SMART Money: Do Financial Incentives Encourage College Students to Study Science?

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April 12, 2013

Abstract

Producing more bachelor's degrees in science and engineering is a major federal education priority. This paper investigates whether providing $4,000 to low-income students in their junior and senior years through the National SMART Grant can encourage them to major in a STEM field. Using administrative data from Ohio public colleges, the paper relies on a regression discontinuity design to identify the causal effect of program eligibility on the pursuit of science majors. Discontinuities exist around the Expected Family Contribution and GPA thresholds necessary to qualify for the SMART Grant. Results from four years of data indicate the financial incentives do not encourage students to choose a science major either at initial or junior year enrollment and do not improve the major persistence of students who initially choose a STEM field. The paper offers several potential explanations as to why students do not respond to the incentive.

[1] I am grateful to Eric Bettinger and Caroline Hoxby for their excellent and insightful comments. I also received helpful comments from seminar participants at the Center for Policy Analysis at Stanford University and the Association for Education Finance and Policy 2012 annual meeting. I wish to thank Andy Lechler at the Ohio Board of Regents for assistance with the data. Funding from the Institute of Education Sciences (IES) Grant #R305B090016 made this research possible, but the findings and conclusions are my own and not approved by IES or the US Department of Education.

I. Introduction

There is widespread belief that the United States is not producing enough science, technology, engineering, and math (STEM) majors for the domestic labor force. The National Science Board (NSB) advocates for an increased federal focus on maintaining the United States' dominance in innovation and scientific discovery and suggests "a high-quality, diverse, and adequately sized workforce…is crucial to our continued leadership and is therefore a vital federal responsibility" (Crosby & Pomeroy 2004 p. 22). The NSB continues by pointing to a lack of growth in the number of science and engineering bachelor's degrees granted in the United States throughout the 1990's and early 2000's even while competition for science talent is growing globally. The news is not entirely dire as interest in STEM fields has actually grown in the last few years, although biological/agricultural and social/behavioral sciences dominate that growth over the physical sciences and mathematics (NSF 2012).

The U.S. federal government spends $60 billion annually on science research, and this investment is justified largely in terms of the economic benefits basic and applied research generates to keep our economy competitive in the global marketplace (Saha & Weinberg 2010). The success of this investment inherently rests on the labor supply of human capital capable of conducting and consuming scientific research. In order to maintain and expand the nation's scientific labor force, we must learn which policy levers can encourage students to study STEM fields.

This paper examines whether financial incentives received in college can increase the nation's stock of scientific human capital by promoting STEM majors. Specifically, it investigates whether the National Science and Mathematics Access to Retain Talent (SMART) Grant improves the probability of postsecondary students majoring in science. The program provides low-income students financial incentives of $4,000 in each of an undergraduate's third and fourth year of study if they major in a STEM discipline.[2] To the extent that financial incentives increase the number of students graduating with degrees in the sciences, the SMART Grant could be a valuable lever to encourage additional human capital investment in scientific knowledge.

The process by which students select a college major has garnered attention in the sociology and education literature and recent interest in the economics literature. There is some evidence that students choose majors based on their expected earnings (Aricidiacono et al. 2010, Montmarquette et al. 2002), their perceived and actual ability in the major (Stinebrickner and Stinebrickner 2011), and the consumption value of the major while in college (Beffy et al. 2012). However, there is no evidence on whether financial aid can motivate students to select certain majors and only one study on whether the financial cost of a major alters students' major choice (Stange 2012). This paper attempts to fill that gap in the literature by providing a causal estimate of the impact of a large financial incentive realized during college on major choice. I examine both initial major choice upon matriculation and subsequent major choice in students' third years.

[2] There is some debate over the exact definition of a STEM major or field. For the purpose of this paper, I take all of the majors eligible under the federal SMART Grant program as STEM majors. Choy et al. (2011) list the complete set of eligible majors.

The impact of the SMART program provides a test of an important research question: Do financial incentives encourage students to major in science? By exploiting the Expected Family Contribution (EFC) and GPA eligibility requirements to receive a SMART Grant, the paper employs a regression discontinuity analysis to answer this question. Administrative, student level panel data from all of the main branch campuses of public universities in Ohio provide a large enough sample for a regression discontinuity approach and contain enough academic and financial details to accurately measure the qualifying criteria. I find very small, statistically insignificant results of eligibility for the financial grant on selecting a STEM major. Even under generous assumptions, the range of plausible impact estimates is low, and the cost per new STEM degree is extremely high.

The paper is organized as follows. Section II provides background on the National SMART Grant. Section III outlines a model of college major choice and incorporates prior literature related to college major selection. Section IV lays out the empirical strategy. Section V summarizes the data. Section VI provides results, and section VII concludes with a discussion of the findings including a cost benefit analysis.

II. National SMART Grant

In their policy report to the US Department of Education, Choy et al. (2011) describe the National SMART Grant in detail. The grant was authorized by the *Higher Education Reconciliation Act of 2005* to promote undergraduate majors in programs deemed nationally critical. It began in the 2006-07 academic year and ended in the 2010-11 academic year, and it provides $4,000 in each of an undergraduate's third and fourth year of baccalaureate education who studies one of a number of selected majors that are predominantly Science, Technology, Mathematics, and Engineering (STEM) fields. The other eligible majors are foreign languages.

Nationally, 62,400 students received the SMART Grant in the 2006-07 school year, the first year of the program. This represents approximately 5% of the Pell Grant recipients, a number that has been stable in each subsequent year of the program although the actual number of grant recipients in both programs has increased slightly since 2006. During the first three years of the program, $610 million were awarded, far less than the congressionally authorized amount. The Department of Education notified students who were financially eligible to receive the grant by mail and email, but students still had to meet the non-financial criteria to receive the award.

A student is eligible to receive the SMART Grant if they meet a variety of criteria. Students must be a US citizen and study fulltime, although both of these requirements were relaxed as of the 2009-10 academic year. The more critical eligibility requirements are that a student must have a cumulative 3.0 college GPA and must be eligible to receive a Pell Grant, the federal government's college grant program for low-income students. Pell Grant eligibility is determined by a complex formula that evaluates answers from the Free Application for Federal Student Aid (FAFSA) which every student must file with the US Department of Education if they want to receive federal financial aid such as grants and subsidized loans. The FAFSA collects data on students and parents income and assets as well as family size and the number of siblings in college. Answers from the FAFSA determine an Expected Family Contribution (EFC) which is the amount the federal government expects a family to contribute to college expenses. There is a strict threshold in the EFC distribution at which students below the threshold receive a Pell Grant while those above do not. The amount of the Pell Grant is determined by a step function of the EFC (the lower the EFC, the more Pell Grant a student receives). Any amount of Pell Grant eligibility is enough to make the student eligible to receive a SMART Grant. The final requirement to receive a SMART Grant is that a student must have formally selected one of the eligible majors that exists at their institution, and they must make course progress in that major to have the grant renewed.[3]

III. Economic Theory and Related Literature

Theories of major choice differ by discipline. Economists tend to focus on human capital theory and consider students as rational decision makers choosing an available major to maximize current and future utility. Many sociologists, psychologists, and education scholars focus on Holland's theory of occupational and major choice. Holland (1985) proposes six different personality types and views occupation selection as a match of personal preferences and abilities with environmental factors. Applied to college major choice, the theory suggests students will pick a discipline in which their abilities and interests fit with those necessary to be successful in the major, and research shows that personality factors do predict major selection (Porter and Umbach 2006). Feldman et al. (2004) argue that students whose abilities and interests are incongruent with their major may suffer a "cost" which can include needing to spend more academic effort than peers whose interests and abilities align with the major; however, their empirical findings suggest these costs may be outweighed by the socialization process of a new discipline which improves students' interests and abilities in that area of study. These theories complement each other well. Students factor Holland's notion of personal fit with a major choice into the utility maximization decision under the economic framework. I focus on the economic framework and evidence below.

Human capital theory argues that investment in education leads to higher earnings (Becker 1962). Those higher earnings are dependent on several factors including the level of education, ability, and the labor market of specific fields. Among students who pursue higher education, opportunities in a certain field are in turn related to college major choice.

The economic literature on major choice demonstrates that students consider several factors when selecting their major. Results of a survey eliciting students' chosen major and alternative majors indicate that students consider their expected future earnings as well as their ability, and the comparative advantage it bestows, in each major they consider (Aricidiacono et al. 2010). Montmarquette et al. (2002) confirm that students evaluate both ability and future earnings, but they find that future expected income drives major choice as the elasticity of major choice is greater with respect to future earnings than with respect to the probability of successfully completing college with

[3] The most commonly chosen eligible majors in my dataset are biology and engineering.

that major. Ryoo and Rosen (2004) provide further evidence that students respond to career prospects and earnings when choosing to enter the engineering field.

There is also evidence that students consider the consumption value of a college major while in school. Beffy et al. (2012) rely on variation in earnings in the French labor market to discover that the elasticity of major choice with respect to future earnings, while statistically significant, is low. They conclude that measures associated with the consumption value of a major while in college motivate students' major choice more than expected earnings. In a working paper, Stange (2012) uses the introduction of differential tuition charges across institutions to examine the effect of the price of a major on degree completion in that major. He finds that higher tuition and fee charges for engineering and business majors result in reduced engineering and business degrees, although the finding is insignificant for business majors. These papers suggest that students may respond to in college financial considerations.

Consistent with the factors influencing major selection, I rely on a model that incorporates in college and post-college utility while considering ability as the likelihood to succeed in a potential major. The model assumes students are rational maximizers of utility and that they choose a major to maximize a combination of their in school and post-college utility.[4]

A student *i* at time *t* can choose any major *k* from choice set C_i which can be thought of as the majors available to the student at his institution of higher education. The student derives utility $U(\mathbf{a}_{itk}, \mathbf{c}_{itk}, \mathbf{x}_{it})$ from choosing major *k*. The vector **a** represents realized outcomes in college such as the hours per week spent studying, the pleasure of enjoying the field of work, parental approval of a major, etc. This can be thought of as the consumption value of the major. The vector **c** represents outcomes that take place in the labor market after leaving college such as finding employment and income. Student characteristics **x** are likely to affect both outcomes realized in college and those after college. For example, a student with a high ability in a certain field will incur less physic cost to studying that field and have higher productivity in the labor market. Because initial major selection occurs before many of the outcomes are realized, the student possesses beliefs about the potential outcomes associated with each available major $P(\mathbf{a}_{itk}, \mathbf{c}_{itk})$. The student then chooses major *m* if it maximizes his utility:

(1) $$m = \arg\max_{k \in C_i} \sum_{t=1}^{T} U(\mathbf{a}_{itk}, \mathbf{c}_{itk}, \mathbf{x}_{it}) P(\mathbf{a}_{itk}, \mathbf{c}_{itk})$$

The student's perception of potential outcomes is notably important in light of recent literature showing that students update their beliefs in response to new information about their own abilities in different majors. Using undergraduate surveys at Northwestern University, Zafar (2011) elicits students' predicted GPAs in their major and alternative majors. A year later, a subsequent survey asks the same questions after students have had one additional year of new information about their academic performance. He finds that students who receive GPAs much higher (lower) than their predictions alter their new prediction up (down), indicating that students update beliefs in response to new information in a Bayesian fashion. Furthermore, finding their selected major too difficult is one of the primary reasons students switch majors, supporting the theory that in college utility and ability drive major choice.

[4] This model is adapted from Zafar's (2011) similar model of major choice.

Stinebrickner and Stinebrickner's (2011) work supports Zafar's study by also concluding that a student's final major is the result of a learning process. By investigating changes in majors at Berea College using a longitudinal survey, they find that many students who initially select science majors switch out of those majors. By evaluating the impact of student's predicted GPAs and expected earnings on major choice using regression, they determine that both ability in the major and expected income are important determinants of major choice. They also analyze effort and find that, despite the increase in hours studying associated with majoring in science, it is students' poor academic performance in the sciences, and not the increased effort required, that drives them away from a STEM major.

Given that students respond to new information and that in college utility impacts major choice, it is reasonable to suspect a financial incentive realized in college could alter a student's major.[5] A major dependent grant changes the vector **a** in equation (1) by introducing a direct financial benefit for selecting a certain major. The probability of that outcome is dependent upon meeting the eligibility criteria of the grant. If the financial incentive induces a student to select a STEM major, the student receives an increase in utility in college and a future financial reward to the extent that STEM degrees are more highly rewarded in the labor market.

A potential puzzle is why any incentive is necessary to encourage STEM majors as the labor market already pays a wage premium to STEM graduates. There are two reasons a financial incentive may be necessary to encourage the study of STEM fields. As argued by Beffy et al., students may be myopic and overweight their in college utility relative to their future expected utility. Evidence from the National Survey of Student Engagement (NSSE) shows that students studying engineering or physical sciences spend 19 and 18 hours respectively preparing for class while students in education, social sciences, and business spend 15, 14, and 14 hours respectively (NSSE 2011). These additional hours are, in part, supplanting hours worked for pay as engineers spend 9 hours per week working for pay while social sciences students spend 13 and business majors spend 16. If students place too much weight on the current consumption value of a college major, a financial incentive realized in college might encourage them to switch into a STEM major.

A second explanation for why major dependent incentives may be necessary is the substantial time lag between supply and demand decisions in the science labor market. Freeman (1975 & 1976) describes this issue in detail for the labor market for engineers and physicists. If students make the decision to enroll in a certain major by looking at the current salary for science majors without anticipating future changes to the labor market, they may incorrectly predict their future job prospects. This is of significant concern in the science labor force due to the often extended time necessary for graduate study.

[5] Economists have studied the ability of financial incentives to alter educational outcomes in other contexts. In addition to the large literature on conditional cash transfers in development economics, Fryer (2011) examines field experiments in which primary and secondary school students received financial incentives for educational outcomes such as reading books and grades.

In either case, there is no evidence on whether financial incentives can alter major choice. This paper contributes to the economics and education policy literature by offering the first rigorous empirical analysis to provide such evidence.

IV. Empirical Strategy

The goal of this analysis is to obtain a causal estimate of the impact of a $4,000 financial incentive for college undergraduates to choose a STEM major, and it employs a regression discontinuity design to obtain that estimate. Regression discontinuity relies on an exogenously determined cutoff along a continuous measure, referred to as either the rating score or forcing variable. On one side of the cutoff, subjects receive the treatment, but on the other side, the subjects do not receive the treatment. The treatment impact is the difference between the limit of the outcome at the threshold approached from the ineligible side and the limit of the outcome at the threshold approached from the eligible side. The causal identification assumption is that the potential outcomes in the absence of the treatment are continuous across the cutoff in the rating score (Bloom 2012). Lee and Lemieux (2010) also characterize regression discontinuity designs as local randomization. Around the threshold, students are essentially randomized to receive treatment, so that the difference in outcomes on either side of the cutoff is the causal treatment effect.

Specific to this study, the treatment is eligibility to receive the financial incentives if a student chooses a STEM major, and the outcome variables are whether or not the student chooses a STEM major at different points in his or her college career. In addition to choosing a STEM major, four factors determine for the SMART Grant. Students must be U.S. citizens, enrolled full-time, low-income, and have a cumulative junior year GPA of at least 3.0.[6] I restrict all analyses to U.S. citizens who are first-time full-time enrollees. The other two eligibility criteria represent two potential continuous rating scores and two cutoff thresholds that can be used to measure the treatment effect.

The first is college GPA. To receive the SMART Grant, a student must have at least a 3.0 cumulative GPA in the junior year. For students meeting the other eligibility requirements, examining students on either side of the GPA threshold will provide an estimate of the program's impact. Unfortunately, it is fairly easy to manipulate GPA in a variety of ways. Students could take easier classes assuring them of a higher GPA or they could lobby professors to change their grade in order to make them eligible for the program. Wherever I rely on the GPA rating score in the analysis, I first check to see if there is any evidence of manipulation by examining the density of observations on either side of the 3.0 threshold. If students manipulated the GPA measure, observations are no longer randomly distributed around the threshold, and I cannot use the discontinuity imposed by the GPA eligibility criterion.

The second rating score is the Expected Family Contribution (EFC). To be eligible for a SMART Grant, students must be eligible to receive a Pell Grant. The EFC determines students' Pell Grant eligibility:

[6] Although Congress eventually relaxed the full-time requirement, it was in force during the period of study analyzed in this paper.

students below a strict cut point in EFC are eligible and students above the threshold are ineligible. For example, students entering college in the fall of 2009 experienced a cut point of $4,616. This means that students with EFCs at or below that threshold were eligible to receive a Pell Grant (and therefore a SMART Grant if they met the other criteria), and students whose EFCs were above that threshold were ineligible.

Attempting to alter your EFC to gain access to the program is virtually impossible. The federal government calculates the EFC annually using a complex, opaque formula that accounts for parental and student income and assets, family size, and the number of siblings attending college. Data used in the formula to calculate EFC is derived from the prior year tax returns, but the threshold for eligibility changes based on congressional appropriations to the Pell program, so it is not known at the time of filing the form that reports the information required to calculate the EFC. I formally test whether there is any evidence of manipulation in the EFC rating score below.

One downside of the linking of SMART Grant eligibility to that of the Pell Grant is that all students eligible to receive major dependent financial incentives also receive a small Pell Grant, but students just on the other side of the threshold do not receive a Pell Grant.[7] This means the regression discontinuity design is not a perfectly clean causal estimate of the effect of being eligible for financial incentives for STEM majors. Instead, it is the causal effect of eligibility for the STEM major incentive plus a small amount of Pell Grant aid. For the 2006 entering cohort, those just over the threshold for eligibility received $400 in Pell Grant aid, while those in the 2009 centering cohort received $976. Because the SMART Grant money is so large, $4,000, relative to the Pell Grant received, I argue that it should dominate any observed effect.

Imbens and Lemieux (2008) nicely outline both sharp and fuzzy regression discontinuity designs. I treat the analysis as a sharp discontinuity with perfect compliance. Unfortunately, I do not observe actual receipt of the SMART Grant or any other form of financial aid; I only observe eligibility. I assert perfect compliance on the basis that federal law prohibits distribution of Pell Grant and SMART Grant to students' who have EFCs above the threshold. The financial aid office at an institution does have the legal authority to alter a student's federal aid award, but this process, called professional judgment, actually alters the student's EFC, which I observe. The remaining concern would be if students decided not to accept the SMART Grant when offered, but it seems highly unlikely that students would leave free grant money on the table.

The literature suggests estimating the treatment effect using both parametric and nonparametric approaches (Lee and Lemieux 2010). The parametric approach uses all of the data on either side of the rating score cutoff to estimate the discontinuity in the outcome. This method is sensitive to functional form specification because if the underlying functional form is not modeled correctly, it leads to a biased

[7] It is likely some of the students eligible for the SMART Grant are also eligible to receive the Academic Competitiveness Grant (ACG) which was established concurrently with the SMART Grant. The ACG gives eligible students $750 in their first year and $1,300 in their second year of postsecondary study. Eligibility is determined by the same EFC threshold as the Pell Grant and by students having taken a rigorous program of courses in high school. I do not observe high school curriculum; therefore, I cannot assess the impact of this program.

estimate of the outcome at the threshold. The nonparametric approach restricts the analysis to a bandwidth of data around the threshold and uses only that data in a local linear regression to estimate the treatment effect. I employ both methods by using a linear and cubic model for the parametric approach and implementing the leave-one-out cross-validation procedure suggested by Ludwig and Miller (2005) and Imbens and Lemieux (2008) to select the appropriate bandwidth for the local linear regression. In practice, both approaches use the same general estimation equation:

(2)

$$STEM\_major_i = \alpha_0 + f(EFC\_centered_i)\boldsymbol{\beta} + \alpha_1 eligible_i + g(EFC\_centered_i) * eligible_i \boldsymbol{\delta} + \varepsilon_i$$

Individual students are indexed by *i*. The equation allows for separate functional forms *f* and *g* on either side of the discontinuity. For ease of interpretation, I run linear probability models as suggested by Angrist and Pischke (2009). The coefficient of interest is α_1 which estimates the difference in the intercept at the threshold once the rating score is centered around the eligibility cutoff. I estimate three different outcomes. The first is whether students choose a STEM major when they initially enroll in the fall of the first year. I also estimate the impact of eligibility on STEM major choice at the beginning of their junior year when the financial incentive is actually disbursed. Finally, I focus only on students who began with a STEM major and investigate whether eligibility for the financial incentive encourages them to persist in a STEM major into their junior year.

Similar to an experimental analysis, I can include covariates to explain more of the variation in the outcomes in order to improve precision. I estimate several models including controls for students' race, gender, in-state residency status, parental education, and ACT scores. I also include campus dummies to account for differences in major availability and popularity across campuses.

Equation (2) provides a causal estimate using one forcing variable, but I potentially have the opportunity to use two forcing variables as eligibility to receive the financial incentive in the junior year is contingent upon both EFC and GPA. Several recent papers discuss the estimation of regression discontinuity in the case of multiple forcing variables.[8] The threshold is no longer along a single dimension but is instead a two dimensional boundary. There are two advantages of this estimation technique over conducting the analysis separately over two different thresholds. The first lies in sample size. Instead of dropping all of the observations that meet the EFC criterion and estimating the effect of the GPA threshold or vice versa, I simultaneously estimate the effect of being eligible on both forcing variables including all of the observations. Although not of any consequence to the current analysis, it is also possible to estimate how the impact of one forcing variable changes as a student becomes eligible on the other. Papay et al. (2011) provide a sixteen coefficient estimation equation that includes a four way interaction (and all lower order interactions) with both forcing variables and both binary eligibility indicators. The coefficient of interest is the interaction between the two eligibility indicators which estimates the additional effect of being eligible on both measures, and therefore eligible to receive the financial incentive, above the effect of being eligible on either one separately.

[8] See Reardon and Robinson (2012), Imbens and Zajonc (2011), and Papay et al. (2011).

V. Data

The study relies on institutional data for all of the entering four-year college students in Ohio's 13 public university main branch campuses. These administrative data are obtained directly from the Ohio Board of Regents (OBR). Data are available for all of the first-time, full-time college students who began their enrollment in the fall of 2006, 2007, 2008, or 2009. The dataset contains term by term enrollment through the spring of 2010 for each student that remains in the state's system of public higher education. Institution of attendance, number of credits, cumulative GPA, and major selection are available in each term. The reported majors are recorded as the exact CIP code so that they can be matched exactly with SMART Grant eligible CIP codes which are obtained from Choy et al. (2011). The OBR data also have demographic variables, ACT scores, and extensive financial information taken from the Free Application for Federal Student Aid (FAFSA). For each student who filed a FAFSA, the dataset provides the exact Expected Family Contribution (EFC) for each student which can be used to determine eligibility for the Pell Grant and therefore the SMART Grant. Unfortunately, the state does not record actual financial aid receipt, but eligibility can be inferred precisely from the existing data and program regulations.

I provide summary statistics in Table 1. The sample contains roughly 37,000 entering students in each year. The students are slightly more likely to be female, as is common in higher education. Ohio has a low percentage of Hispanic and Asian students, so the sample is dominated by white and black matriculants. About half of the sample has a parent that graduated from college, and over 87 percent of students are Ohio residents. About two-thirds of the students took the ACT. This number is lower than may be expected because some students took the SAT, whose data is not recorded by OBR, and a few of the institutions do not require the submission of test scores for admission as they are open enrollment. The average ACT score of 22.6 is well above the national average of 21.1 reflecting the fact that higher scoring students are more likely to enroll in four-year colleges.

Almost 75 percent of entering students applied for federal financial aid and have an average first-year EFC of nearly $14,700. This is much higher than the median EFC of $8,700 because many high income families file a FAFSA in order to access federal student loans. Of those that filed a FAFSA, 35.1 percent were eligible to receive a Pell Grant. Data for at least two years after initial enrollment exists for the entering cohorts of 2006 and 2007, and two-thirds of these students obtain junior year status during the data period. However, only a subset of those students remained in a four-year institution. Additionally, many students from the entering 2008 cohort achieve junior status in the time period available. Of all students achieving junior status in the dataset, 62 percent filed a FAFSA in their junior year with an average EFC of $15,351, and 29 percent of the FAFSA filers were eligible for a Pell Grant. Their average cumulative GPA when they reach their junior year is 3.13.

Finally, the outcome of interest is whether students choose a STEM major. Nearly 90 percent of students in Ohio choose a major at matriculation, and 19.9 percent initially chose a STEM major. Of the students remaining to the junior year, 20.4 percent enrolled in a STEM field. The most popular non-science majors at initial enrollment are a combination of general studies/liberal arts studies and business. By the time students reach their junior year, psychology is the largest non-science major followed by nursing, accounting, and marketing. The most popular STEM fields in the first and third years are biology, engineering, and zoology.

Table 1. Summary Statistics of First-Time First-Year Students

Variable	Mean	Observations
Female	0.522	147792
White	0.782	147792
Black	0.125	147792
Asian	0.024	147792
Hispanic	0.024	147792
Other Race	0.044	147792
OH Resident	0.872	147792
Took ACT	0.656	147792
ACT Composite Score	22.58	96916
	(4.53)	
Father Completed College	0.462	112677
Mother Completed College	0.505	113013
STEM Major in 1st Year	0.199	147792
Filed FAFSA in 1st Year	0.738	147792
EFC in 1st Year	14728	109023
	(18702)	
Pell Eligible in 1st Year	0.351	109023
Persist to Junior Year (2006 and 2007 cohorts only)	0.665	72708
STEM Major as Junior	0.204	60930
GPA as Junior	3.13	60930
	(0.53)	
Filed FAFSA as Junior	0.620	60930
EFC as Junior	15351	37801
	(17298)	
Pell Eligible as Junior	0.290	37801

Notes: The standard deviation of non-binary variables is given in parentheses. The table includes all first-time, first-year students at the 13 main branch campuses of Ohio four-year public universities for the entering fall cohorts of 2006, 2007, 2008, and 2009. The persist to junior year variable includes only students who began enrollment in 2006 or 2007, but all other junior variables include any student attaining junior status who began in 2006-2009.

VI. Results

This section first presents the regression discontinuity analysis of the effect of SMART Grant eligibility on initial major selection before turning to the impact of the financial incentives on major selection at the beginning of the junior year and examining any potential persistence in major impact.

Major Choice at Initial Enrollment

Balance of covariates around the threshold

In line with considering regression discontinuity as local randomization, it is important to check whether the treatment and control groups appear equivalent on baseline characteristics. I directly test this question by comparing the mean values of covariates within $1,000 of EFC on either side of the EFC eligibility threshold. Table 2 reports these results. Only one of the twelve variables appears significantly different. There are slightly more black students in the treatment group than the control group. Black students are slightly less likely to choose a STEM major at initial enrollment (15 percent relative to 20 percent of white students), although controlling for race in the regression analysis eliminates any bias associated with this difference. Still, if black students have other characteristics related to STEM major selection not controlled for in the analysis, there is potential for a small bias.

Table 2. Balance Check of Covariates within $1,000 of EFC Threshold at Initial Enrollment

Variable	Treatment Mean	Control Mean	P-value of Difference
Female	0.541	0.536	0.669
Black	0.131	0.116	0.047*
Asian	0.021	0.018	0.293
Hispanic	0.024	0.024	0.961
Other Race	0.041	0.041	0.983
OH Resident	0.999	0.999	0.629
Father Completed College	0.331	0.339	0.455
Mother Completed College	0.410	0.424	0.217
ACT English Score	21.37	21.35	0.844
ACT Math Score	21.69	21.79	0.361
ACT Reading Score	22.41	22.38	0.780
ACT Science Score	22.03	22.00	0.807

Notes: p-value significance denoted by *0.05, **0.01, ***0.001.

Density of forcing variable around the threshold

This section presents results of testing the EFC threshold for evidence of manipulation. One of the fundamental assumptions of regression discontinuity design is that there should not be any manipulation of the forcing variable. Altering the EFC in an attempt to be just over the threshold for Pell Grant eligibility is very challenging, but it is not impossible. Examining a histogram of the EFCs around the threshold provides a visual check of manipulation. Figure 1 plots the frequencies of EFCs around the Pell Grant eligibility threshold in $50 bins. The EFC is centered so that the threshold occurs at $0. There is no apparent bunching of observations on the left side of the threshold (students are eligible if their centered EFC is less than $0), indicating students are not manipulating their EFC to make themselves just eligible for the Pell Grant or SMART Grant.

McCrary (2008) offers a formal test of density of observations around the threshold by smoothing a histogram of the forcing variable using local linear regression. Figure 2 displays the results of the McCrary test around $1,000 on either side of the discontinuity for pooled initial year enrollees. Any perceived difference in density on either side of the threshold is well within the standard error bands, so there is no evidence of forcing variable manipulation.

Figure 1. EFC Distribution around the Pell Grant Eligibility Threshold at Initial Enrollment

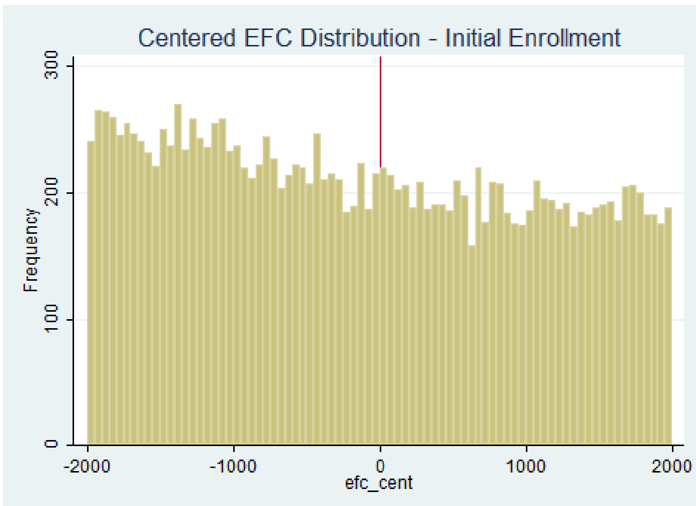
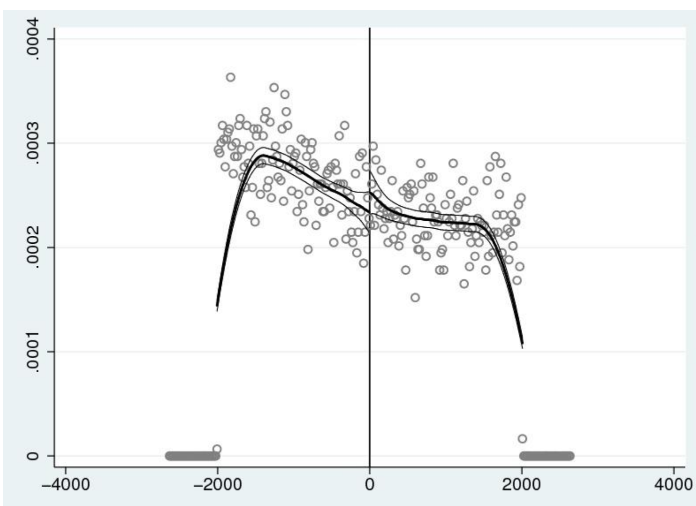


Figure 2. Density of the EFC Distribution around the Threshold at Initial Enrollment (McCrary Test)

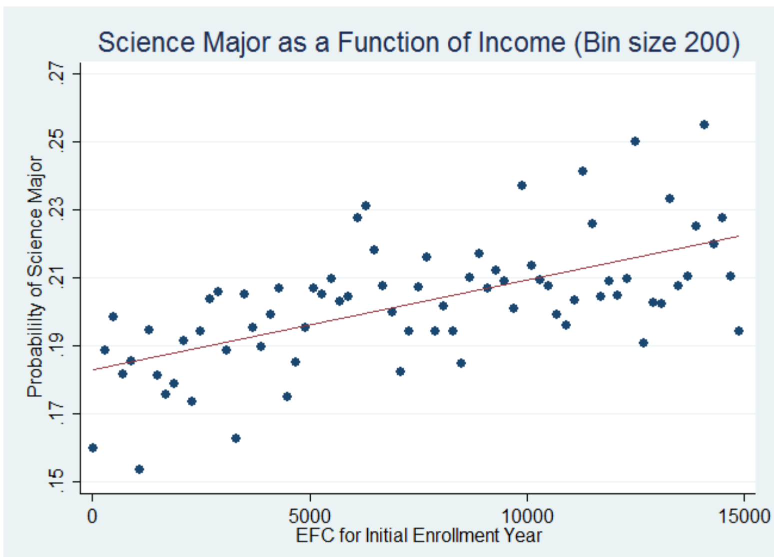


Visual inspection of grant eligibility impact on major selection

Before turning to the regression results of equation (2), I first present graphs of any potential discontinuity of the effect of the financial incentive on students choosing an eligible major.

To provide context, Figure 3 shows a scatter plot of the probability of selecting a STEM major at initial enrollment as a function of EFC. To smooth out the binary nature of the outcome, I take the mean probability of majoring in a STEM field in bins of $200. There is a clear upward slope to the data indicating an increase in the probability of selecting an initial STEM major associated with a higher EFC among students who apply for federal financial aid. A univariate regression over the entire range of data indicates a $1,000 increase in EFC is associated with a highly significant 0.14 percentage point increase in the likelihood of choosing a STEM major at initial enrollment. If the range is restricted to EFCs below the mean of $15,000 as pictured in Figure 3, the slope increases to 0.41 percentage points. This suggests lower income students' selection of a STEM major may be more responsive to increases in income (grant aid).

Figure 3. Probability of Choosing a STEM Major at Initial Enrollment as a Function of EFC



To visually inspect whether a discontinuity exists around the threshold, Figures 4 and 5 graph scatter plots of the probability of majoring in a STEM field against the forcing variable centered at the threshold for two different bin sizes. The range is restricted to $2,000 around the threshold. The data in Figure 4 are erratic, but the larger bin size in Figure 5 smoothes the graph enough to see that no discontinuity in the outcome is apparent. Figures 6, 7, and 8 demonstrate that no large jump in the probability of choosing a STEM major occurs at the threshold. Figure 6 adds linear regression lines with the same slope on either side of the threshold while Figure 7 relaxes the same slope constraint. Both figures show a positive impact of being eligible to receive a future SMART Grant, but the size of the impact is a fraction of a percentage point.

Regression discontinuity results are often sensitive to functional form. If the underlying relationship is non-linear, a linear functional form will provide biased point estimates of the treatment effect. To check whether a low-order polynomial fits the data better, Figure 8 graphs a cubic function on either side of the discontinuity. Figure 8 shows a negative estimated treatment effect of about 1 percentage point, but it does not obviously fit the data better than the linear models.

In summary, the graphical analysis concludes that a promise of future financial incentives of $4,000 does not motivate students to select a STEM major when they initially enroll.

Figure 4. Scatter Plot of the Probability of Selecting a STEM Major at Initial Enrollment around the EFC Eligibility Threshold

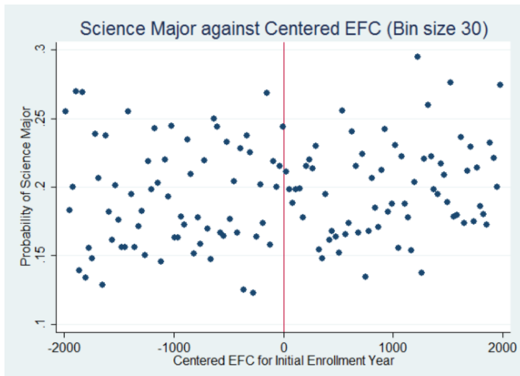


Figure 5. Smoothed Scatter Plot of the Probability of Selecting a STEM Major at Initial Enrollment around the EFC Eligibility Threshold

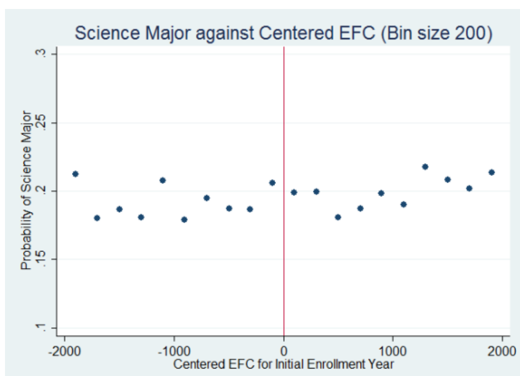


Figure 6. Examining the Discontinuity with a Linear Same Slope Model

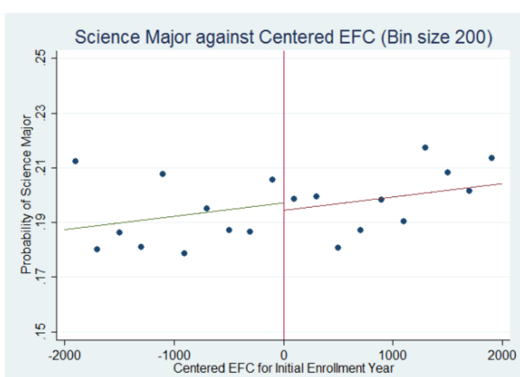


Figure 7. Examining the Discontinuity with a Linear Different Slope Model

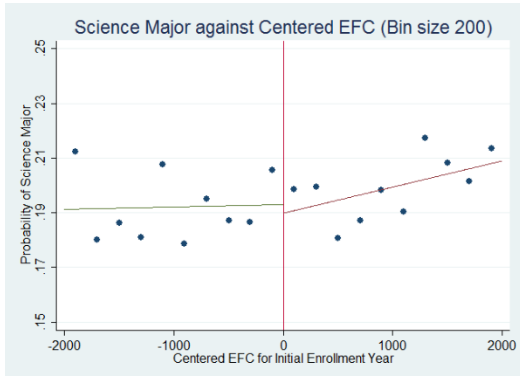
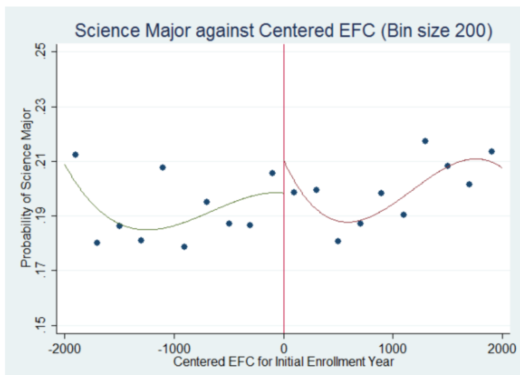


Figure 8. Examining the Discontinuity with a Cubic Model



Parametric Regression Analysis

I now turn to the regression results of fitting equation (2) and report results in Tables 3 and 4. In contrast to the graphical analysis, which focuses on a range of data near the threshold, the parametric regression analysis uses all of the data on either side of the threshold to predict the limit of value at the threshold from the left and the right. The difference in those two limits is the causal effect of eligibility on selection of a STEM major and is represented by the Eligible variable in the tables.

Table 3 reports results from six different linear models. In each model, the EFC is divided by 1000 to make the results easier to interpret. For example, a $1,000 increase in EFC is associated with about a 0.1 percentage point increase in the likelihood of selecting a STEM major at initial enrollment in model 1.

Model 1 constrains the slope to be the same on either side of the threshold. This produces a large, significant, and negative effect of the program with a point estimate of a 3 percentage point decline in the probability of being a STEM major. However, as already mentioned above, there are different slopes at low and high income levels in the relationship between STEM majors and EFC, so imposing the same slope on either side of the threshold is a poor functional form choice.

Table 3. Linear Parametric Regression Discontinuity Results for STEM Major Selection at Initial Enrollment

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Eligible	-0.02825***	-0.01316*	-0.01391*	-0.00481	-0.00582	-0.00626
	(0.00347)	(0.00620)	(0.00608)	(0.00586)	(0.00586)	(0.00580)
EFC/1000	0.00089***	0.00088***	0.00071***	-0.00018*	-0.00011	-0.00009
	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(0.00009)
EFC/1000XPell		0.00506**	0.00062	-0.00628***	-0.00606***	-0.00543***
		(0.00170)	(0.00171)	(0.00165)	(0.00165)	(0.00164)
Female			-0.16527***	-0.10727***	-0.10775***	-0.10195***
			(0.00282)	(0.00283)	(0.00284)	(0.00280)
Black			-0.03623***	0.06474***	0.06478***	0.05386***
			(0.00417)	(0.00425)	(0.00426)	(0.00440)
Asian			0.14335***	0.09031***	0.09181***	0.07782***
			(0.01133)	(0.01079)	(0.01080)	(0.01071)
Hispanic			-0.01851*	0.02171*	0.02142*	0.03086***
			(0.00904)	(0.00871)	(0.00872)	(0.00860)
Other Race			-0.00269	0.03376***	0.03388***	0.02617***
			(0.00737)	(0.00714)	(0.00714)	(0.00705)
OH Resident			-0.05354	-0.06406	-0.06582	-0.04634
			(0.08737)	(0.08747)	(0.08740)	(0.08916)
ACT English				-0.00448***	-0.00434***	-0.00422***
				(0.00044)	(0.00044)	(0.00044)
ACT Math				0.02224***	0.02235***	0.02102***
				(0.00046)	(0.00046)	(0.00047)
ACT Reading				-0.00276***	-0.00275***	-0.00288***
				(0.00039)	(0.00039)	(0.00039)
ACT Science				0.01224***	0.01221***	0.01200***
				(0.00052)	(0.00052)	(0.00051)
Father College					-0.01079***	-0.00873**
					(0.00304)	(0.00302)
Mother College					-0.00174	0.00028
					(0.00290)	(0.00287)
Campus Dummies						X
Constant	0.21026	0.21049	0.35194	-0.29157	-0.2887	-0.21561
	(0.00238)	(0.00239)	(0.08741)	(0.08785)	(0.08779)	(0.08965)
Adjusted R^2	0.0041	0.0042	0.0492	0.1285	0.1287	0.1496
N	83025	83025	83025	83025	83025	83025

Notes: Robust standard errors are included in parentheses; p-value significance denoted by *0.05, **0.01, ***0.001.

Table 4. Treatment Coefficients and 95% Confidence Intervals for STEM Major Selection at Initial Enrollment

Panel A: Linear Regression					
	Basic	Demographics	ACT Scores	Parents' Education	Campus Dummies
Eligible	-0.0132*	-0.0139*	-0.0048	-0.0058	-0.0063
	(0.0062)	(0.0061)	(0.0059)	(0.0059)	(0.0058)
	[-0.0253 -0.0010]	[-0.0258 -0.0020]	[-0.0163 0.0067]	[-0.0173 0.0057]	[-0.0176 0.0051]
Adjusted R^2	0.0042	0.0492	0.1285	0.1287	0.1496
N	83025	83025	83025	83025	83025
Panel B: Cubic Regression					
	Basic	Demographics	ACT Scores	Parents' Education	Campus Dummies
Eligible	-0.0079	-0.0037	0.0014	0.0013	-0.0012
	(0.0127)	(0.0125)	(0.0121)	(0.0121)	(0.0119)
	[-0.0328 0.0171]	[-0.0281 0.0208]	[-0.0223 0.0251]	[-0.0224 0.0250]	[-0.0246 0.0223]
Adjusted R^2	0.0045	0.0494	0.1285	0.1287	0.1495
N	83025	83025	83025	83025	83025
Panel C: Local Linear Regression using a $1,700 Bandwidth					
	Basic	Demographics	ACT Scores	Parents' Education	Campus Dummies
Eligible	-0.0004	-0.0006	-0.0024	-0.0023	-0.0019
	(0.0154)	(0.015)	(0.0145)	(0.0145)	(0.0143)
	[-0.0306 0.0297]	[-0.0300 0.0288]	[-0.0308 0.0260]	[-0.0307 0.0260]	[-0.0300 0.0261]
Adjusted R^2	-0.0001	0.0456	0.1156	0.1155	0.1362
N	11079	11079	11079	11079	11079

Notes: Robust standard errors are included in parentheses; p-value significance denoted by *0.05, **0.01, ***0.001.

Relaxing this constraint in model 2 makes the result small and insignificant, although it remains negative. Models 3-5 add demographic variables, ACT scores, and indicator variables for each campus. The addition of these covariates further reduces the magnitude of the effect, confirming the graphical analysis that there is no discontinuity in the propensity to select a STEM major upon initial enrollment around the EFC threshold for eligibility for the SMART Grant.

Several of the coefficients on the covariates act as expected. Women are less likely to choose a STEM major by about ten percentage points relative to men, and higher scores on the ACT math and science exams strongly predict higher probabilities of majoring in a STEM field. A potentially surprising result is that, relative to white students, minority students are more likely to choose a STEM major. One partial explanation is that one of the schools in the sample, Central State University, is a historically black college with a prominent engineering school attracts some minority students into STEM, but Central State's overall level of STEM major selection is lower than the average across all institutions.

Because the parametric regression model estimates are potentially sensitive to functional form specification, I also implement a cubic model whose estimates produce results even closer to 0, albeit with higher standard errors. Table 4 reports the point estimates, standard errors, and 95 percent confidence intervals for the treatment coefficient in the linear and cubic regression models. In each case, the point estimate is very small and insignificant, and the confidence intervals show low plausible impact estimates. As can be seen in Panel B, even in the cubic case where standard errors are an order of magnitude larger than the point estimates, any plausible values of the effect are very small.

Nonparametric Regression Analysis

Using observations with very high and low EFCs to predict the outcome at the threshold may introduce unnecessary bias to the estimation procedure. If the chosen functional form is inaccurate, the estimated points at the threshold from the left and the right will be incorrect resulting in a biased treatment effect. Therefore, I employ a nonparametric approach to check the sensitivity of the above results. In practice, I use local linear regression on a bandwidth of data around the eligibility cutoff and implement a cross-validation procedure to choose the optimal bandwidth. This procedure eliminates any bias caused by points very far from the eligibility threshold by estimating a linear regression using only points closer to the threshold. Panel C of Table 4 presents the results of this analysis using a bandwidth of $1,700 on either side of the eligibility threshold.[9] Results are robust to bandwidth selection.

Similar to the linear and cubic regressions using the entire data, the point estimate is extremely close to 0. The confidence interval is slightly larger due to the increase in standard errors resulting from the reduction of sample size by focusing on the observations around the threshold. Both the parametric and nonparametric estimation techniques confirm what the graphical analysis suggests. Eligibility for the SMART Grant does not increase the probability of a student choosing a STEM major upon initial college enrollment.

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[9] I use a range of 5% of the data on either side of the discontinuity to estimate the optimal bandwidth, although using 10% and 25% of the data provide similar results.

Major Choice at Junior Enrollment

The promise of $4,000 two years into the future may not be a sufficient incentive to motivate students to select a STEM major when they initially enroll in college. However, eligible students actually receive the money in their junior year, so perhaps the financial incentive motivates students to select a STEM major in their junior year. Using longitudinal data from first-time, full-time entering students, I examine whether those that persisted until their junior year are more likely to select a STEM major when they are eligible to receive the SMART Grant. Before limiting the sample to students in their junior year, I first check for whether eligibility for the SMART Grant in the future affects persistence.

Does eligibility affect persistence to the junior year?

Before conditioning on persistence to test whether the financial incentive alters major behavior in the junior year, I check for whether eligibility for the SMART Grant affects persistence. I limit the sample to only those students beginning in the 2006 and 2007 cohorts as they had at least two years to become a junior. I then check that their EFC does not appear to have been manipulated in Figure 9. The EFC appears to be a valid threshold across which I run a regression discontinuity with persistence to the junior year as the outcome. Table 5 reports these results. As can be seen by the small and insignificant coefficient on the eligibility variable, students who met eligibility on the EFC threshold at enrollment are not more likely to persist to the junior year than students who do not meet eligibility. Because eligibility for the financial incentive does not affect persistence, I continue with the analysis of the impact of the financial incentive on junior year major selection

Figure 9. Density of the EFC Distribution around the Threshold at Initial Enrollment for the 2006 and 2007 Cohorts (McCrary Test)

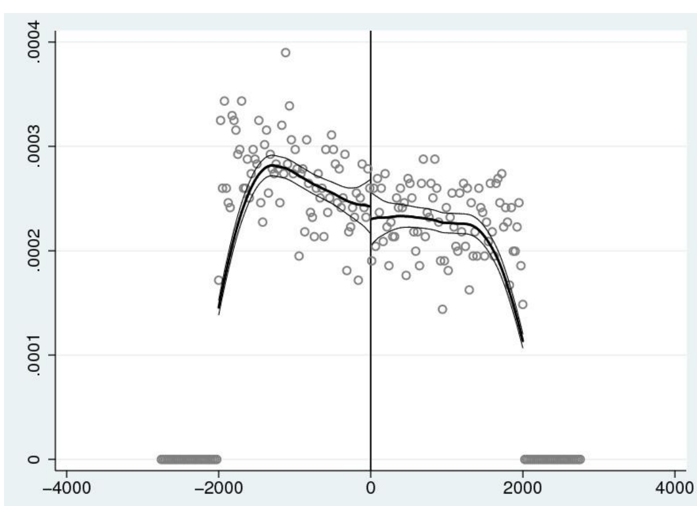


Table 5. Linear Parametric Results for Persistence to the Junior Year Based on Initial Year Eligibility (2006 and 2007 Cohorts)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Eligible	-0.15755***	-0.02132	-0.02329*	-0.01411	-0.00884	-0.00901
	(0.00583)	(0.01097)	(0.01084)	(0.01031)	(0.01030)	(0.01022)
EFC/1000	0.00301***	0.00291***	0.00271***	0.00134***	0.00095***	0.00049***
	(0.00012)	(0.00012)	(0.00012)	(0.00012)	(0.00012)	(0.00012)
EFC/1000XPell		0.04896***	0.03516***	0.02390***	0.02249***	0.02255***
		(0.00336)	(0.00338)	(0.00323)	(0.00322)	(0.00319)
Female			0.02330***	0.05007***	0.05278***	0.04696***
			(0.00444)	(0.00449)	(0.00449)	(0.00444)
Black			-0.18542***	-0.04356***	-0.04532***	-0.05787***
			(0.00790)	(0.00783)	(0.00784)	(0.00787)
Asian			0.09549***	0.05297***	0.04441***	0.02981*
			(0.01347)	(0.01269)	(0.01271)	(0.01271)
Hispanic			-0.04454**	0.01005	0.01197	-0.0024
			(0.01634)	(0.01543)	(0.01546)	(0.01520)
Other Race			-0.10171***	-0.05764***	-0.05922***	-0.04621***
			(0.01249)	(0.01180)	(0.01177)	(0.01165)
OH Resident			0.04038	0.08451	0.10389	0.11506
			(0.14493)	(0.14456)	(0.14612)	(0.14509)
ACT English				0.01334***	0.01259***	0.01015***
				(0.00069)	(0.00069)	(0.00069)
ACT Math				0.01812***	0.01758***	0.01419***
				(0.00071)	(0.00071)	(0.00071)
ACT Reading				0.00036	0.00028	-0.00073
				(0.00061)	(0.00061)	(0.00060)
ACT Science				0.00161*	0.00178*	0.00169*
				(0.00081)	(0.00080)	(0.00080)
Father College					0.05358***	0.04449***
					(0.00483)	(0.00479)
Mother College					0.01972***	0.01263**
					(0.00468)	(0.00462)
Campus Dummies						X
Constant	0.69974	0.70157	0.66478	-0.1511	-0.17901	-0.10963
	(0.00356)	(0.00356)	(0.14497)	(0.14520)	(0.14674)	(0.14592)
Adjusted R^2	0.0568	0.0626	0.08	0.1712	0.175	0.1963
N	40777	40777	40777	40777	40777	40777

Notes: Robust standard errors are included in parentheses; p-value significance denoted by *0.05, **0.01, ***0.001.

Density of forcing variable around the threshold

SMART Grant eligibility in the junior year rests on two components: EFC eligibility and GPA eligibility. If both show no evidence of manipulation, it is possible to run a multiple forcing variables analysis. Figures 10 and 11 show the McCrary density tests for each of the potential forcing variables. Although the EFC variable exhibits a drop in density around the threshold, this occurs on both sides and shows no signs of manipulation. The GPA variable does exhibit evidence of manipulation. More students are found just above the threshold for eligibility at a cumulative 3.0 GPA than just below it indicating that some form of manipulation exists. I do not know whether students strive harder to maintain a B average or specifically request professors give them higher grades to make them eligible for grant aid, but the evidence of manipulation precludes using the GPA measure as forcing variable for the analysis. Therefore, all subsequent analyses in the junior year rely only on the EFC eligibility criterion while restricting the data to only those students who meet the GPA criterion.

Figure 10. Density of the EFC Distribution around the Threshold at Junior Enrollment (McCrary Test)

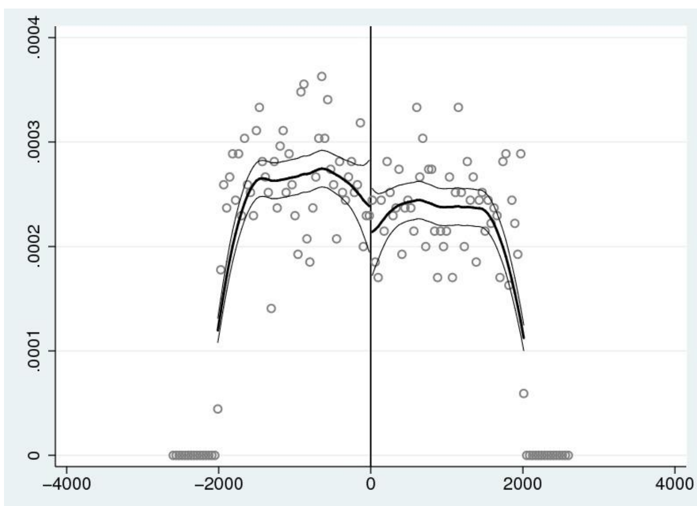
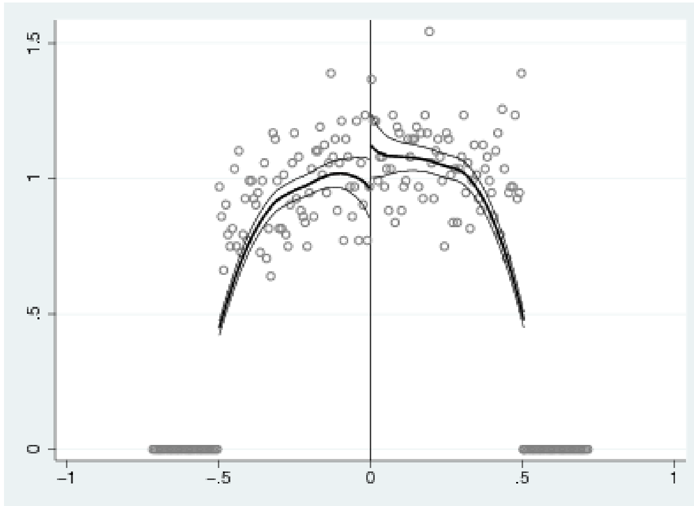


Figure 11. Density of the GPA Distribution around the Threshold at Junior Enrollment (McCrary Test)



Visual inspection of grant eligibility impact on major selection

Following the previous analysis for initial major selection, I examine STEM major choice at the junior year graphically before turning to regression results. Figure 12 shows the probability of having chosen a STEM major in the junior year within $2,000 of EFC on either side of the threshold. Observations are grouped in $200 bins to smooth the data. Eligible students show a remarkably consist pattern of about 19 percent choosing a STEM major while students to the right of the threshold are more erratic. Still, it appears that any discontinuity in the outcome works against the goal of the financial incentives as the ineligible students have higher probabilities of choosing a STEM major. Figures 13 and 14 demonstrate this by fitting same slope and different slope linear models on either side of the threshold, and Figure 15 displays the same pattern using a cubic model. In all cases, the predicted value of the outcome at the threshold for ineligible students is higher than for eligible students.

Figure 12. Scatter Plot of the Probability of Selecting a STEM Major at Junior Enrollment around the EFC Eligibility Threshold

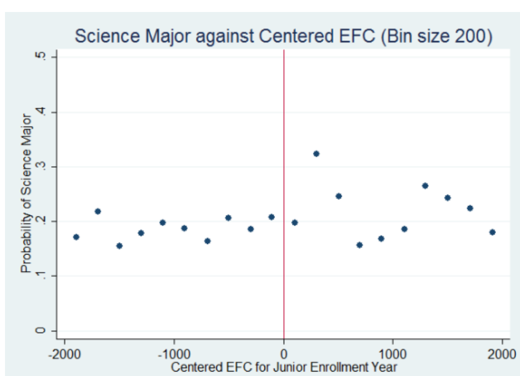


Figure 13. Examining the Discontinuity with a Linear Same Slope Model

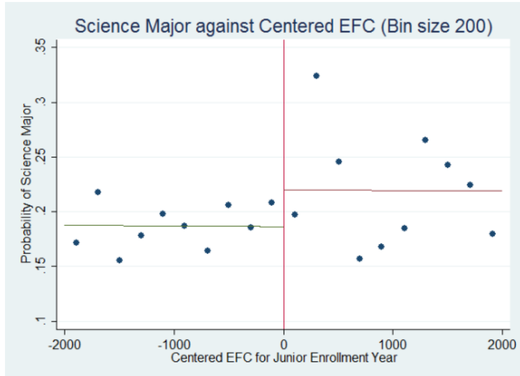


Figure 14. Examining the Discontinuity with a Linear Different Slope Model

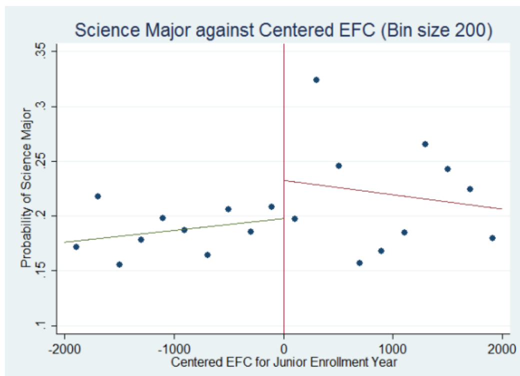
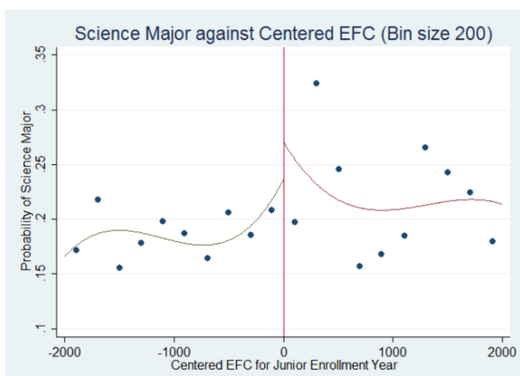


Figure 15. Examining the Discontinuity with a Cubic Model



Parametric Regression Analysis

Table 6 provides numeric results using all of the data for the six different linear models previously discussed. Consistent with results at initial enrollment, women are less likely and minority students are more likely to choose a STEM major in the junior year, and higher ACT math and science scores predict an increased chance of choosing a STEM major.

After controlling for ACT score, parental education, and institution, model 6 estimates a positive but insignificant treatment effect of well under one percentage point. Unfortunately, it is slightly more difficult to explain variation in junior STEM major selection than at initial enrollment, which, combined with the smaller sample size, increases the standard error of the treatment coefficient.

Given the relatively high standard errors, it is interesting to consider plausible ranges of treatment effects. Table 7 provides the point estimates, standard errors, and 95 percent confidence intervals for models 2-6 for linear and cubic parametric regressions. The cubic model produces a higher point estimates, but the standard errors are substantially larger than the coefficients; therefore, I focus on the linear model with the full set of controls including campus dummies. The 95 percent confidence interval shows that plausible treatment effects range from eligible students being 2.4 percentage points less likely to choose a STEM major to 2.5 percentage points more likely.

Nonparametric Regression Analysis

Following the pattern with initial enrollment, I employ local linear regression on a bandwidth of data around the eligibility cutoff. The optimal bandwidth procedure suggests using $2,500 around the EFC threshold, although the general results are robust to different bandwidths, all yielding negative coefficients. Table 7 Panel C displays the treatment coefficient and 95 percent confidence interval using local linear regression for different regression models. I focus on the full model which includes all student covariates and controls for campus of enrollment.

The treatment effect estimate is negative when employing the local linear regression approach, although it remains insignificant. As expected, the standard errors increase due to limiting the sample size around the threshold, and both of the point estimates from the parametric approach fall within the confidence interval. The local linear regression results support the conclusion from the graphical and parametric approaches that the financial incentive does not induce students to choose a STEM major at the start of their junior year.

Table 6. Linear Parametric Regression Discontinuity Results for STEM Major Selection at Junior Enrollment

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Eligible	-0.01002	0.00186	-0.00169	-0.00043	-0.00087	0.00068
	(0.00762)	(0.01361)	(0.01297)	(0.01261)	(0.01262)	(0.01251)
EFC/1000	0.00048*	0.00047*	0.00037*	-0.00016	-0.00012	0.00009
	(0.00019)	(0.00019)	(0.00019)	(0.00018)	(0.00018)	(0.00018)
EFC/1000XPell		0.00425	0.00197	-0.00307	-0.00298	-0.0033
		(0.00398)	(0.00383)	(0.00374)	(0.00374)	(0.00372)
Female			-0.18890***	-0.11996***	-0.12026***	-0.11639***
			(0.00612)	(0.00619)	(0.00621)	(0.00613)
Black			-0.02106	0.05774***	0.05735***	0.06085***
			(0.01303)	(0.01300)	(0.01303)	(0.01343)
Asian			0.17498***	0.12347***	0.12416***	0.11261***
			(0.02120)	(0.01975)	(0.01976)	(0.01978)
Hispanic			0.01522	0.05488**	0.05461**	0.06465**
			(0.02190)	(0.02113)	(0.02114)	(0.02095)
Other Race			0.01565	0.03406*	0.03420*	0.02793
			(0.01789)	(0.01731)	(0.01731)	(0.01731)
OH Resident			-0.08693	-0.05336	-0.05351	-0.04072
			(0.14442)	(0.12955)	(0.12969)	(0.12675)
ACT English				-0.00338***	-0.00330***	-0.00279**
				(0.00090)	(0.00090)	(0.00090)
ACT Math				0.02092***	0.02097***	0.02115***
				(0.00092)	(0.00092)	(0.00093)
ACT Reading				-0.00397***	-0.00397***	-0.00361***
				(0.00077)	(0.00077)	(0.00077)
ACT Science				0.01294***	0.01291***	0.01253***
				(0.00111)	(0.00111)	(0.00110)
Father College					-0.00718	0.00143
					(0.00599)	(0.00597)
Mother College					0.00115	0.0056
					(0.00589)	(0.00584)
Campus Dummies						X
Constant	0.19451	0.19467	0.39046	-0.33121	-0.33027	-0.28972
	(0.00463)	(0.00463)	(0.14450)	(0.13110)	(0.13124)	(0.12877)
Adjusted R^2	0.0007	0.0007	0.0608	0.1344	0.1344	0.1506
N	19037	19037	19037	19037	19037	19037

Notes: Robust standard errors are included in parentheses; p-value significance denoted by *0.05, **0.01, ***0.001.

Table 7. Treatment Coefficients and 95% Confidence Intervals for STEM Major Selection at Junior Enrollment

	Basic	Demographics	ACT Scores	Parents' Education	Campus Dummies
Panel A: Linear Regression					
Eligible	0.0019	-0.0017	-0.0004	-0.0009	0.0007
	(0.0136)	(0.0130)	(0.0126)	(0.0126)	(0.0125)
	[-0.0248 0.0285]	[-0.0271 0.0237]	[-0.0251 0.0243]	[-0.0256 0.0239]	[-0.0238 0.0252]
Adjusted R^2	0.0007	0.0608	0.1344	0.1344	0.1506
N	19037	19037	19037	19037	19037
Panel B: Cubic Regression					
	Basic	Demographics	ACT Scores	Parents' Education	Campus Dummies
Eligible	0.0152	0.012	0.0097	0.0099	0.0147
	(0.0283)	(0.0268)	(0.0261)	(0.0261)	(0.0260)
	[-0.0403 0.0707]	[-0.0405 0.0645]	[-0.0413 0.0608]	[-0.0412 0.0610]	[-0.0362 0.0656]
Adjusted R^2	0.0008	0.0609	0.1345	0.1344	0.1507
N	19037	19037	19037	19037	19037
Panel C: Local Linear Regression using a $2,500 Bandwidth					
	Basic	Demographics	ACT Scores	Parents' Education	Campus Dummies
Eligible	-0.04	-0.0267	-0.0355	-0.0355	-0.0289
	(0.0278)	(0.0266)	(0.0258)	(0.0258)	(0.0257)
	[-0.0946 0.0146]	[-0.0789 0.0255]	[-0.0861 0.0151]	[-0.0861 0.0151]	[-0.0793 0.0215]
Adjusted R^2	0.0007	0.0775	0.1356	0.1353	0.149
N	3523	3523	3523	3523	3523

Notes: Robust standard errors are included in parentheses; p-value significance denoted by *0.05, **0.01, ***0.001.

Persistence in STEM Major

The effect of financial incentives on major selection appears nonexistent at initial and junior year enrollment; however, it is possible the financial incentives encourage students who are initially interested in a STEM major to stick with it.[10] I can estimate this causal effect by limiting the analysis to students who began in a STEM major and observing any difference in persistence within the major to the junior year between eligible and ineligible students around the eligibility threshold. I restrict all of the analyses in this section to students entering in 2006 and 2007 because they are the only entering cohorts who had at least two full years to become juniors.

Do financial incentives affect persistence of initial STEM majors to the junior year?

Before evaluating whether eligible students are more likely to persist in a STEM major, I ensure that the financial incentives did not have an overall impact on persistence in higher education to the junior year among students who initially chose a STEM field. Figure 16 shows the density around the threshold of initial year EFC for students who began with a STEM major. Although the density increases on both sides around the threshold, there is no evidence of manipulation.

Figure 16. Density of the EFC Distribution around the Threshold at Initial Enrollment for STEM Majors

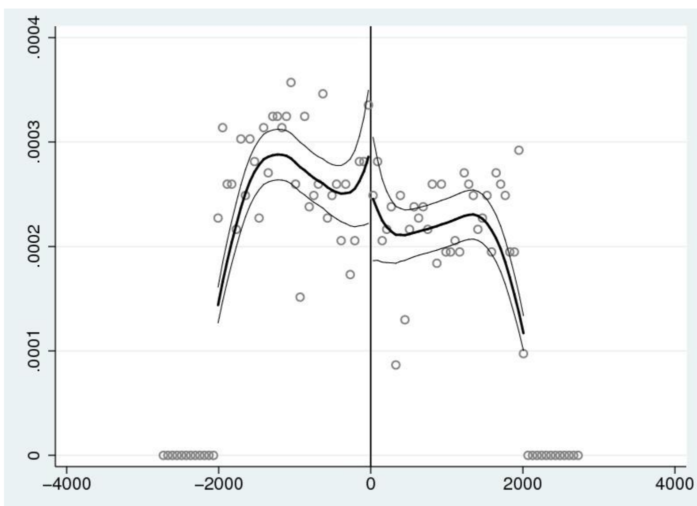


Table 8 displays the regression results for testing whether SMART Grant eligibility encouraged persistence to the junior year of students who initially chose a STEM major for the 2006 and 2007 entering cohorts. Although the standard errors have increased because of the sample size restriction, the point estimate on the Eligible variable is negative and statistically insignificant. This result confirms that eligibility for the financial incentive does not alter overall persistence to the junior year.

Do financial incentives affect persistence in a STEM major?

[10] See Bettinger (2010a) for a descriptive analysis of the percent of students moving into and out of STEM majors through their college careers using similar but earlier data from Ohio public colleges.

Because eligibility for the SMART Grant does not affect persistence for those who initially choose a STEM major, it is possible to examine directly whether it affects persistence in a STEM major. The analysis begins with the subset of 2006 and 2007 entrants who initially chose a STEM major. It then examines whether eligibility for the $4,000 grant in their junior and senior year improves their probability of still being enrolled in a science major when they begin their junior year.

First, I eliminate concerns regarding manipulation of the forcing variables. Because eligibility in the junior year is conditional on both an EFC and GPA cutoff, I examine both thresholds in Figures 17 and 18. Neither graph demonstrates evidence of manipulation of EFC or GPA; therefore, both forcing variables can be used in the data analysis.

As discussed in the empirical strategy section, I estimate the effect of being eligible on both the EFC and GPA criteria simultaneously. I run a linear regression using all of the available data.[11] The interaction of eligibility on the EFC and GPA measures is the coefficient of interest. This coefficient estimates the effect of being eligible on both measures over and above the impact of being eligible on just one of the criteria. The estimated result is -0.012 with a standard error of 0.102. Consistent with the previous findings, the point estimate is close to zero indicating the effect of eligibility for the SMART Grant does not improve the likelihood of students persisting in a STEM major if they initially chose a STEM major upon matriculation. Unfortunately, the measure is very imprecise as the standard error has ballooned to nearly 9 times the point estimate. Only slightly more than 6,000 students who began with a STEM major in their first year of college maintained enrollment and filed a FAFSA in their junior year, which severely limits the sample size. Additionally, the covariates explain less of the variation in STEM major selection in the junior year among students who already selected a STEM major initially.

The results do not provide evidence that financial incentives encouraged students who initially began with a STEM major to persist in their STEM intentions.

Figure 17. Density of the EFC Distribution around the Threshold at Junior Enrollment for Initial STEM Majors

[11] Due to the number of coefficients estimated and conditioning on persistence to the junior year, the standard errors are already very high. Further limiting the bandwidth around both thresholds results in extremely imprecise estimates.

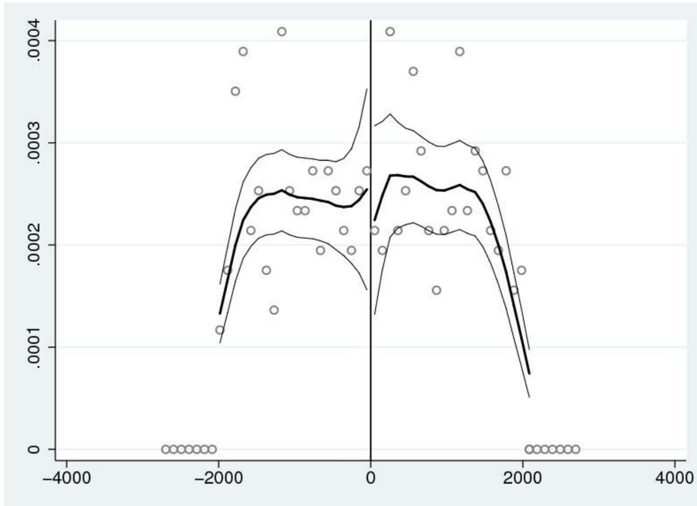


Figure 18. Density of the GPA Distribution around the Threshold at Junior Enrollment for Initial STEM Majors

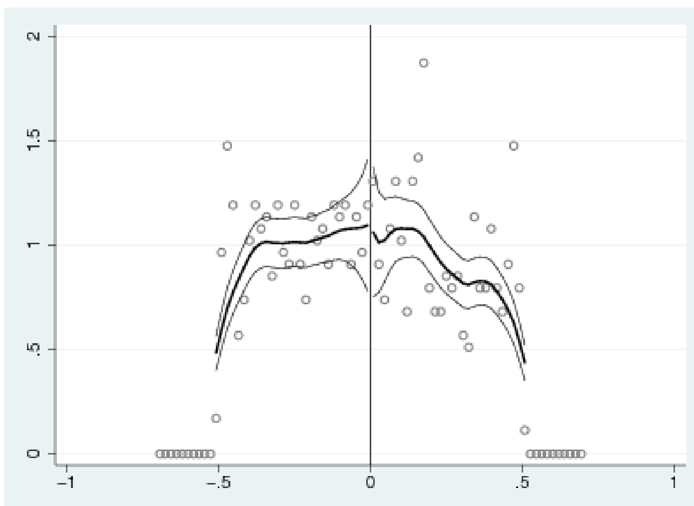


Table 8. Persistence to Junior Year of Initial STEM Majors for the 2006 and 2007 Cohorts

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Eligible	-0.16674***	-0.06137*	-0.05907*	-0.03766	-0.03318	-0.03306
	(0.01299)	(0.02466)	(0.02433)	(0.02322)	(0.02318)	(0.02303)
EFC/1000	0.00204***	0.00197***	0.00180***	0.00066**	0.00033	-0.00002
	(0.00023)	(0.00022)	(0.00022)	(0.00022)	(0.00022)	(0.00022)
EFC/1000XPell		0.03873***	0.02993***	0.02147**	0.01999**	0.02079**
		(0.00787)	(0.00787)	(0.00751)	(0.00750)	(0.00743)
Female			0.04523***	0.06144***	0.06202***	0.04825***
			(0.00963)	(0.00978)	(0.00976)	(0.00976)
Black			-0.17161***	-0.0374	-0.04010*	-0.05283**
			(0.02026)	(0.01983)	(0.01989)	(0.02011)
Asian			0.08718***	0.04539*	0.03712	0.01853
			(0.01955)	(0.01903)	(0.01913)	(0.01916)
Hispanic			-0.05838	-0.02521	-0.02465	-0.04784
			(0.03725)	(0.03442)	(0.03451)	(0.03397)
Other Race			-0.09831***	-0.04238	-0.04229	-0.03938
			(0.02803)	(0.02715)	(0.02694)	(0.02679)
OH Resident			0.19537	0.25779	0.27977	0.25801
			(0.19830)	(0.21209)	(0.20735)	(0.20812)
ACT English				0.01045***	0.00990***	0.00808***
				(0.00144)	(0.00145)	(0.00144)
ACT Math				0.02011***	0.01929***	0.01657***
				(0.00149)	(0.00150)	(0.00151)
ACT Reading				-0.00057	-0.00067	-0.00159
				(0.00128)	(0.00128)	(0.00127)
ACT Science				-0.00128	-0.0011	-0.00138
				(0.00158)	(0.00158)	(0.00157)
Father College					0.04714***	0.04068***
					(0.01023)	(0.01017)
Mother College					0.01984*	0.01667
					(0.01004)	(0.00995)
Campus Dummies						X
Constant	0.78149	0.78267	0.58393	-0.20543	-0.22873	-0.13265
	(0.00716)	(0.00716)	(0.19844)	(0.21422)	(0.20951)	(0.21123)
Adjusted R^2	0.0547	0.0584	0.0747	0.1563	0.1599	0.1761
N	7998	7998	7998	7998	7998	7998

Notes: Robust standard errors are included in parentheses; p-value significance denoted by *0.05, **0.01, ***0.001.

VII. Discussion

The results provide fairly clear data across all three outcomes that financial incentives do not encourage students to study science in higher education. Estimates of treatment effects close to zero are robust to functional form for parametric estimation techniques and bandwidth selection for local linear regression. Not only does the SMART Grant program not encourage students to choose a STEM field upon initial or junior year enrollment, but the financial aid does not even encourage students who initially select a STEM field to persist at higher rates than ineligible students (although the sample size for this estimate is small resulting in imprecise measurements).

This null result is somewhat unexpected in the context of financial aid literature. Although positive impact estimates for the Pell Grant program are difficult to find (Kane 1995), the field has developed consensus that $1,000 of financial aid increases college enrollment probabilities by three to four percentage points (Deming & Dynarski 2009). The impact of financial aid on college persistence has also garnered attention. In two papers, Bettinger (2004 & 2010b) finds that Pell Grants likely improve persistence and that a $750 increase in state grant aid decreased drop-out rates by 2 percentage points. Castleman and Long (2012) focus on degree receipt and use regression discontinuity to estimate that $1,000 in grant aid increases the chances of obtaining a degree by 4.6 percentage points.

Given these results from prior literature, it may be surprising that $4,000 in grant aid is not enough to shift at least some students into studying a STEM field among a low-income population. One commonly cited reason why studies of Pell Grants have failed to produce similar results to other aid programs is that applying for the aid is difficult due to the complex nature of the FAFSA (Bettinger et al. 2012). That argument does not apply to the findings in this study because it is limited only to students who have already filed a FAFSA. My study is not the only research to find negative effects, however. Goldrick-Rab et al. (2011) find neither an enrollment nor a persistence effect in a randomized experiment of providing need-based financial aid to students.

Another potential explanation for the findings is students' high discount rates combined with the necessity of early preparation for science degrees. The promise of grant aid two years in the future may be heavily discounted by entering college students, so finding no impact at initial enrollment is somewhat sensible. However, that argument can not apply to the junior year. Perhaps by the time students realize the financial incentive is worth transitioning into an eligible major, they are too far behind the required coursework to be successful in a science degree and still graduate on time. If transitioning into a STEM field requires another one to two terms of coursework, the incentive is radically diluted.

If this explanation is valid, the SMART Grant program design is flawed. By providing an early incentive that can be realized at college entry, the program may induce some students to start preparing for a science major at the beginning of college thereby leading to an increase in STEM degrees.

An additional explanation for the findings is that the grant is actually quite small compared to the lifetime earnings stream of STEM graduates. I examine the income differences between a STEM and non-STEM major in a simple two period model (during college and after college). Equation (3) sets Δ equal to the financial gain associated with selecting a STEM major for student i.

(3)

Y represents the in college or post-college earnings for either STEM majors or other majors. Students discount future earnings by a discount factor that incorporates their personal taste for present consumption over future consumption (δ) and the market discount rate (r) with $\delta < 1$ and $r < 1$.

It is possible to use real world estimates and a few assumptions to generate a basic approximation of what a low-income student who majors in a STEM field can expect to earn above a non-STEM major. I evaluate the terms of equation (3) based on the value of the financial incentive (incentive), the probability of being eligible for the SMART Grant ($P(gpa \geq 3.0)$), the probability of graduating from college with a bachelor's degree in a STEM field ($P(BA_S)$) and a non-STEM field ($P(BA_O)$), and the lifetime incomes of science majors (Y_S), other majors (Y_O), and dropouts (Y_D). To simplify the model, I assume that GPA only determines eligibility for the financial incentive and does not determine future earnings. Replacing the expectations in equation (3) with these values and probabilities yields equation (4).

(4)

Which, assuming dropouts from all majors earn equal amounts, simplifies to

(5)

I now use the following estimates for these parameters.

For the probability of a Pell eligible student receiving at least a 3.0 GPA when choosing a SMART major, I employ the Beginning Postsecondary Survey 2009 (BPS), a nationally representative longitudinal survey of students starting college in the 2003-04 school year conducted by the National Center for Education Statistics. Almost 37 percent (36.9%) of Pell Grant recipients in science fields during their first year of four-year college enrollment had a cumulative college GPA of at least 3.0.

Average annual incomes of science majors with only a bachelor's degree ($66,750), non-science majors with only a bachelor's degree ($55,333), and college dropouts ($39,806) are obtained from the American Community Survey 2009-2010 (Carnevale et al. 2012) and the Current Population Survey 2009 (for dropouts) for workers aged 30-54 and 35-44 (for dropouts). These estimates are for the population of college graduates, not those of Pell recipients. The analysis therefore assumes earnings are independent of Pell receipt. I multiply each annual earnings amount by 40 as a crude estimate of lifetime earnings.

The probability of finishing college with a BA for Pell recipients when the initial major selection is a STEM field versus another field is also provided by BPS. For Pell recipients who start at a four-year college and initially choose a STEM major, 43.5 percent have completed a BA by 2009 as opposed to 44.4 percent of students who initially choose a non-STEM field. The total in college value of the financial incentive is $8,000 ($4,000 in each of a student's junior and senior years).

Plugging in these estimates to equation (5) yields the expected in college and discounted after college financial advantage of choosing to major in a STEM field for low-income students after the implementation of the SMART Grant.[12]

(6)

Because the wage premium for STEM majors is so high and because STEM and non-STEM majors graduate college with nearly the same likelihood, it appears as if there is a substantial benefit to majoring in a STEM field even without the impact of the in college financial incentive. In fact, the financial incentive is dwarfed by the future earnings potential even after discounting. Hamermesh and Donald (2008) show that some difference in future earnings across majors can be attributable to ability and background characteristics; however, they also provide evidence that engineering and science majors fare well in terms of future earnings against many other majors such as education, humanities, and architecture supporting the general conclusion that there is a payoff to a STEM major. The above approximation may explain why the financial incentive had little effect. If the financial benefit to studying science is already very high yet students still choose not to pursue STEM majors, money (even when realized earlier) may not matter.

This interpretation suggests some other factor may deter students from pursuing science fields despite the financial reward. The most likely explanation is ability. Arcidiacono's (2004) considers the sorting of high ability college students into majors and finds that high ability students are more likely to sort into STEM fields. He attributes this phenomenon to student preference for STEM fields over the competing explanation of a desire for high earnings because he finds that high math ability students have greater earnings across all majors. Combined with Stinebrickner and Stinebrickner's (2011) results showing students select out of science majors due to poor academic performance, a clear pattern emerges that ability and academic performance are the factors driving STEM major selection.

I investigate whether the grant impacts high ability students in my sample by running the regression discontinuity model for junior year enrollment with an interaction for ACT math score. I do not find any effect. This result implies higher ability students are not moving into STEM fields as a result of the grant, although many of those students are already enrolled in STEM majors. It is still likely that many students with inadequate academic preparation are interested in science but avoid STEM majors for fear of poor academic performance.

There is an important policy implication if ability and academic performance are the leading factors deterring students from STEM majors. Investing in mathematics and scientific preparation before college and quality teaching and academic support during college may have a greater payoff than

[12] In this two period model, the discount factors will be very large as they are discounting an entire future earnings stream over many forty years.

providing financial incentives to students who are not able to maintain a STEM major even if they want to.

A final potential explanation of the findings is that students might not be aware that the program exists. Zafar's work indicates that students will respond to new information and adjust their expectations, but if the information never reaches them, they have no reason to adjust their major based on a large improvement in their potential college utility. The extent to which students were aware of the SMART Grant is an open question. A policy report on the status of the SMART Grant program uses student interviews from the National Postsecondary Student Aid Study in 2007-08 (NPSAS: 08), to show that only 5% of low-income college juniors and seniors indicated familiarity with the SMART Grant program (Choy et al. 2011). On the surface this seems an extremely low percentage, but it does not account for the fact that only a subset of low-income students have eligible GPAs and will consider STEM fields, so the proportion of truly eligible students aware of the program may be higher. Additionally, in the first year of the program, the U.S. Department of Education sent emails and letters to students who met the non academic eligibility criteria to inform them that they may be eligible (Choy et al. 2012).

Limitations of the Study

Both the data and method employed in this analysis limit the generalizability of the findings. Ohio is a fairly typical state demographically, so assuming the observed effects apply nationally is probably a good approximation. However, all of these results only apply to public institutions as the data contain no information on private college enrollments. Two-thirds of all SMART Grant recipients nationally attend four-year public institutions, but if students attending private universities experience different treatment effects, the estimated benefits may be biased.

Regression discontinuity imposes a few other limitations. Because the threshold for eligibility of the SMART Grant is dependent on EFC, the results are only applicable for financial aid applicants. It seems unlikely, however, that providing financial incentives to upper income students would have a larger impact on major selection than for lower income students. The major disadvantage of the regression discontinuity method is that it relies only on variation occurring around the threshold to estimate a treatment effect; hence, the estimates are only causal for students close to the threshold. Although the estimates apply to low-income students who are marginally eligible for Pell Grants, I cannot estimate the impact of financial incentives on the very poorest students who have an EFC of $0. It is possible that the impact of the financial incentive is larger for those students; however, those students are already receiving over $4,000 in Pell Grant awards more than the students at the threshold, so the additional financial incentive might have less impact.

Cost Benefit Analysis

By combining expenditure data with my estimates and imposing a few assumptions, I can estimate the cost of the SMART Grant program per additional STEM degree. This is simply the overall expenditure on the program divided by the number of people induced to pursue a STEM degree because of the program. Over the first three years of the program's implementation, an average of 64,000 juniors and seniors received a SMART Grant each year nationwide for a total federal expenditure of $610 million (Choy et al. 2011).[13]

Calculating the number of students induced to pursue a STEM major requires a few calculations and assumptions. I multiply the treatment effect by the number of students who are eligible for the program. For a generous plausible estimated treatment effect, I take the upper bound of the 95 percent confidence interval for the local linear regression model with full covariates estimating the impact on junior year STEM major selection. The treatment impact is then 2.15 percentage points.

To determine the number of eligible students nationally, I use data from the 2008-2009 Pell Grant End-of-Year Report published by the U.S. Department of Education (2010). To approximate first-time students, I only select applicants who are dependent on their parents for financial support. The total number of full-time, dependent Pell recipients at four-year colleges is 1,387,358 (896,006 at public colleges, 396,471 at private colleges, and 94,881 at proprietary colleges). Unfortunately, the Department of Education does not report Pell Grant recipients by academic level. Simply assuming one quarter of these students are juniors is a high overestimate considering only 50 percent of Pell recipients in their first year reached junior status for the 2006 and 2007 cohorts in my sample. I therefore assume 18 percent of total Pell recipients are juniors for 249,724 students eligible to receive the SMART Grant on the EFC criterion. I multiply this number by 0.52, the percent of students who are Pell Grant eligible in their junior year who have a junior year cumulative GPA of at least 3.0 in my sample. This leaves 129,856 students who are eligible SMART Grant recipients as juniors.

Multiplying the eligible juniors by the treatment effect nets an additional 2,792 students per year pursuing a STEM degree nationally that would not in the absence of the SMART Grant. If I again overweight the program's positive benefits and assume that all students with a junior year STEM major graduate with a STEM degree, the total federal cost per additional STEM degree over the first three years of the program is $72,827. This analysis is subject to the same caveats as discussed above: the observed average treatment effect is applied nationally to all students even though the estimates only strictly apply to Ohio students in public institutions near the thresholds for eligibility. Still, the positive assumptions of effect size and Pell recipient persistence imply that this estimate is a best case scenario of the cost effectiveness of the program. It is easy to envision more cost effective policies to increase the population of STEM degrees.

[13] This does not equal the maximum award times the number of recipients because just over half of the recipients actually receive the full award of $4,000 because of enrolling less than full-time or graduating in the middle of the year.

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