figure 3.3 are presented in Table 3.3. While it is sometimes appropriate to estimate the function of the running variable, *f()* and *g()*, with quadratic or higher order functions, in this instance a visual inspection suggests that a linear function is appropriate.

The discontinuity in initial eligibility ranges from 16.8 percentage points for black students down to 13 percentage points for female students. All discontinuities are significant at the 1% level. The addition of demographic control variables to the full sample does not significantly alter the results without controls.

Second stage FRD results are presented in Table 3.4 with graphical representations presented in Figures 3.4-3.7. Estimates provided on the graph represent intent to treat effects, τ_{red} in Equation 3. Local average treatment effects can be found by dividing intent to treat effects by the discontinuity in the first stage, δ in Equation 1. Results should be interpreted as local average treatment effects of the impact of hope eligibility on the outcome. The results show negative impacts on graduation rates for the full and low income samples of students, 18.5 and 26.2 percentage points respectively. While this seems unexpected, results from Bruce & Carruthers (2014) suggest that some students choose to attempt a four-year degree in lieu of starting out in a two-year program as a result of the HOPE scholarship. Some of the negative impact on graduation could be a result of students just “trying out" a four year program, but not finishing. However, this is unlikely to be fully driving the results since magnitudes were small with less than a four percentage point increase in initial enrollment in four-year public programs.

Since I do not observe students after they leave this particular university I cannot say whether they go on to complete or attempt a two-year program or even attempt completion at a different four-year program. The impacts that I observe could reflect students “trying out" a four-year program, then leaving and going back to a two-year school. Costs for low income student would likely exacerbate these effects since they would be the students that are more likely to be swayed toward the more expensive degree program if financial constraints are a part of their decision between a two and four year program.

An unsurprising result is that in the full sample of students there is a negative impact on students choosing an initial major when they enter school and that the effect is larger for female students. The 8.4 percentage point drop for students in the full sample is suggestive of the fact that some students may find it more difficult to keep and maintain a HOPE scholarship in a STEM field where classes are likely more difficult. However, it should be noted that this does not translate to fewer students actually graduating with a STEM degree. Perhaps students’ initial concerns about difficulty lead to students reconsidering STEM while they are enrolled. The amplified result of a 11.8

percentage point drop for initial STEM majors for female students may be suggestive of an apprehension for women in STEM. It should be noted again that this does not translate to a significant drop in actual female STEM graduates. Again, concerns that female students may have about difficulty or fit may change over time as they are actually enrolled.

Of particular note are the results from the subsample of black students. Black students show positive increases in both the number of semesters spent as a STEM major and the rate of graduating with a STEM degree. Results from recent research examining the impact of Tennessee HOPE on community college outcomes shows a similar pattern (Welch, 2014). Non-white students showed increased rates of earning associate's degrees of roughly 10 percentage points and increased rates of earning bachelor's degrees of slightly more than 20 percentage points. These estimates are consistent with the estimates that I find.

5.2 Ongoing HOPE Eligibility

First stage results for each subsample are presented in Table 3.5. Graphical representations of the first stage results for the full, low income, female, and black samples are shown in the top left graph in Figures 3.8-3.11. The discontinuity at the GPA threshold is much larger than for ACT score. This is due to the fact that there are fewer factors that determine whether a student is awarded a HOPE scholarship after initial eligibility has been met. For initial eligibility a student could have overcome a low ACT score with a higher high school GPA. When examining HOPE retention the only factors that determines eligibility is a student's cumulative GPA and full time enrollment, both of which are necessary to maintain HOPE.[5] The HOPE Scholarship does allow students who fall below the maintenance threshold to regain HOPE one time if they bring their cumulative GPA back up to acceptable levels. If they fall below the threshold a second time they are ineligible for HOPE regardless of how high their future GPA may be. Additionally, in the time during the transition from the 2.75 to 3.0 threshold students can maintain HOPE below a cumulative 3.0 as long as their current term GPA is at or above 3.0. For these reasons some students can still be considered treated below the threshold.

These reasons explain why we may have some students below the threshold still receiving HOPE and some students above the threshold without HOPE. The graphical representations of ongoing HOPE eligibility show that as students increase their GPA above the threshold needed, they near 100% compliance. Discontinuities in the first stage are all above 40 percentage points.

Second stage FRD results are presented in Table 3.6 with graphical representations shown in Figures 3.8-3.11. Results of whether a student majors in a STEM field are overwhelmingly positive with students being 5.7 percentage points more likely to have a STEM major in a given semester. Female and black students show even larger estimates at 6.2 and 8 percentage point increases, respectively. Noticeably absent

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[5] Students can only receive HOPE for a maximum of 5 years. It is possible that some students lose HOPE for staying in school too long. However, this is probably rare since full time students are unlikely to have not completed a degree in 5 years.

from the positive significant results are students from the low income sample. They have a smaller point estimate of a 3 percentage point increase in majoring in STEM, but more importantly this is not shown to be significant despite the strong significance in the other samples.

Term GPA represents the GPA that a student receive in the given semester. Other studies have suggested that having to maintain a higher GPA for the scholarship would induce students to put forth more effort in classes. While I cannot definitively show that students are trying harder and not just taking courses that allow for higher grades with the same amount of effort, the increased GPA along with increased rates of STEM suggest that students are not necessarily shying away from what may be a difficult major. One pillar of support for this idea is that the group with the largest positive increase in term GPA is the low income students. Further examination of the results show an inverse relationship between positive STEM results and positive term GPA results. The larger increase we see in STEM the relatively smaller the positive increase in term GPA we see. Another reason for this result may be that because of the financial award that comes with the scholarship students may not have to work as many hours in jobs outside the classroom, leaving more time for studying and schoolwork.

There are also positive results for credit hours taken in a semester. The full sample reveals that HOPE increases credit hours taken by roughly one third of a credit hour and is significant at the 5% level. Results from the subsamples of black and low income students show larger estimates. Black students see an increase in credit hours of 0.47 credit hours per semester, significant at the 10% level. With low income students the effect is much larger with almost a 0.6 increase in credit hours per semester, significant at the 1% level. These results may provide evidence for financial constraints affecting enrollment intensity. If students are constrained by incomes, as the low income and black subsamples are relative to the whole, the HOPE scholarship may allow them extra money to increase their course load. Again, because of HOPE students may have to work fewer hours at jobs outside of the classroom leaving them more time to actually take courses.

5.2.1 Expanded Major Choice

To further explore the lack of positive result for low income students majoring in STEM I also estimate the impact of HOPE on the college that a student belongs to in a given semester. The seven university colleges are examined along with the Nursing major independently. Nursing is measured independently since it is the single largest major by number of students at the university with more nursing students than students in the entire College of Education or University College.[6] It should also be noted that the College of Basic & Applied Science does not encompass all STEM degrees. For example, Computer Information Systems is part of the College of Business and Information Technology is part of University College. Results for the full sample as well as results by income quartile are provided in Table 3.7. HOPE has a positive and significant impact on the number of students majoring in nursing with a 5.5 percentage point increase in the number of majors for the full sample. If we look independently at each income quartile

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[6] This excludes Regents Online Degree Program students in the University College that are not included in my analysis.

the second quartile has the largest increase in nursing with a roughly 7.5 percentage point increase in the number of nursing majors as a result of HOPE.

Other gains are shown in the College of Education with a 2.6 percentage point increase for the full sample and a 4.6 and 4.7 percentage point increase for the second and third quartiles, respectively. The College of Behavioral Sciences shows a 3.5 percentage point increase in the number of students in the full sample with significance at the 10% level, but no significant results when examined by income quartile. The students entering nursing, education, and behavioral sciences seem to be coming from the College of Business. In the full sample there is a statistically significant 8 percentage point decrease in the number of business students with even larger negative estimates of -13.6, -9.1, and -9.4 in the second, third, and fourth quartiles, respectively. The College of Basic & Applied Science has negative and insignificant estimates for each income quartile

What cannot be determined from this information is whether there is other information that is driving students into or away from specific field. One explanation is that if HOPE induces students to attempt a four-year instead of a two-year degree, as is shown in Bruce & Carruthers (2014), it is possible that this happens asymmetrically by field of study. According to the 2014 Tennessee Higher Education Factbook the largest area of concentration in the Tennessee community college system is Practical Nursing.[7] If we are proportionally adding students by field of concentration that would have gone to a community college without the HOPE scholarship it may have a disproportionate

[7] https://www.tn.gov/assets/entities/thec/attachments/2014-15_Factbook.pdf

positive effect on the number of nursing majors. However, the number of students being induced is relatively modest with roughly 900 extra students spread among all public four year universities over the period of three years. So while results may be slightly biased upward the effect is likely small. Alternatively, if students are less likely to be induced into four year programs when they have a viable two year alternative program in the same field this would put downward pressure on estimates.

5.2.2 Undecided Students & Efficient Sorting

Another explanation as to why STEM graduation rates are not impacted even though there are fewer initial STEM majors may be a result of students making better decisions about initial major. If students choose no major at all when they start and use their experience in school to make better informed decisions about what they want to do perhaps students who were less likely to finish with a STEM major do not choose STEM initially. Tables 3.8 and 3.9 explore this idea in two different ways. Table 3.8 presents the FRD results of entering college with no major, or “undecided." Students from the low income group are almost 20 percentage points more likely to start with no major at all. For the full sample, students are roughly 11 percentage points more likely to have no declared major at initial enrollment. If students are at first undecided then choose a major having gained at least a semester of insight they may be less likely to change in the future.

In Table 3.9 I present the results of the likelihood of a student changing their major, leaving out students who are undecided. Students with an initial HOPE scholarship are less likely to change their major in the future across all samples. Low income students are over 8.6 percentage points less likely to change their initial major as a result of HOPE with students being 5.5 percentage points less likely to switch in the full sample. Coupled with higher rates of being undecided, this is further evidence that HOPE may be allowing students to make better initial choices in their major. Female and black students have decreased rates of major changing as a result of HOPE, but initial rates of being undecided are not statistically significant.

If HOPE does allow students to better sort into certain majors it may also be reflected in the time it takes them to graduate. I restrict the sample to only those students who have graduated and see if HOPE lessens the number of semesters it takes to earn a degree. If students are picking better initial majors and switching major less often it stands to reason that they may also graduate sooner. Results presented in Table 3.10 show negative point estimates for each sample, but none are statistically significant.

5.3 Falsification Tests

Tests using alternate ACT composite thresholds for initial HOPE eligibility are presented along with the results in Table 3.4. A false high threshold of a 22 composite ACT score is tested in the second panel. One significant result shows in the full sample for initial STEM major. This result is only significant at the 10% level and represents just 2.5% of the overall falsification tests. As such, it may be significant only by chance. Visual inspection of the discontinuity in eligibility at a composite ACT of 22 on Figure 3.3

doesn't reveal any obvious break at this point. There are no significant results with the false lower ACT score presented in the third panel with no significant effects present.

Alternate GPA thresholds are also explored for maintaining HOPE eligibility. It should be noted that since the samples in this case were restricted to only those within 1 GPA point of the normalized threshold that sample sizes are different for each falsification test. The false high threshold shown in the “False High Threshold" panel presents results from an alternative threshold 0.2 GPA points higher than the actual threshold, with no significant results found. The false low threshold shown in the “False Low Threshold" panel presents results from an alternative threshold 0.2 GPA points lower than the actual threshold, with no significant results found again.

5.4 Sensitivity to Bandwidth

Since the full sample bandwidth of ACT score was used for the analysis on initial HOPE eligibility I explore the sensitivity of the results to alternate bandwidth specifications using non-parametric estimates based on Nichols (2011). Figures 3.12-3.15 show point estimates and 95% confidence intervals for each outcome using 11 different bandwidth choices. The fourth bandwidth in each sample in each figure represents the optimal bandwidth that minimizes mean squared error as outlined by Imbens & Kalyanaraman (2009). While using smaller bandwidths than what is considered optimal does have noticeable results on the estimates using larger bandwidths does not seem to greatly bias the results. Paying special attention to Figures 3.13 and 3.14 we see that the positive impacts on STEM semesters taken and graduating with a STEM degree are robust to various bandwidths. The point estimates are slightly different, but remain positive and significant regardless of the bandwidth chosen.

6 Discussion & Concluding Remarks

Much has been written on the roles that various merit scholarships play in the outcomes of college students. One of the lesser explored areas is the impact that merit scholarships have on STEM. While some studies do show negative impacts on graduating with a STEM degree as a result of being in a state with a merit scholarship, to my knowledge there has been no studies that show that there is a causal relationship between the two (Sjoquist & Winters, 2015a,b).

This study exploits arbitrary thresholds necessary for the eligibility and continued renewal of the Tennessee HOPE Scholarship. These thresholds allow me to investigate the role that this merit scholarship has on STEM, graduation, grade point averages, enrollment intensity, and field of study in a causal way.

Focusing on initial eligibility and ACT scores, I compare student outcomes for students who fall short of and students who surpass the composite ACT score barrier of 21 that is needed for the scholarship. While there is a clear impact on the eligibility for the HOPE Scholarship at this point, I find relatively modest impacts on behavior as a result of this. I find negative significant impacts on enrolling in college with a STEM major. For black students there are positive and significant impacts on both graduating with a STEM major and number of semesters majoring in STEM. While these results seem counter intuitive they are robust to multiple bandwidths and similar results have been found in related work (Welch, 2014). Impacts on overall graduation rates should be interpreted with caution. Since I only observe a student at one university I cannot conclude whether or not this student ever graduates, be it from a different four-year or possibly even a two-year program. This result could be interpreted more accurately as the impact of graduating *at this university*. Students who would have otherwise graduated may be transferring or otherwise finishing their studies at a different university.

Turning toward students while they are already enrolled I focus on student who enroll in the university with HOPE. From there I compare the behavior of students who fall just below and those who just surpass the threshold necessary to keep their scholarship. Students earn higher GPAs and take more credit hours per semester as a result of HOPE. This is in line with previous studies using merit scholarships that show similar results suggesting that students increase their GPA and trade out of what they perceive to be more difficult courses, though their results do not identify a causal link between merit scholarships and this behavior (Cornwell, Lee, \& Mustard, 2006). When investigating major choice behavior grouped by college another pattern emerges. Students who remain eligible for HOPE increasingly flock toward nursing degrees and education degrees while leaving business fields. However, others have shown that the selection of students attempting a four year degree may be slightly biased by HOPE eligibility. Further study and more robust data is needed to test the overall impact on the results presented here. However, it should be noted that the effects are at best very modest and should not call into question the overall results of this study.

The findings in this paper suggest that further study is needed to answer some of the questions about the impacts of HOPE on students in Tennessee. While student behavior while in college is important, I do not have enough information to determine whether this has any impact on long-term outcomes. Some effects may be a result of the idiosyncrasies of this particular university. Different institutions with different STEM majors, different peer institutions, or different student populations may exhibit differing effects. Wider applicability to other merit scholarships is also not clear. The effects of initial eligibility may be different in states that have stricter or more lax rules. States that provide relatively smaller or larger awards may have different effects, especially for students that are more financially constrained. Additionally, while regression discontinuity has strong internal validity the results do not necessarily have strong external applicability, meaning effects measured around the threshold may not apply to students at areas higher or lower than the threshold.

REFERENCES

1. Arcidiacono, P., Aucejo, E. M., and Spenner, K. What Happens After Enrollment? An Analysis of the Time Path of Racial Differences in GPA and Major Choice. IZA Journal of Labor Economics 1, 1 (2012), 1–24.

2. Bruce, D. J., and Carruthers, C. K. Jackpot? The Impact of Lottery Scholarships on Enrollment in Tennessee. Journal of Urban Economics 81, C (2014), 30–44.

3. Cohodes, S. R., and Goodman, J. S. Merit Aid, College Quality, and College Completion: Massachusetts' Adams Scholarship as an In-kind Subsidy. American Economic Journal: 23 Applied Economics 6, 4 (October 2014), 251–85.

4. Cornwell, C., Lee, K. H., and Mustard, D. B. The Effects of State Sponsored Merit Scholarships on Course Selection and Major Choice in College. IZA Discussion Papers 1953, Institute for the Study of Labor (IZA), Jan. 2006.

5. Deming, D., and Dynarski, S. Into College, Out of Poverty? Policies to Increase the Postsecondary Attainment of the Poor. Working Paper 15387, National Bureau of Economic Research, September 2009.

6. Dynarski, S. Hope for Whom? Financial Aid for the Middle Class and Its Impact on College Attendance. NBERWorking Papers 7756, National Bureau of Economic Research, Inc, June 2000.

7. Goodman, J. Who Merits Financial Aid?: Massachusetts' Adams Scholarship. Journal of Public Economics 92, 10–11 (2008), 2121 – 2131.

8. Griffith, A. L. Persistence of Women and Minorities in STEM Field Majors: Is it the School that Matters?. Economics of Education Review 29, 6 (2010), 911 – 922.

9. Hahn, J., Todd, P., and Van der Klaauw, W. Identification and Estimation of Treatment Effects with a Regression Discontinuity Design. Econometrica 69, 1 (2001), 201–209.

10. Imbens, G., and Kalyanaraman, K. Optimal Bandwidth Choice for the Regression Discontinuity Estimator. Review of Economic Studies 79, 3 (2012), 933–959.

11. Imbens, G. W., and Lemieux, T. Regression Discontinuity Designs: A Guide to Practice. Journal of Econometrics 142, 2 (February 2008), 615–635.

12. Kane, T. J. A Quasi-experimental Estimate of the Impact of Financial Aid on College-going. Working Paper 9703, National Bureau of Economic Research, May 2003.

13. Lee, D. S. Randomized Experiments from Non-random Selection in US House Elections. Journal of Econometrics 142, 2 (2008), 675 – 697. The regression discontinuity design: Theory and applications.

14. Lee, D. S., and Card, D. Regression Discontinuity Inference with Specification Error. Journal of Econometrics 142, 2 (2008), 655–674.

15. Lee, D. S., and Lemieux, T. Regression Discontinuity Designs in Economics. Journal of Economic Literature 48, 2 (June 2010), 281–355.

16. McCrary, J. Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test. Journal of Econometrics 142, 2 (February 2008), 698–714.

17. Nichols, A. Causal Inference for Binary Regression with Observational Data. CHI11 Stata Conference 6, Stata Users Group, July 2011.

18. Reynolds, C. L. Where to Attend? Estimating the Effects of Beginning College at a Two-year Institution. Economics of Education Review 31, 4 (2012), 345 – 362.

19. Sjoquist, D., and Winters, J. The Effect of Georgia's HOPE Scholarship on College Major: a Focus on STEM. IZA Journal of Labor Economics 4, 1 (December 2015), 1–29.

20. Sjoquist, D. L., and Winters, J. V. State Merit Aid Programs and College Major: A Focus on STEM. Journal of Labor Economics 33, 4 (2015), pp. 973–1006.

21. Stinebrickner, R., and Stinebrickner, T. R. A Major in Science? Initial Beliefs and Final Outcomes for College Major and Dropout. Review of Economic Studies 81, 1 (2014), 426–472.

22. Welch, J. G. Hope for Community College Students: The Impact of Merit Aid on Persistence, Graduation, and Earnings. Economics of Education Review 43, C (2014), 1–20.

APPENDIX C

Table 3.1. Descriptive Statistics

	Full Sample		Female Students		Black Students		1st Income Quartile	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Graduated	0.537	0.498	0.579	0.493	0.487	0.499	0.447	0.497
Graduated STEM	0.092	0.289	0.089	0.285	0.058	0.234	0.071	0.257
Initial STEM Major	0.209	0.407	0.212	0.408	0.223	0.416	0.218	0.413
STEM Semesters	0.947	2.112	0.956	2.101	0.938	2.027	0.955	2.083
Started TN HOPE	0.689	0.462	0.714	0.451	0.547	0.497	0.604	0.489
Age	19.537	1.629	19.485	1.606	19.337	1.542	19.468	1.619
Female	0.541	0.498	-	-	0.597	0.490	0.558	0.496
Black	0.178	0.382	0.196	0.397	-	-	0.344	0.475
Hispanic	0.025	0.158	0.025	0.158	-	-	0.032	0.176
Asian	0.024	0.153	0.022	0.149	-	-	0.036	0.187
ACT Composite	22.08	3.663	21.95	3.638	19.33	2.985	20.77	3.590
Parent's Income ($1000)	77.735	63.264	75.721	62.052	48.381	43.487	18.456	9.127
Observations	23940		12978		4276		5972	

Table 3.2. Checks for Covariate Discontinuities

	Full	Female	Black	Low Income
Age	-0.077	0.084	0.726	0.557
	(0.232)	(0.311)	(0.542)	(0.452)
Female	-0.093	-	-0.110	-0.147
	(0.071)	-	(0.174)	(0.139)
Black	0.069	0.097	-	0.171
	(0.067)	(0.094)	-	(0.164)
Hispanic	0.003	-0.019	-	0.060
	(0.023)	(0.030)	-	(0.049)
Asian	-0.001	0.029	-	0.041
	(0.021)	(0.028)	-	(0.052)
Low Income	-0.007	-0.030	0.161	-
	(0.060)	(0.082)	(0.174)	-
Observations	23940	12978	4276	5972

Robust standard errors in parentheses.

Table 3.3. First Stage Results - HOPE Eligibility

	Full	Low Income	Female	Black	w/ Controls
HOPE Eligability	0.153***	0.163***	0.130***	0.168***	0.149***
	(0.0213)	(0.0202)	(0.0236)	(0.0270)	(0.0214)
Observations	23940	5972	12978	4276	23940

The table lists the first stage estimates of the impact of passing the ACT score threshold. Robust standard errors clustered by ACT Composite score in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Table 3.4. **Initial HOPE Eligibility**

						Composite ACT 22				Composite ACT 19		
		STEM	Graduated	Started		STEM	Graduated	Started		STEM	Graduated	Started
	Graduated	Semesters	STEM	STEM	Graduated	Semesters	STEM	STEM	Graduated	Semesters	STEM	STEM
Full	-0.185**	-0.363	-0.015	-0.084**	-0.089	-0.629	-0.078	-0.163*	-0.157	-0.411	0.018	-0.077
	(0.085)	(0.351)	(0.046)	(0.042)	(0.105)	(0.463)	(0.055)	(0.091)	(0.146)	(0.661)	(0.078)	(0.088)
	23940	23940	23940	23940	23940	23940	23940	23940	23940	23940	23940	23940
Low Income	-0.262*	0.015	0.045	-0.069	-0.114	-0.189	-0.065	-0.327	-0.055	0.329	0.103	-0.271
	(0.155)	(0.564)	(0.068)	(0.087)	(0.189)	(0.964)	(0.076)	(0.232)	(0.194)	(0.854)	(0.101)	(0.200)
	5972	5972	5972	5972	5972	5972	5972	5972	5972	5972	5972	5972
Female	-0.154	-0.383	-0.029	-0.118*	0.020	-0.257	-0.033	-0.106	0.305	0.572	0.088	-0.005
	(0.149)	(0.473)	(0.059)	(0.065)	(0.126)	(0.674)	(0.067)	(0.144)	(0.242)	(0.927)	(0.111)	(0.139)
	12978	12978	12978	12978	12978	12978	12978	12978	12978	12978	12978	12978
Black	0.058	1.160**	0.204***	-0.074	-0.110	-0.615	-0.208	-0.316	-0.166	0.049	0.082	-0.051
	(0.137)	(0.542)	(0.070)	(0.095)	(0.348)	(1.594)	(0.153)	(0.274)	(0.159)	(0.679)	(0.081)	(0.114)
	4276	4276	4276	4276	4276	4276	4276	4276	4276	4276	4276	4276
w/Controls	-0.166**	-0.366	-0.015	-0.081*	-0.023	-0.713	-0.084	-0.168	-0.187	-0.292	0.00168	-0.0620
	(0.081)	(0.357)	(0.048)	(0.043)	(0.110)	(0.559)	(0.067)	(0.112)	(0.135)	(0.585)	(0.0726)	(0.0806)
	23940	23940	23940	23940	23940	23940	23940	23940	23940	23940	23940	23940

The estimates presented are two stage least squares from Equation 2. Robust standard errors clustered by ACT Composite score in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Table 3.5. First Stage Results - Maintaining HOPE

	Full	Low Income	Female	Black	w/ Controls
HOPE Eligability	0.415***	0.433***	0.405***	0.441***	0.414***
	(0.038)	(0.044)	(0.041)	(0.038)	(0.038)
Observations	65757	15190	38370	10462	65757

The table lists the first stage estimates of the impact of passing the GPA threshold. Robust standard errors clustered by GPA in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Table 3.6. HOPE Maintenance

				False High Threshold			False Low Threshold		
	STEM	Term GPA	Term Credit Hours	STEM	Term GPA	Term Credit Hours	STEM	Term GPA	Term Credit Hours
Full	0.0571***	0.357***	0.349**	0.0400	-1.164	-2.590	-0.151	-0.618	-1.242
	(0.0137)	(0.0539)	(0.146)	(0.134)	(2.624)	(5.754)	(0.176)	(2.871)	(3.834)
	65757	65757	65757	54680	54680	54680	62963	62963	62963
Low Income	0.0379	0.459***	0.599***	-0.0977	-0.256	-3.789	-0.156	-1.006	-3.234
	(0.0322)	(0.0673)	(0.187)	(0.296)	(3.434)	(6.028)	(0.435)	(3.142)	(4.950)
	15190	15190	15190	13403	13403	13403	14473	14473	14473
Female	0.0623***	0.374***	-0.00964	0.238	-1.596	-4.323	-0.0729	-0.898	-2.890
	(0.0153)	(0.0593)	(0.185)	(0.253)	(3.024)	(6.003)	(0.271)	(3.438)	(4.457)
	38370	38370	38370	30966	30966	30966	36753	36753	36753
Black	0.0800**	0.298***	0.473*	0.223	-0.563	-6.434	0.658	-0.936	5.428
	(0.0313)	(0.0786)	(0.246)	(0.564)	(2.858)	(7.222)	(0.520)	(2.376)	(3.306)
	10462	10462	10462	9812	9812	9812	9998	9998	9998
w/Controls	0.0590***	0.323***	0.365**	0.0231	-0.844	-3.756	-0.160	-0.472	-1.496
	(0.0135)	(0.0481)	(0.144)	(0.132)	(2.050)	(8.399)	(0.163)	(1.616)	(5.518)
	65757	65757	65757	54680	54680	54680	62963	62963	62963

The estimates presented are two stage least squares from Equation 2. Robust standard errors clustered by Cumulative GPA in parentheses.
*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Table 3.7. Choice of College

		Income Quartiles			
	Full Sample	1st	2nd	3rd	4th
Basic & Applied	-0.0149	-0.0223	-0.00802	-0.00230	-0.0151
Science	(0.0225)	(0.0295)	(0.0286)	(0.0378)	(0.0322)
Nursing	0.0555***	0.0374***	0.0748**	0.0538**	0.0611***
	(0.0122)	(0.0125)	(0.0289)	(0.0223)	(0.0147)
Business	-0.0813***	-0.0199	-0.136***	-0.0911***	-0.0938***
	(0.0129)	(0.0318)	(0.0242)	(0.0241)	(0.0240)
Education	0.0266***	0.000657	0.0461***	0.0477***	0.0159
	(0.00601)	(0.00773)	(0.0144)	(0.0128)	(0.0134)
Behavioral Science	0.0359*	0.0486	0.00706	0.0408	0.0504
	(0.0188)	(0.0329)	(0.0251)	(0.0285)	(0.0327)
Liberal Arts	0.00385	-0.0166	0.0309	0.00133	0.000638
	(0.0161)	(0.0236)	(0.0323)	(0.0256)	(0.0332)
Mass	-0.00357	-0.0218	0.0118	-0.0213	0.00999
Communication	(0.0139)	(0.0152)	(0.0292)	(0.0195)	(0.0212)
University College	-0.0103	-0.00162	0.00310	-0.0310***	-0.0104
	(0.00909)	(0.0153)	(0.0168)	(0.0112)	(0.0126)
Observations	65757	16440	16443	16436	16438

The estimates presented are two stage least squares from Equation 2. Robust standard errors clustered by Cumulative GPA in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Table 3.8. Major Undecided

	Full	Low Income	Female	Black
Undecided	0.107*	0.195**	0.0938	0.118
	(0.0581)	(0.0910)	(0.0603)	(0.0879)
Observations	23940	5972	12978	4276

The estimates presented are two stage least squares from Equation 2. Robust standard errors clustered by ACT Composite score in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Table 3.9. Changing Major

	Full	Low Income	Female	Black
Changed Major	-0.0553***	-0.0869***	-0.102***	-0.0409*
	(0.0109)	(0.0176)	(0.0148)	(0.0245)
Observations	62230	14386	36565	10086

The estimates presented are two stage least squares from Equation 2. Robust standard errors clustered by Cumulative GPA in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Table 3.10. Semesters to Graduate

	Full	Low Income	Female	Black
Semesters to Graduate	-0.434	-1.383	-0.0278	-1.384
	(0.857)	(1.642)	(1.325)	(2.266)
Observations	12874	2671	7518	2083

The estimates presented are two stage least squares from Equation 2. Robust standard errors clustered by ACT Composite score in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

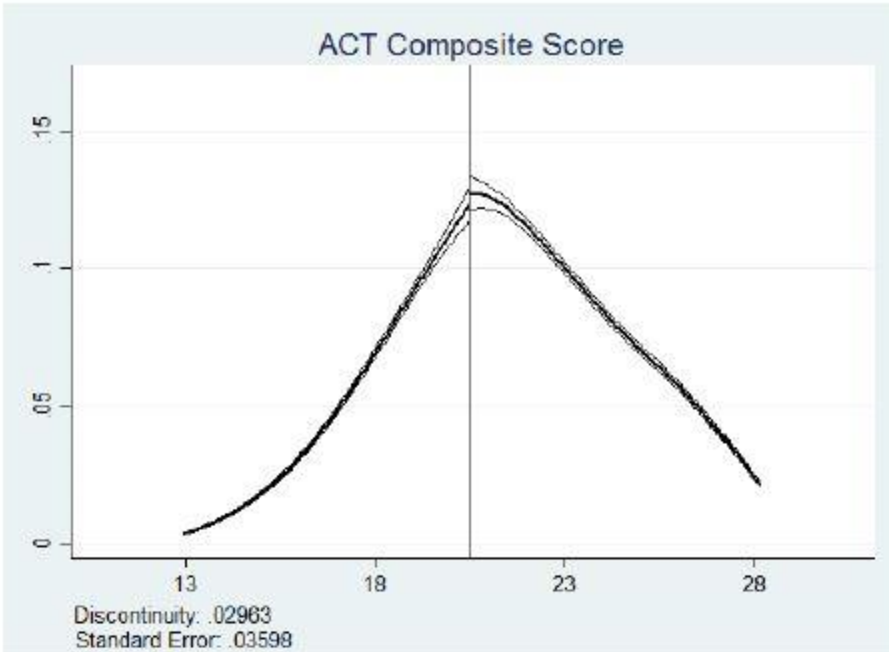

Figure 3.1: Test for Manipulation of ACT

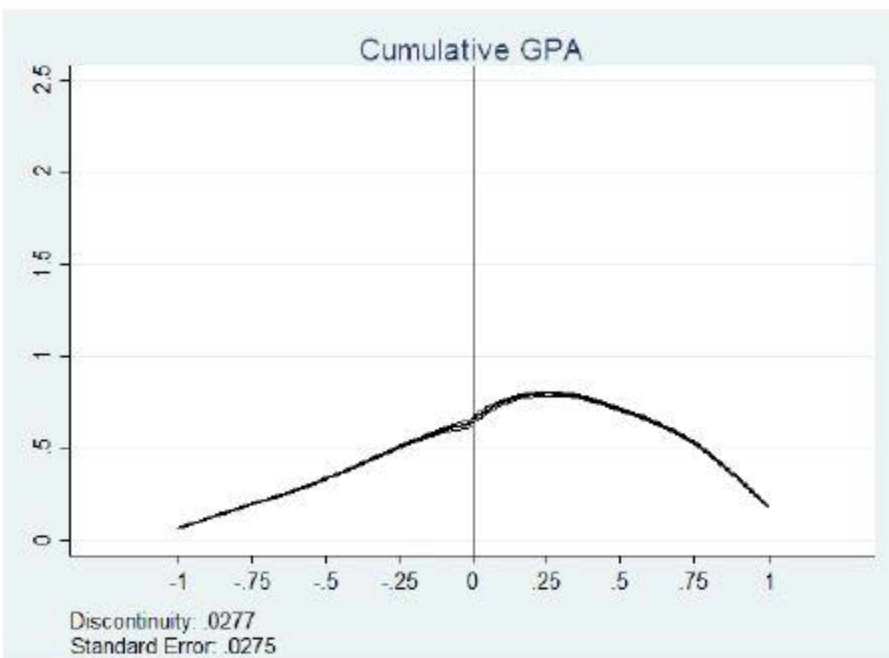

Figure 3.2: Test for Manipulation of GPA

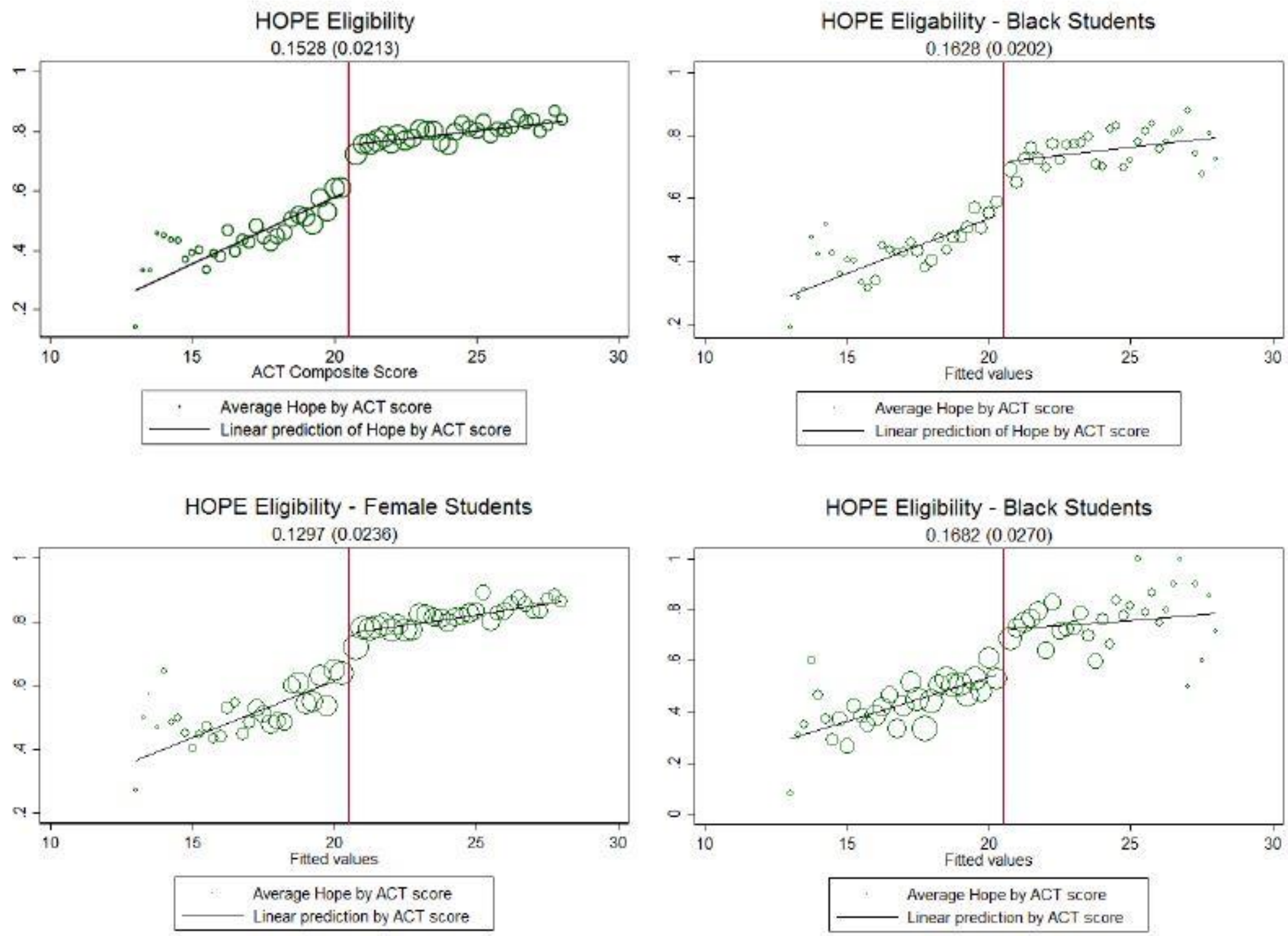

Figure 3.3: First Stage HOPE Eligibility

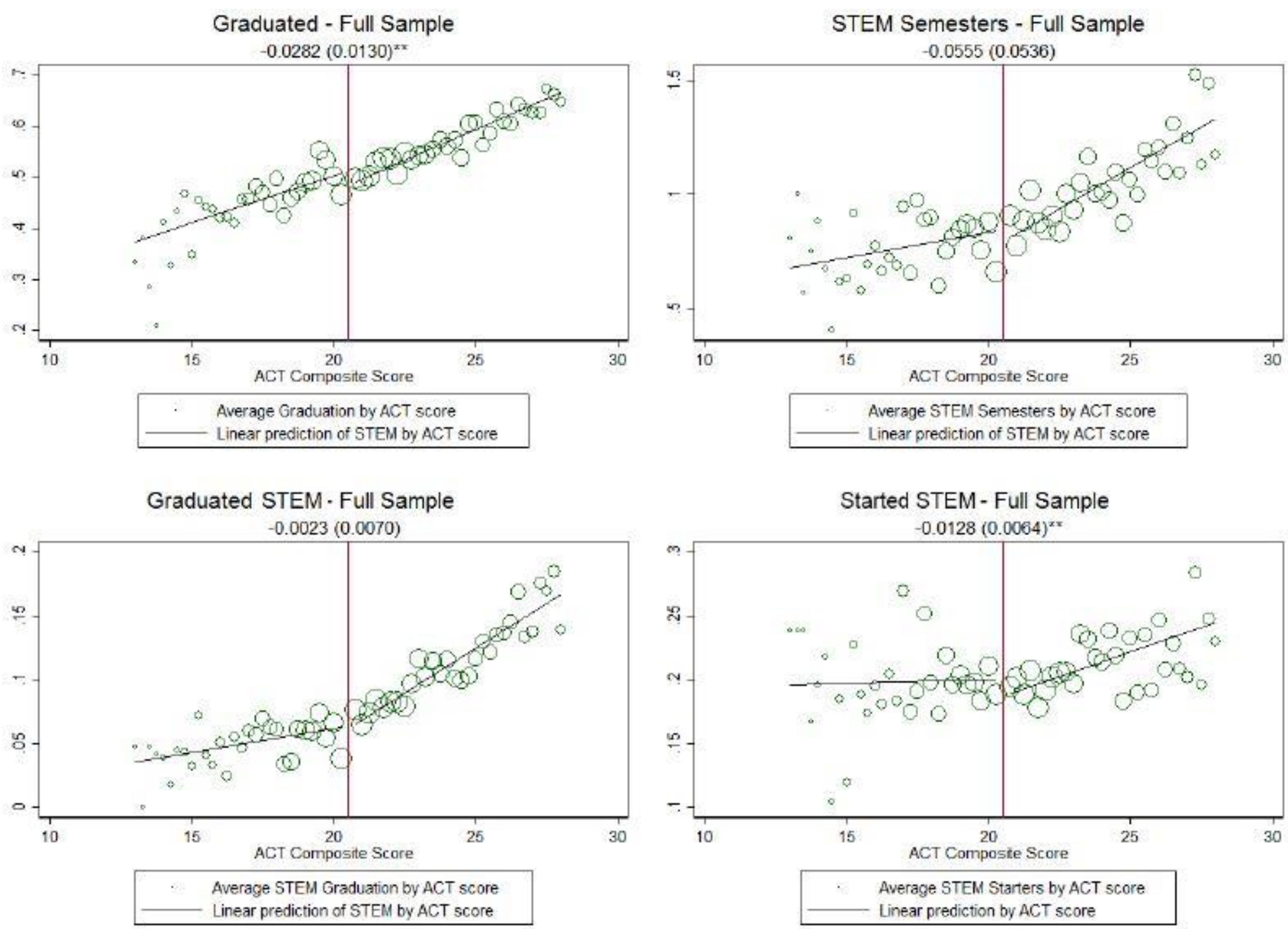

Figure 3.4: HOPE Eligibility Discontinuities - Full Sample

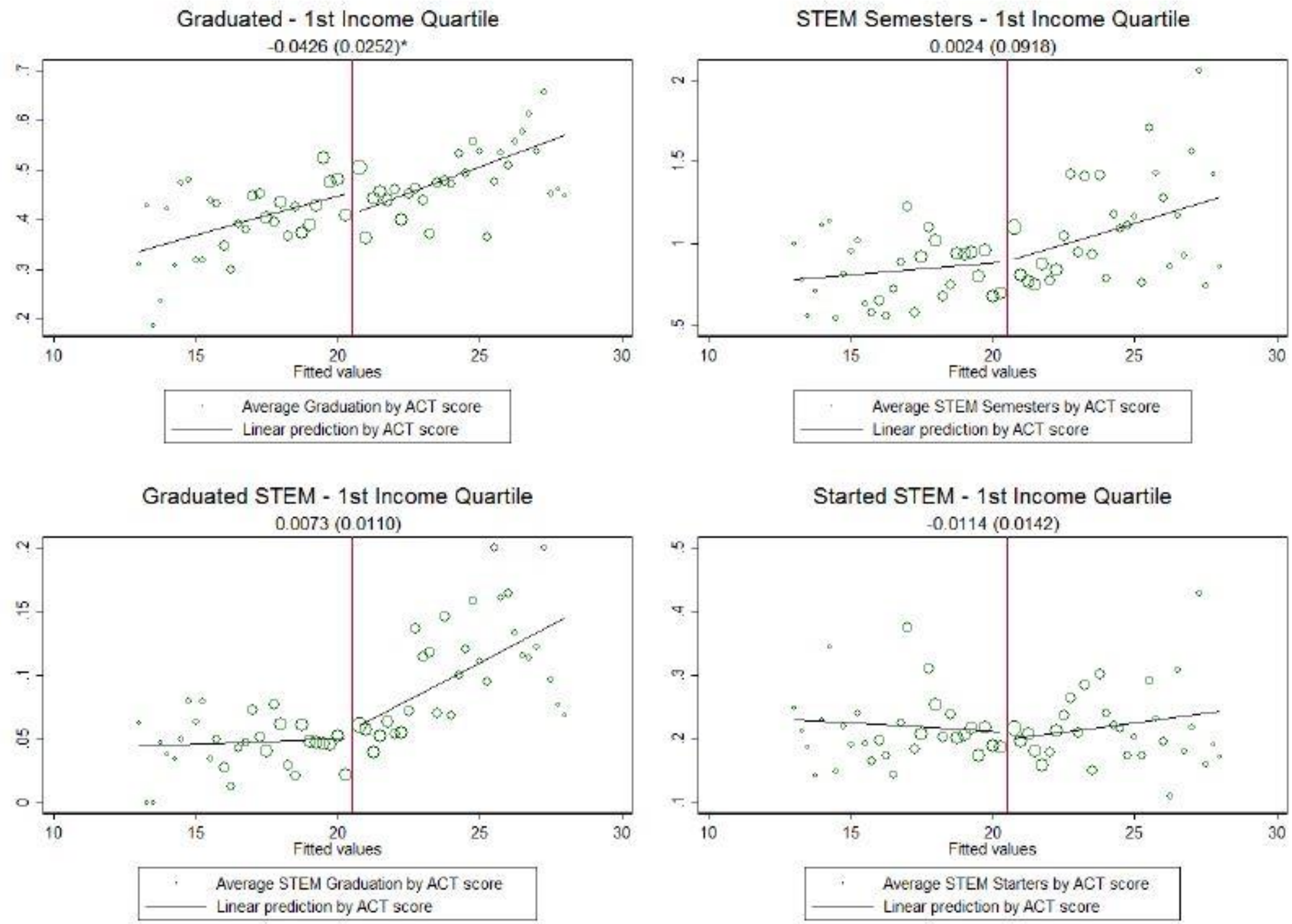

Figure 3.5: HOPE Eligibility Discontinuities - Low Income Students

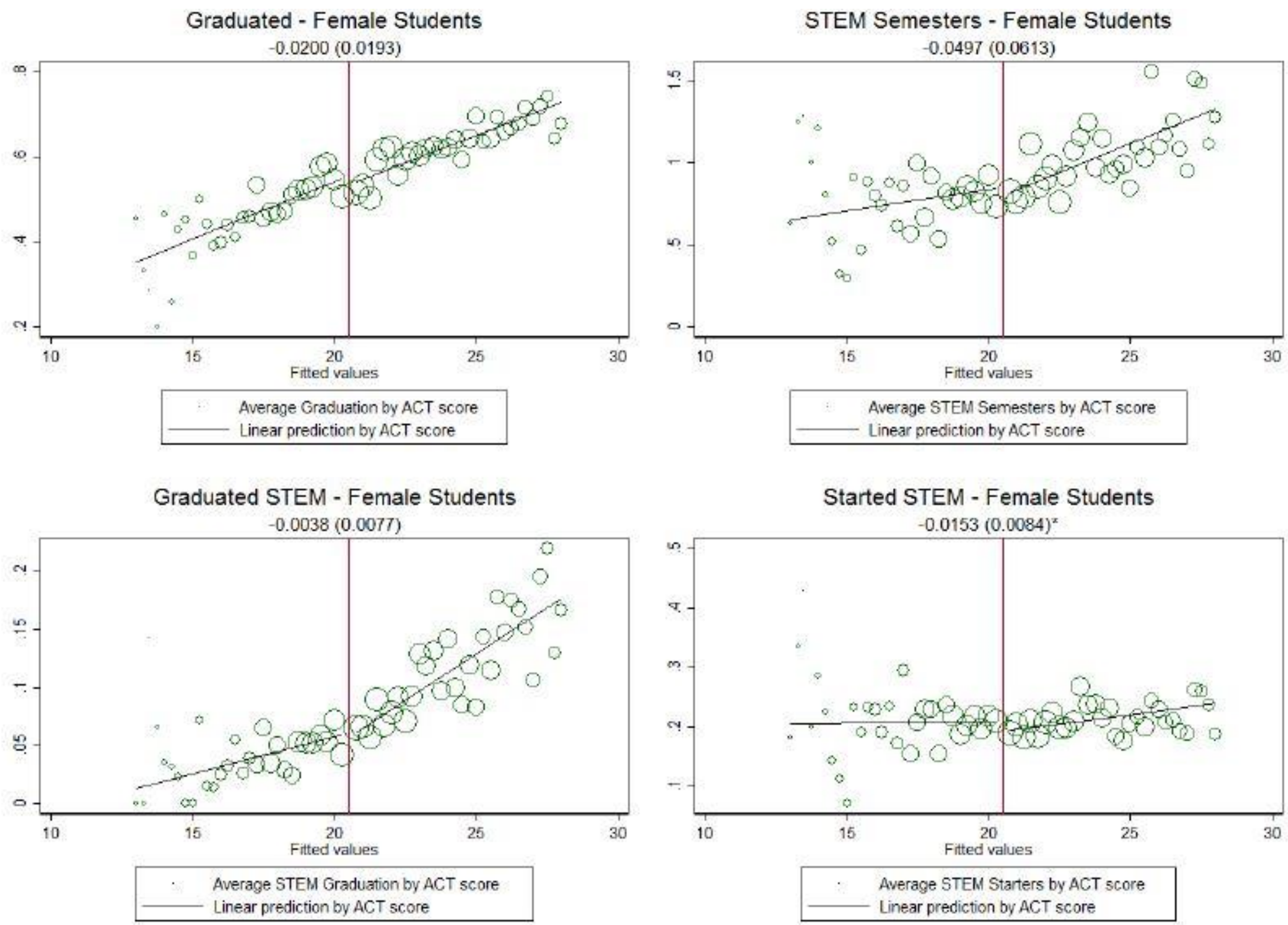

Figure 3.6: HOPE Eligibility Discontinuities - Female Students

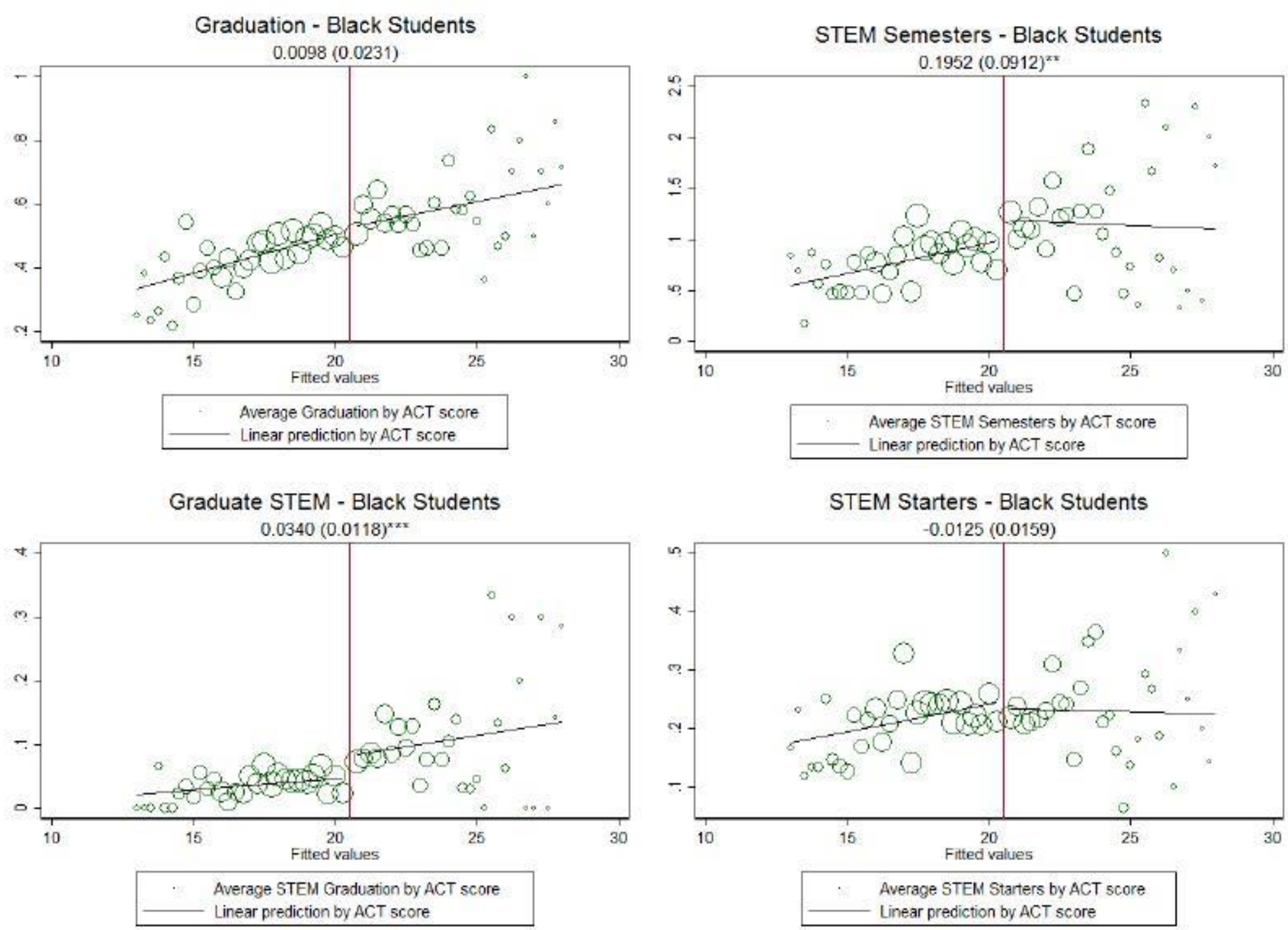

Figure 3.7: HOPE Eligibility Discontinuities - Black Students

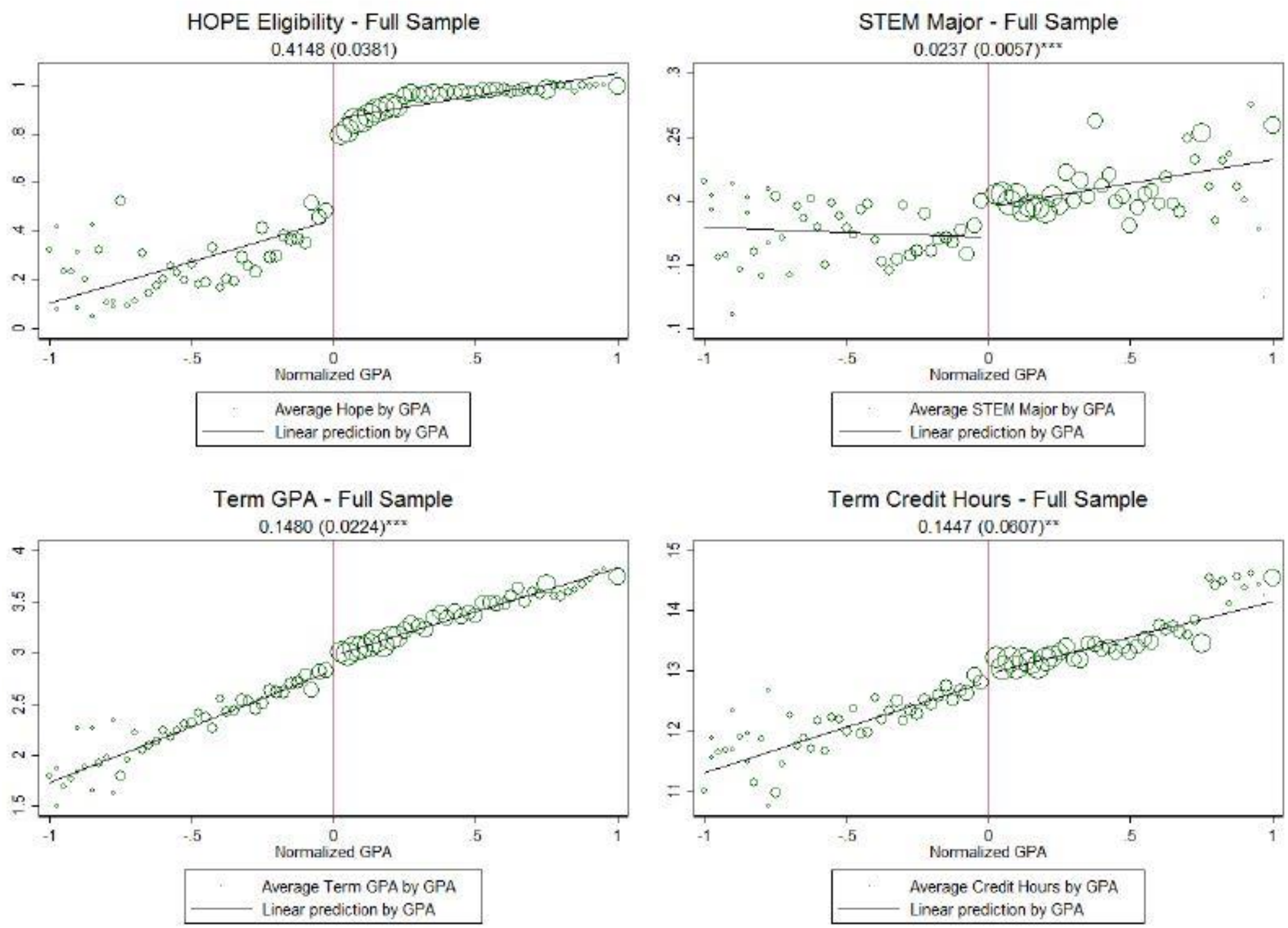

Figure 3.8: GPA Discontinuities - Full Sample

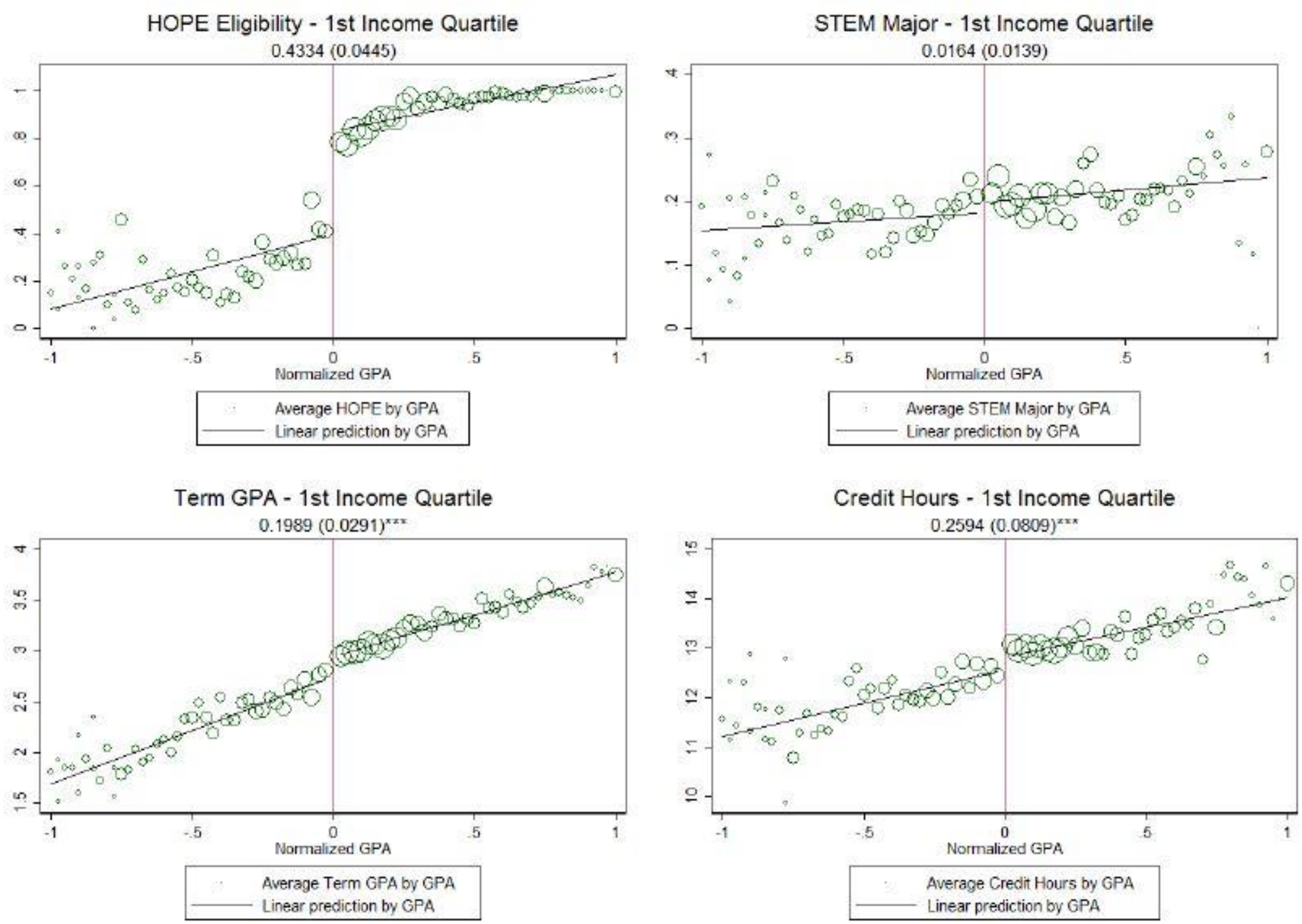

Figure 3.9: GPA Discontinuities - Low Income

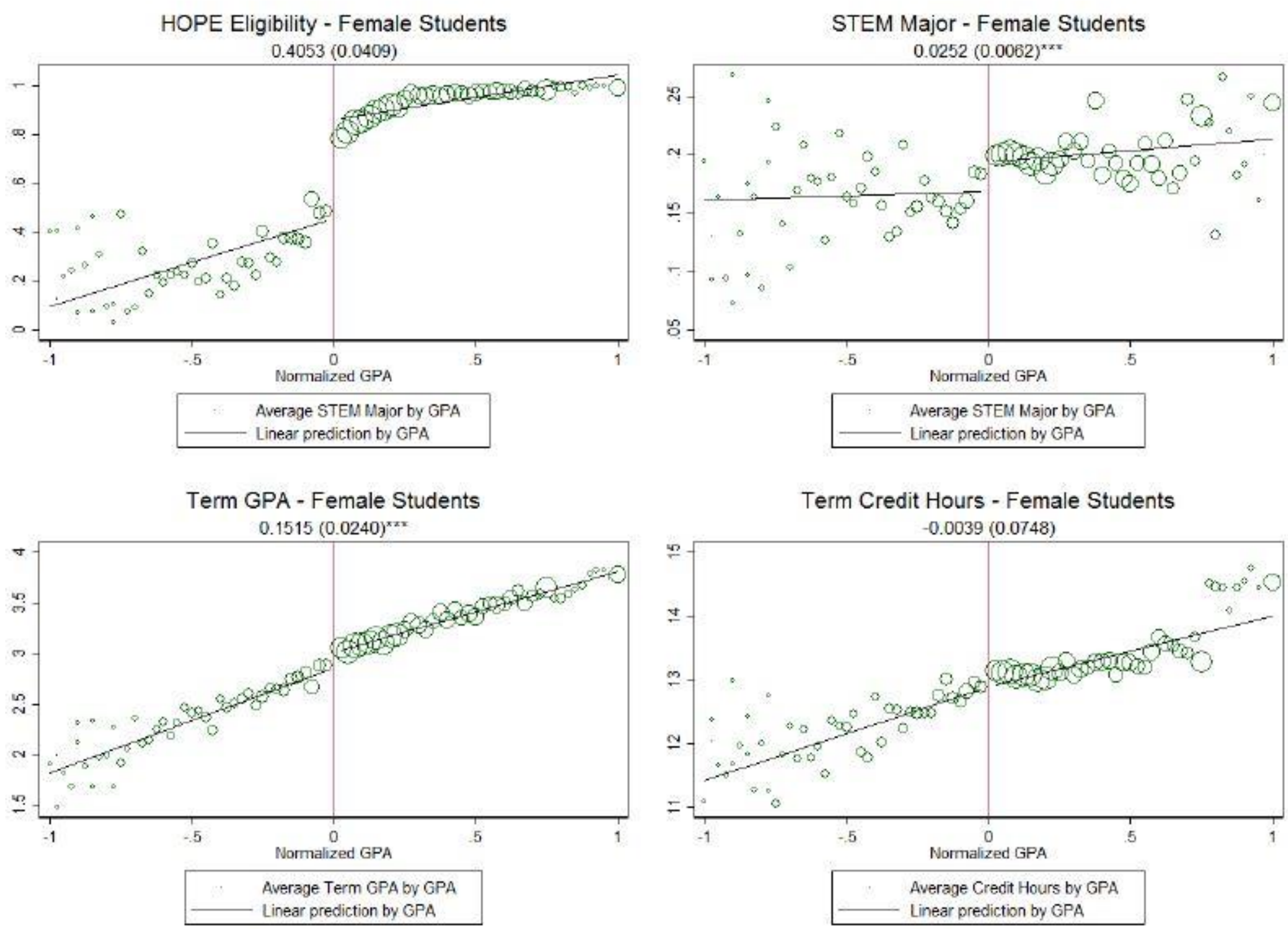

Figure 3.10: GPA Discontinuities - Female

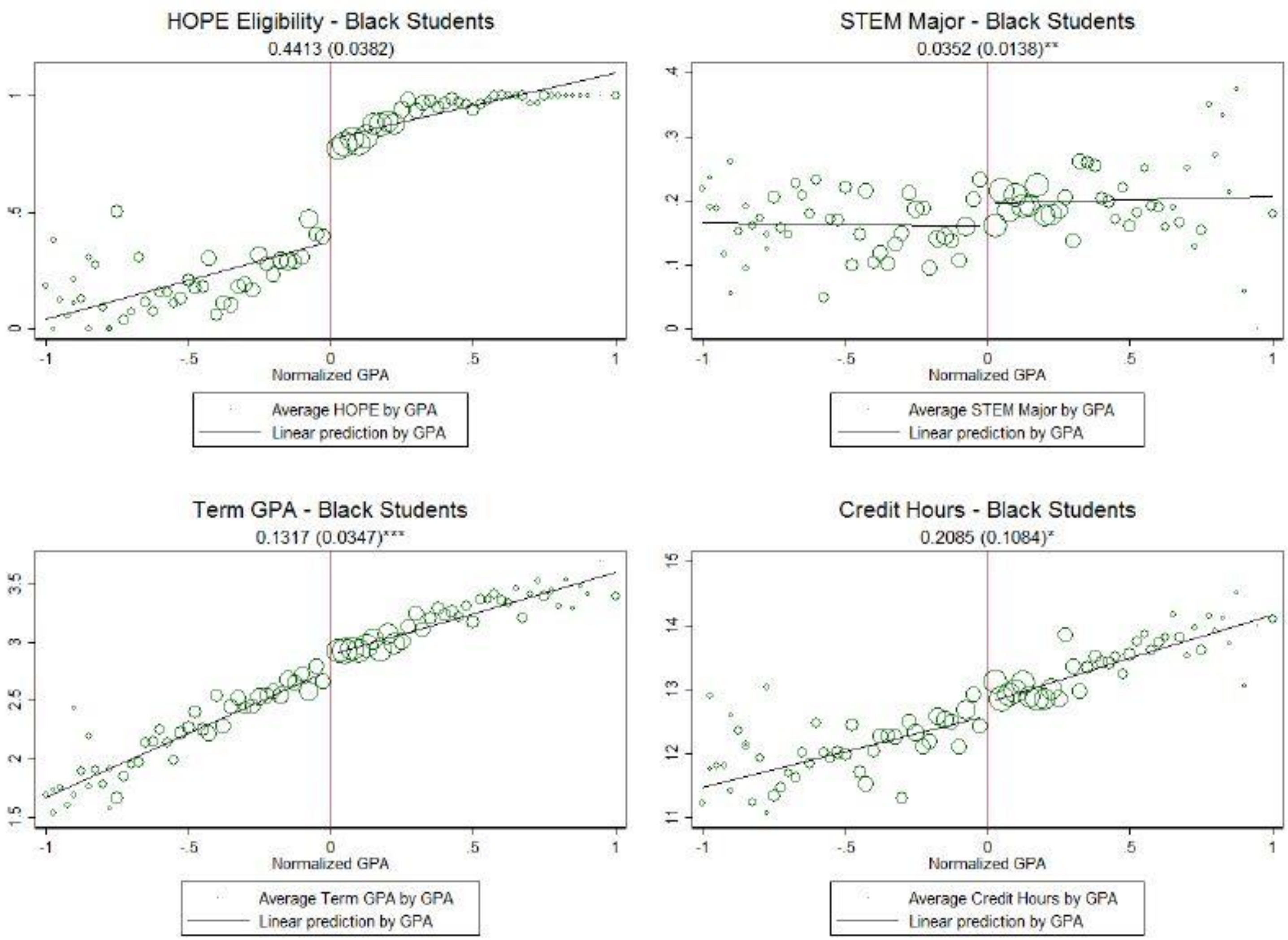

Figure 3.11: GPA Discontinuities - Black

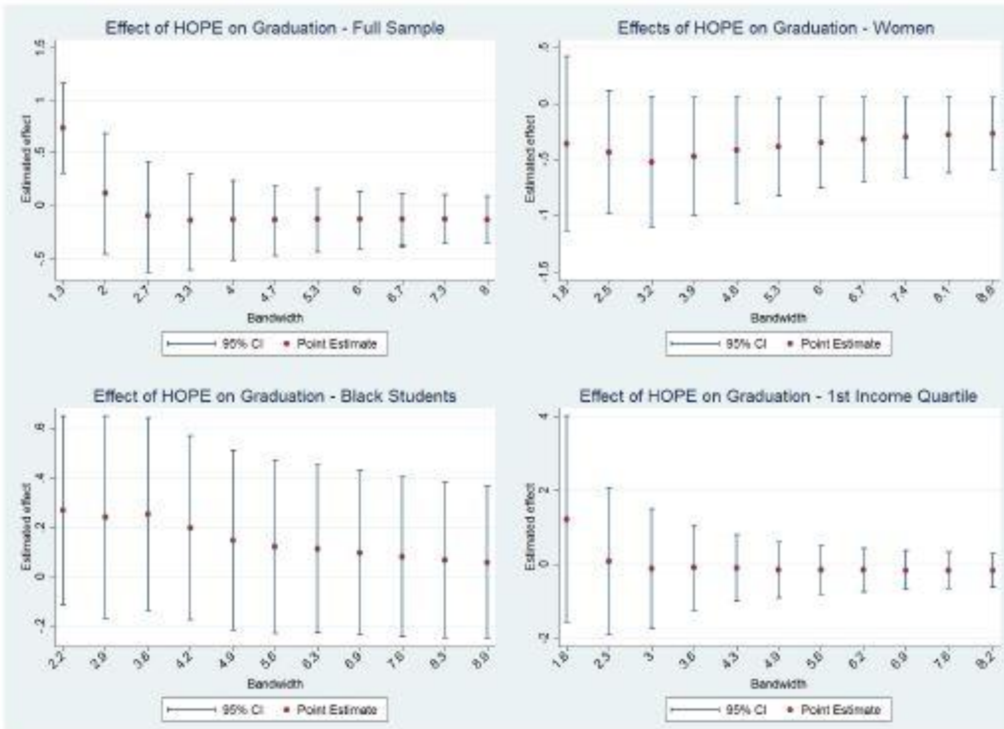

Figure 3.12: Bandwidth Sensitivity - Graduated

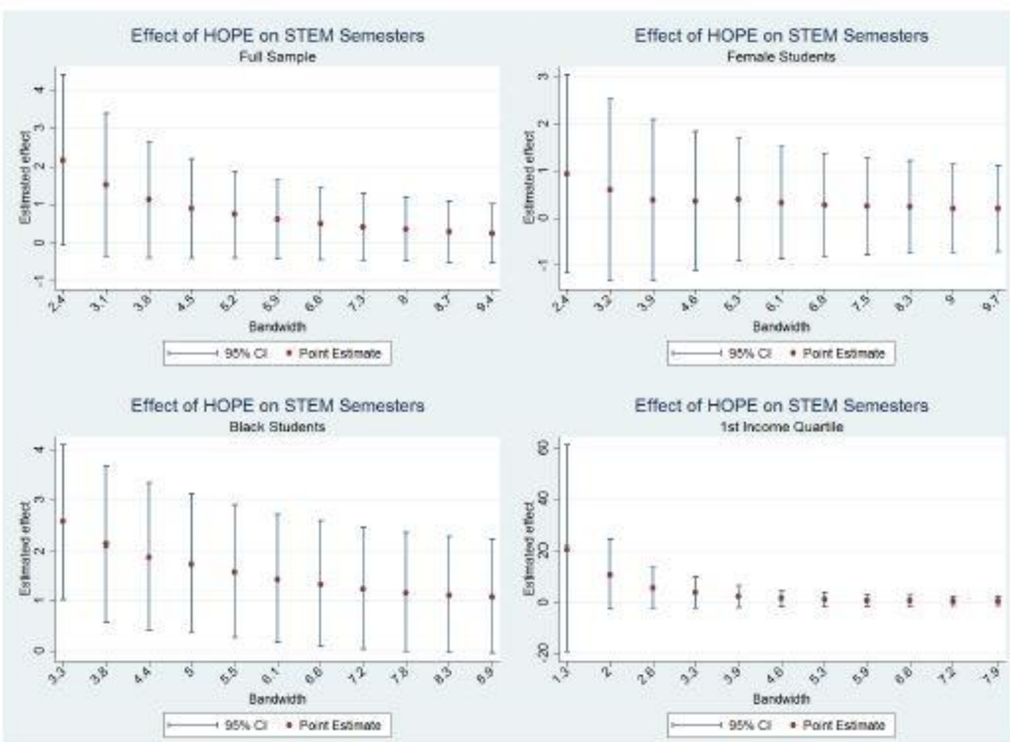

Figure 3.13: Bandwidth Sensitivity - Semesters STEM

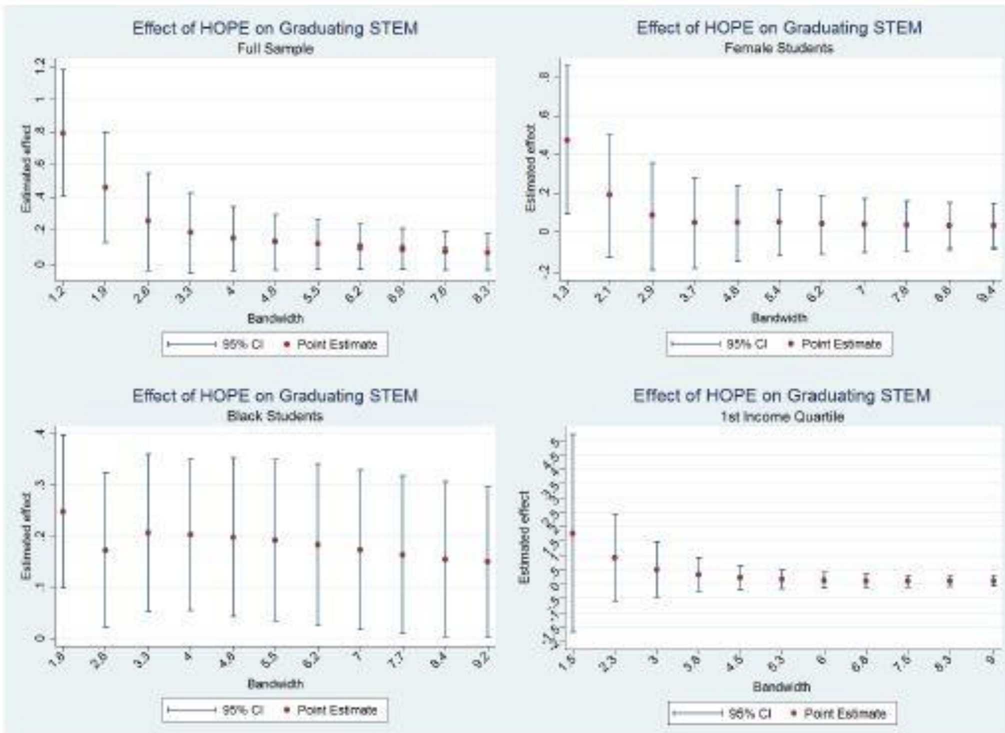

Figure 3.14: Bandwidth Sensitivity - Graduated STEM

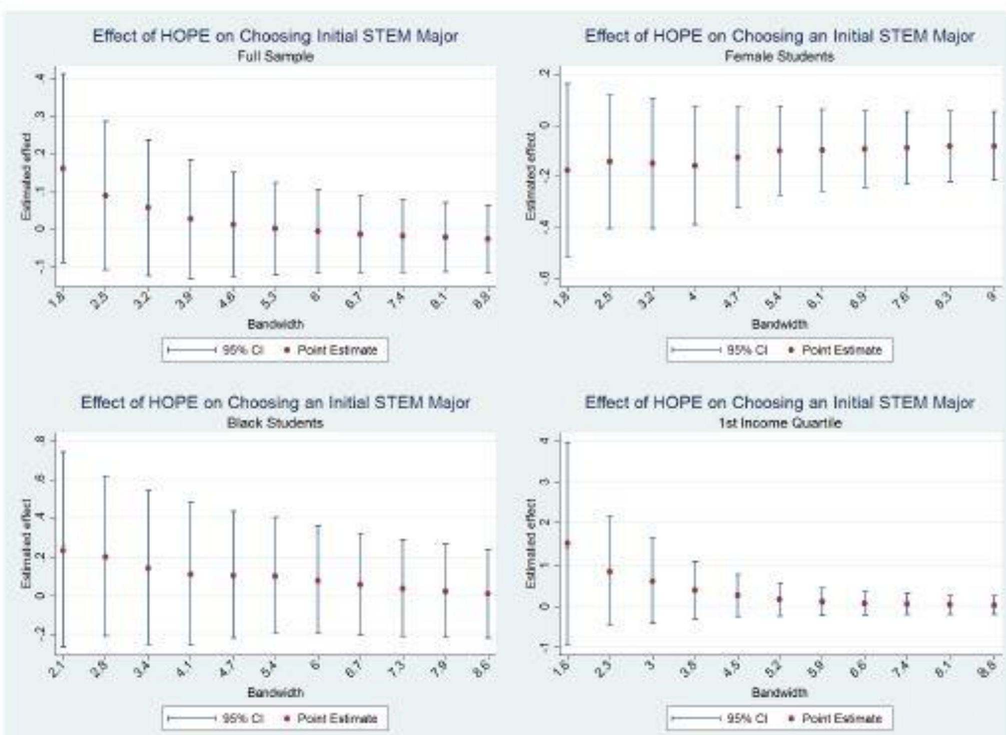

Figure 3.15: Bandwidth Sensitivity - Initial STEM Major

CONCLUSION

The cost of a college education has never been higher than it is today. At the same time the need for a college education has, arguably, never been higher than it is today. Many states have stepped in with new scholarship programs that seek to reward and incentivize their best students to both attend college and stay in their state of residence. These new state merit scholarships have been shown to have some good characteristics. However, like many policies there may be unintended consequences that go along with these scholarships.

Through the previous three chapters I have demonstrated causal links between state merit based scholarships and changes in the types of college degree that students pursue. As a result of these scholarship programs fewer students enter STEM fields and students take fewer STEM courses, which may lead to lower incomes and increased levels of unemployment in the future. Additionally, I find that the students most likely to experience these negative impacts are concentrated among the lower income groups.

These results do paint state merit programs in a somewhat poorer light, but it should be mentioned that chapters one and two take all state merit scholarships together. Chapter three demonstrates that individual state programs may produce differing effects based on either the characteristics of that particular program or the students within that state that participate in the program.

Together this should be used not to argue against merit scholarship programs, but instead to inform policy makers of the various considerations that need to be made and the consequences that go along with them. With any policy decision the benefits as well as the costs need to be weighed and merit scholarship programs are no exception. The results of each study are relevant to both policy makers and researchers. With college education becoming an increasingly more important part of our educational system and state funding for education becoming a more and more contentious issue, my findings can help inform policy makers of some unconsidered or unintended effects of this kind of education funding.