Who Does Aid Help? Examining Heterogeneity in the Effect of Grant Aid on Achievement

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Abstract

Does grant aid impact achievement differently for low- and high-income students? I exploit the eligibility requirements of a state scholarship program that awards additional aid to merit-aid students majoring in STEM fields. A triple-difference design, using administrative data from a large institution and exploiting differences over time, by merit-aid recipient status, and by major type (STEM or non-STEM), shows that grant aid increases the GPAs and graduation prospects of low-income students but has little impact on high-income students. Additional analysis suggests that reduction in student part-time work among low-income students may be a potential mechanism for the heterogeneous achievement effects of grant aid by income. These results suggest that merit aid programs could be targeted more effectively than most currently are.

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1 Introduction

Once nonexistent, merit-based aid now constitutes a considerable share of state grant aid in the U.S. among undergraduate students, as many states have shifted focus away from need-based aid towards merit-based aid.[1] This shift has led to a compositional effect on grant aid recipients, as high income students are now provided the opportunity to receive new grant aid. Additionally, this shift led to a national debate over how best to allocate grant aid dollars among low- and high-income students.[2] The debate is further intensified given the college-completion gap that exists between low- and high-income students.[3]

In order to determine how best to allocate grant aid dollars among low- and high-income students, it is important to understand how these student types, as it relates to academic achievement, differentially respond to grant aid. Given that low-income students may be more liquidity-constrained, it is plausible to expect that these students might be impacted most by grant aid (Dynarski 2000). On the contrary, if additional aid creates or further perpetuates a wedge in the accessibility of supplementary educational inputs[4] between low- and high-income students, where high-income students gain greater access to these inputs, perhaps high-income students might be most impacted by grant aid. Considering total grant aid to undergraduate students totaled \$113 billion[5] in school year 2017-18 (see Figure 2),

[1]Grant aid does not have to be repaid and is typically divided into two categories: merit-based aid, which is based on academic ability, and need-based aid, which is based on financial need. Among states, need-based-only aid accounted for 46 percent of total financial aid among undergraduates in 2015-16, down from 57 percent in 2002-03. During this same time-frame, aid that included some merit-based component represented roughly 40 percent of total financial aid, up from 34 percent in 2002-03 (National Association of State Student Grant and Aid Programs 2016). Also, see Alon (2011), College Board (2018), Ehrenberg, Zhang & Levin (2005), Goodman (2008), Long & Riley (2007), and Monks (2009), which discuss the shift towards merit-aid programs. Figure 1 displays the share of total undergraduate state grant aid that is non-need based by year.

[2]Those opposed to states shifting focus to merit-based aid argue that such awards disproportionately go to high-income students, many of whom would attend and graduate college absent the aid (Doyle 2010, Long 2010, Wall Street Journal 2012). Some policymakers justify awarding grant aid dollars to high-income students by arguing such aid would help to retain talented students across the income spectrum within their respective states, although research shows that migration decisions are not impacted by such aid (Fitzpatrick & Jones 2012, Levitz & Thurm 2012).

[3]A 2015 NCES study found that a college-completion gap exists between low- and high-income students, with the latter group graduating at lower rates even after controlling for college enrollment.

[4]Educational inputs that are not mandatory to purchase as a condition of college/classroom enrollment.

[5]This amount excludes loans and work-related aid.

approximately 0.6 percent of U.S. GDP at the time, optimal targeting of such aid would be impactful if heterogeneous achievement effects of grant aid exist.

In this study, I examine whether grant aid impacts college performance and completion and, if so, whether grant aid has differential effects for low- and high-income students. I exploit the eligibility requirements of a state scholarship program, the South Carolina Math and Science Scholarship Enhancement Program, using a difference-in-difference-in-differences (triple-difference) design to estimate the effect of grant aid. The program awards state merit-aid recipients with additional money if they major in a science, technology, engineering, or math (STEM) field. This targeted financial incentive not only could have a direct impact on achievement (via an incentive effect) but also compositional effects on enrollment, major choice, and student part-time work, all of which could impact achievement. To isolate compositional effects on enrollment and major choice, I estimate the effect of grant aid among a subset of students already enrolled in college and who sorted between the STEM and non-STEM choice prior to the program's introduction. Having the ability to isolate compositional effects on enrollment and major choice is important given these decisions could directly impact treatment in this study. I also conduct additional analyses to consider the possibility of an incentive effect of grant aid, which also could directly impact treatment. Using student-level enrollment and financial aid data from the University of South Carolina, I identify the effect of grant aid, estimated across all recipients, by exploiting differences over time, by merit-aid recipient status, and by major type (STEM or non-STEM). Moreover, I estimate the differential achievement effect of grant aid for low-income students relative to high-income students to test if grant aid impacts these student types differently, the main focus of the paper.

To preview the results, I find that grant aid impacts low-income, merit-aid recipients most, increasing their GPAs and likelihood of graduation by 0.169 GPA points and 10.7 percentage points, respectively. I next examine work-study dollars earned, a proxy for time-spent working, to consider differential work behavior effects of grant aid by income as a potential mechanism for the differential achievement effects of grant aid by income. Low-income students are more likely than their more affluent peers to work while in school .[6] This is important since several studies indicate that working while in school harms academic performance.[7] Further, many low-income students work for financial reasons and among students that work for financial reasons, an increase in grant aid is likely to change their work behaviors (Broton et al. 2016, Lobel 1991, Scott-Clayton 2012). I find that the additional grant aid leads to reductions in work-study dollars earned for low-income students only. This result, coupled with the results on achievement, suggest that, among merit-aid recipients, low-income students are impacted most from the receipt of grant aid as a result of working less.

This study contributes to the existing literature on student aid by focusing on the heterogeneous achievement effects of grant aid by income.[8] Much of the literature that examines heterogeneity by income in the effect of student aid focuses on college enrollment, where the results are mixed.[9] The literature examining heterogeneity by income in the effect of student aid on college performance and completion, equally important outcome measures, is scant. There are a few exceptions.

Alon (2011) examines the impact of need-based grants on college persistence for a nationally representative sample of college students enrolled at four-year institutions, using an instrumental variables approach and exploiting the discontinuity created in Pell grant amounts that is driven by whether or not students have siblings attending college. The

[6]See: Broton, Goldrick-Rab & Benson (2016); Roksa & Velez (2010); Scott-Clayton (2012); Scott-Clayton & Minaya (2016); Walpole (2003).

[7]See: Broton et al. (2016); Bound, Lovenheim & Turner (2012); Darolia (2014); DeSimone (2008); Scott-Clayton (2011a); Scott-Clayton & Minaya (2016); Soliz & Long (2014); Stinebrickner & Stinebrickner (2003).

[8]Previous literature has examined the effect of student aid on college enrollment (see: Castleman & Long (2016); Cornwell, Mustard & Sridhar (2006); Dynarski (2003); Fitzpatrick & Jones (2016); Goldrick-Rab, Harris, Kelchen & Benson (2012); Henry, Rubenstein & Bugler (2004); Kane (2003); Kane (2007); Monks (2009)) and performance (see: Bettinger (2004); Castleman & Long (2016); Denning (2018); Dynarski (2003); Dynarski (2008); Fitzpatrick & Jones (2016); Henry et al. (2004); Scott-Clayton (2011b); Sjoquist & Winters (2012); Stater (2009)), with most of these studies showing that student aid increases college enrollment and improves college performance, on average.

[9]See: Dynarski (2000); Goodman (2008); Kane (1994); Van der Klaauw (2002).

author finds that need-based grants positively impact the likelihood of graduating within six years for low-income students only, increasing graduation prospects by 0.006 and 0.010 percentage points for every $100 spent on students in the bottom and second-to-bottom income-quartiles, respectively. Despite the unique source of variation identifying the effect of need-based grants, there are selection concerns that, if present, would bias the estimated treatment effects on low- and high-income students in Alon's study.[10] Further, examining Pell grants to consider the heterogeneous effects of aid by income may not be ideal because many high-income students do not receive Pell grants (Protopsaltis & Parrott 2017).

Denning (2018), whose main focus is estimating the effect of financial aid on inframarginal students (current college enrollees) at Texas public universities, conducts additional analyses to consider the heterogeneous effects of student aid by income. Specifically, students age 24 or older are considered independent for purposes of applying for federal financial aid. Because of this, these students are not required to report their parent's information when applying for federal financial aid and may receive additional Pell grant and federal loan amounts, as a result. Using a regression-discontinuity design around the age cutoff for independent status, the author finds that financial aid positively impacts the likelihood of graduating within four years for low-income students only, increasing their graduation prospects by about 0.003 percentage points for every $100 spent. Although Denning finds that there is no effect of financial aid on graduation for high-income students, the fact that the additional aid amount may vary across students within the low- and high-income groups makes it difficult to conclude with surety that high-income students did not benefit from the additional aid. Also, given that need-based grant and loan amounts could both be impacted by the treatment, it is difficult to disentangle whether low-income students benefit because of additional need-based grant amounts or loan amounts or a combination of both. Nevertheless, the current study compliments Denning (2018) by examining the heterogeneous achievement effects of grant aid by income among traditional college students, those between the ages of 18-23.

[10]The additional aid may affect the enrollment decision and if such decisions impact college completion, the results would be biased.

In examining the heterogeneous achievement effects of grant aid by income, the current study exploits a program design that is ideal. All treated students receive the same aid amount, alleviating concerns that heterogeneity by income in the aid amount might be biasing the estimated effect of aid within income groups, and treatment only impacts grant aid, avoiding any issues with pinpointing which aid type(s) impact achievement. Although the study focuses on a single grant aid program and does not compare need-based aid versus merit-based aid, the results provide a better understanding of how states can efficiently allocate grant aid within merit programs, which is relevant to the general debate about grant aid allocation.

The remainder of the paper is organized as follows: Section 2 provides an overview of the scholarship program, including eligibility requirements. Section 3 discusses the data and the empirical strategy. Section 4 reviews the main results. Section 5 provides further examination including robustness and falsification tests and the consideration of differential part-time work effects of grant aid by income as a possible mechanism driving the main results. Section 6 concludes with a summary of the findings and a discussion of the policy implications of the results.

2 The South Carolina Math and Science Scholarship Enhancement Program

The South Carolina Math and Science Scholarship Enhancement Program was established, with little fanfare, near the end of the 2007 legislative session and took effect starting in school year 2007-08. The program provides a financial incentive for state merit-aid recipients who major in an approved STEM field.[11] Specifically, qualifying students are given a scholarship enhancement, a grant amount that is awarded in addition to the merit-aid

[11] Table A1 displays the list of approved STEM fields for the scholarship enhancement as determined by the South Carolina Commission on Higher Education (CHE).

monies they are receiving. The scholarship enhancement, awarded beginning in a student's sophomore year, is an annual award of $2,500 that is disbursed equally between the fall and spring semesters.[12] To qualify, a student must be a current recipient of either the Legislative Incentive for Future Excellence (LIFE) scholarship or the Palmetto Fellows scholarship, two merit-based awards for South Carolina residents.[13] In addition, a student's declared major must be in an approved STEM field. If eligibility is met, the scholarship enhancement is automatically applied to a student's financial aid package, although the award is limited to three school years. Further, students do not have to apply for the award.

A student who was a sophomore, junior, or senior, a recipient of either the LIFE or Palmetto Fellows scholarship, and who was majoring in an approved STEM field during the 2007-08 school year experienced an exogenous, positive shock to their aid amount. This assertion is true so long as merit-aid recipient status and college major choice are exogenous to the scholarship enhancement program.

3 Data and Empirical Strategy

3.1 Data

The data is from the Office of Institutional Research, Assessment, and Analytics at the University of South Carolina and covers the institution's multiple campuses that are located

[12]The scholarship enhancement is a sizable award, equaling roughly 30 percent of in-state tuition at the costliest campus within the University of South Carolina system in 2007.

[13]The LIFE scholarship awards up to $5,000 to first-time entering freshman attending an eligible four-year institution in South Carolina. For initial eligibility, first-time entering freshman are required to meet two of the following criteria: 1. Earn a cumulative 3.0 GPA on a 4-point scale upon graduating high school; 2. Score an 1100 on the SAT or an equivalent 24 on the ACT; or 3. Rank in the top 30 percent of their graduating class. In order to retain eligibility after a student's first year in college, a student must earn an average of 30 credit hours and earn a minimum 3.0 cumulative GPA by the end of each school year. Recipients of the Palmetto Fellows scholarship are awarded $6,700 during the freshman year and $7,500 in subsequent years, but the scholarship's eligibility requirements are more stringent. Unlike the LIFE scholarship, students cannot be awarded the Palmetto Fellows scholarship if they were not initially eligible in high school. Further, the Palmetto Fellows scholarship cannot be regained once loss. For a four-year program, both scholarships are limited to eight consecutive terms from a recipient's initial enrollment date. A student cannot be the recipient of both scholarships (CHE).

across the state. The data is available at the student-term level and contains enrollment and financial aid information for all undergraduate students from school years 2004-05 through 2011-12. Enrollment information of a given student include classification level (freshman, sophomore, junior, senior), GPA, course hours carried, major choice, campus attended, and graduation date if the student graduated. Student financial aid information include expected family contribution (EFC), serving as a proxy for family income, and dollar amounts for the LIFE or Palmetto Fellows scholarship, federal and private loans, earned work-study, other scholarships, and grants. EFC is a dollar estimate of how much a family is expected to contribute to their student's college cost for a given school year and is determined by the U.S. Department of Education based on students' family income (among other things), which is verified by financial aid offices. By design, lower income students have a smaller EFC than higher income students. The data also contains the student's gender, race, birth year, county of residence, SAT score, and high school attended.

All students in my analysis are observed at all classification levels, although freshman observations are not included because the scholarship enhancement is awarded beginning in the sophomore year. Restricting the data in this way ensures that compositional changes across time, in terms of student classification, do not contribute to the effect of grant aid, especially if a concern is that a student observed from freshman year to senior year is very different from a student observed in a subset of that range. Given that students in the sample are observed at all classification levels, estimated treatment effects do not take into account the effect of grant aid among recipients that drop out of college before their senior year. Despite the scholarship enhancement, these students may have been struggling academically. This exclusion could bias the estimated treatment effect upward. In a later section, I show that relaxing this restriction does not change the main conclusion. Also, all students are observed, at some point, both before and after the introduction of the scholarship enhancement program. The data sample does not include students who were freshman in school year 2007-08 or later. These students would have known about the scholarship enhancement and the awareness of its existence could have impacted their decision-making. Further, all students opted into a STEM or a non-STEM field prior to the introduction of the scholarship enhancement program and remained within their initial STEM or non-STEM choice after the introduction of the program. Students can change their major within their initial STEM or non-STEM choice. Given that students in the sample are not switching between STEM and non-STEM fields, estimated treatment effects do not take into account the effect of grant aid among recipients that opted out of STEM. These students may have been struggling academically within STEM and decided to sort out of STEM as a result. This exclusion could also bias the estimated treatment effect upward. In a later section, I show that relaxing this restriction does not change the main conclusion. Also, students that would have opted out of STEM but, because of the scholarship enhancement, chose not to contribute to the identification of the effect of grant aid. The inclusion of these students could bias the estimated effect downward.

Lastly, the data only includes students who completed the Free Application for Federal Student Aid (FAFSA), which is a large majority of all students observed. To observe a student's EFC, the student must have completed the FAFSA. Despite this restriction, students observed in the data are well represented across the reported EFC spectrum, which ranges from $0 (the poorest students) to $99,999 (the wealthiest students).[14] Table 1 provides the summary statistics for the sample. The data sample is disproportionately more female, is roughly equal in terms of observations where EFC is either greater than or equal to zero, and includes 4,263 unique students.

3.2 Empirical Models

Treated students in my sample are those who, starting in school year 2007-08, majored in an approved STEM field and were merit-aid recipients. For the primary empirical model that is used to estimate the effect of grant aid on GPA, hours carried, and other aid sources,

[14]Although there is no maximum EFC, reported EFC values were top-coded at $99,999 during the time period examined.

I exploit within-student variation. The basic model being estimated, using a triple-difference design, takes on the following form:

$$\begin{aligned} Y_{it} = \alpha &+ \beta_1 Post_t \times STEM_i \times Merit_{it} + \beta_2 Post_t + \beta_3 STEM_i + \beta_4 Merit_{it} \\ &+ \beta_5 Post_t \times STEM_i + \beta_6 Post_t \times Merit_{it} + \beta_7 STEM_i \times Merit_{it} \\ &+ \boldsymbol{\beta_8 Term_t} + \boldsymbol{\beta_9 Level_{it}} + \boldsymbol{\beta_{10} Term_t} \times \boldsymbol{Level_{it}} + \boldsymbol{\beta_{11} Major_{it}} \\ &+ \boldsymbol{\beta_{12} Campus_{it}} + \boldsymbol{\tau_i} + \epsilon_{it}, \end{aligned} \tag{1}$$

where Y_{it} is the outcome for student i in term t, $Post_t$ is an indicator variable equal to 1 if the observation is in or after the Fall 2007 term and 0 otherwise, $STEM_i$ is an indicator variable equal to 1 if the student's major is in an approved STEM-field and 0 otherwise, and $Merit_{it}$ is an indicator variable equal to 1 if the student is either a LIFE or Palmetto Fellows merit award recipient in term t and 0 otherwise. Further, $\boldsymbol{Term_t}$ is a vector of semester fixed effects, $\boldsymbol{Level_{it}}$ is a vector of student classification fixed effects, $\boldsymbol{Major_{it}}$ is a vector of major fixed effects, $\boldsymbol{Campus_{it}}$ is a vector of campus fixed effects, $\boldsymbol{\tau_i}$ is a vector of student fixed effects, and ϵ_{it} is the error term, which is clustered at the student level. Student-level clustering of the standard errors was chosen not only since the level of treatment is at the student level but also to establish inferences about students not observed in the sample. β_1 is the effect of grant aid, estimated across all recipients, and, in a separate model, is interacted with an indicator variable equal to 1 if the student is classified as low-income, which are those students with a zero EFC, and 0 otherwise to examine heterogeneity by income. Aside from the data sample being roughly equal in terms of observations where EFC is greater than or equal to zero, a considerable share of Pell grant recipients have a zero EFC (Protopsaltis & Parrott 2017).[15]

[15] Although the methodology for determining a student's EFC is rather involved, certain students automatically qualify for a zero EFC. Specifically, an automatic zero EFC is calculated for students who meet both of the following criteria: 1. the student has a household member (as determined by FAFSA) that is a beneficiary of a means-tested federal benefit program or the student's parents are eligible to file an IRS Form 1040A or 1040EZ or are not required to file any income tax return or the student's parent is a dislocated worker and 2. the student's parents income is $31,000 or less for school year 2011-12. Independent students

Since there is no within-student variation for the graduation outcome, I limit the sample to each student's last semester observed. For this outcome variable, the linear probability model being estimated takes on the following form:

$$\begin{aligned} Graduation_i = \alpha &+ \beta_1 \#ofPostYears_i \times STEM_i \times EverMerit_i \\ &+ \beta_2 \#ofPostYears_i + \beta_3 STEM_i + \beta_4 EverMerit_i \\ &+ \beta_5 \#ofPostYears_i \times STEM_i \\ &+ \beta_6 \#ofPostYears_i \times EverMerit_i \\ &+ \beta_7 STEM_i \times EverMerit_i \\ &+ \boldsymbol{\beta_8 SchoolYearEntered_i} + \boldsymbol{\beta_9 X_i} + \boldsymbol{\beta_{10} Campus_i} + \epsilon_i, \end{aligned} \tag{2}$$

where $Graduation_i$ is an indicator variable equal to 1 if student i graduated and 0 otherwise, $\#ofPostYears_i$ is a variable that captures the number of school years a student is observed in during the post period, starting with the 2007-08 school year. $\#ofPostYears_i$ takes into account the fact that the maximum number of times a student could have been awarded the scholarship enhancement depended on how many school years they were observed in following the introduction of the scholarship enhancement program. Further, despite the fact that the scholarship enhancement is limited to three school years, $\#ofPostYears_i$ takes into account the possibility that the effects of grant aid are cumulative across school years. $STEM_i$ is an indicator variable equal to 1 if the student's major is in an approved STEM-field and 0 otherwise, and $EverMerit_i$ is an indicator variable equal to 1 if the student was ever a recipient of either the LIFE or Palmetto Fellows scholarship and 0 otherwise. Further, $\boldsymbol{SchoolYearEntered_i}$ is a vector of school years, capturing the first school year student i started college to control for cohort effects, $\boldsymbol{X_i}$ is a vector of characteristics for student$i$, which includes their gender, race, birth year, county of residence, SAT score, and major choice in their last term observed, and ϵ_i is the robust error term. In the model

with dependents other than a spouse must meet a similar criteria.

specified in equation (2), β_1 is the potential dosage effect of grant aid (estimated across all recipients) on the likelihood of graduating for a given school year, on average. Also, β_1, in a separate model, is interacted with an indicator variable equal to 1 if the student is classified as low-income at any point and 0 otherwise to examine heterogeneity by income. For readability, β_1 in equation (1) and β_1 in equation (2) are both referenced in the result tables as $Post \times STEM \times Merit$. For causal identification of the heterogeneous achievement effects of grant aid by income, the underlying assumption is that, among those treated, there are parallel trends in achievement outcomes between low- and high-income students.

The triple-difference design takes into account the possibility that other programs impacting all students, STEM students, or merit-aid recipients were introduced around the time that the scholarship enhancement program was implemented. Specifically, the estimated effect of grant aid on achievement is the the average difference in achievement outcomes before and after the introduction of the scholarship enhancement program among treated students, controlling for average differences in achievement outcomes before and after the introduction of the scholarship enhancement program among STEM, non-merit students, non-STEM, merit-aid recipients, and non-STEM, non-merit students.

4 Main Results

4.1 The Impact of Grant Aid on GPA

GPA is an important achievement outcome as it is the standard measure of academic performance and impacts the prospect of graduation. Further, the positive GPA-earnings relationship, even after controlling for graduation, suggests that the benefits of a higher GPA extend beyond college (Jones & Jackson 1990). Table 2 provides the effects of grant aid on GPA, estimated using within-student variation. Columns (1) and (2) report the estimated effect of grant aid, with and without controls, respectively. Based on these results, grant aid appears to have no impact on GPA, on average. This finding is similar to Denning (2018), who shows no impact of aid on GPA, on average.

Column (3) tests, among merit-aid recipients, whether the impact of grant aid on GPA differs for low- and high-income students, the main focus of the paper. In column (3), the coefficient on $Post \times STEM \times Merit \times LowIncome$ is the differential effect of grant aid on low-income students and tests whether or not the effect of grant aid on GPA is significantly different for these students. The overall effect of grant aid on GPA for low-income students is the linear combination of the $Post \times STEM \times Merit$ and $Post \times STEM \times Merit \times LowIncome$ coefficients. Based on column (3), the effect of grant aid on GPA is significantly higher (0.192) for low-income students relative to their high-income peers. In fact, grant aid does not impact GPA for high-income students at all—the effect for high income students (-0.050) is not statistically different from zero. For low-income students, grant aid increases their GPA by 0.142 GPA points, on average.

Column (4), displaying the preferred results, takes into account the possibility that the heterogeneous effects of grant aid by income observed are capturing heterogeneous effects of grant aid by skill. In this model, the treatment variable (β_1) is also interacted with an indicator variable equal to 1 if the student's SAT score is below the median (1110) and 0 otherwise. Goodman (2008) cautions against examining heterogeneous effects by income without taking into account the possibility of heterogeneous effects by skill since, in some instances, skill and income may be positively correlated. Based on column (4), the results are robust to controlling for heterogeneous effects by skill. For low-income students, grant aid increases their GPA by 0.169 GPA points, on average.

Among those treated, low-income students in the sample were awarded the scholarship enhancement in a total of five terms (2.5 school years), on average. As a result, these students were awarded a total of $6,250, on average. Henry et al. (2004) and Scott-Clayton (2011b) find that, on average, merit aid increases GPA by as much as 0.170 and 0.160 GPA points over four years, respectively. Henry et al. (2004) examine the impact of Georgia's HOPE scholarship program on students that graduated from a Georgia high school and enrolled at an institution within the University of Georgia system. The program awarded students in their sample with roughly up to $10,000 over a four-year period, assuming students did not lose the scholarship. For comparison, $6,250 spent on students in the Henry et al. (2004) study would increase GPAs by at least 0.11 GPA points, on average. Scott-Clayton (2011b) examines the impact of West Virginia's PROMISE scholarship on students enrolled in a West Virginia public institution. Under the PROMISE scholarship, students in the sample were awarded $10,000 over a four-year period, on average. For comparison, $6,250 spent on students in the Scott-Clayton (2011b) study would increase GPAs by 0.10 GPA points, on average. Given that I am able to isolate the achievement effect of grant aid from compositional changes that could impact treatment status, I might expect my estimate to be larger than the estimates from previous studies. On the contrary, I might expect my estimate to be smaller than the estimates from previous studies given that treated students in my study are high achievers in two dimensions (STEM majors and merit-aid recipients), perhaps with relatively little room for improvement.

4.2 The Impact of Grant Aid on College Completion

In examining the impact of grant aid on college completion, I estimate the effects of grant aid on the likelihood of graduating. In the model for graduation, I am no longer able to exploit within-student variation (Equation 2). Table 3 provides the effects of grant aid on the likelihood of graduating. Based on column (1), grant aid has no impact on the likelihood of graduating, on average. This result remains in column (2), where controls are added. In comparison, Dynarski (2008) finds that merit aid increases college completion rates for four-year degrees by 2.5 percentage points, exploiting merit programs in Arkansas and Georgia. Between these programs, students could have received an award amount between $10,000 and $12,000 across a four-year period, although it is unclear what the average award amount was for treated students. Scott-Clayton (2011b) finds a 9.4 and 4.5 percentage point increase in four-year and five-year graduation rates, respectively. Castleman & Long (2016), examining the impact of a need-based grant, the Florida Student Access Grant, on students enrolled at Florida public institutions, find that an additional \$1,300 in grant aid eligibility increased six-year graduation rates by 4.6 percentage points. Results across the studies may vary because of differences in how college completion is defined and/or in the type(s) of students that are treated.

When heterogeneity by income is considered, the results demonstrate that, among merit-aid recipients, only low-income students benefit. For low-income students, grant aid increases the likelihood of graduating by 10.7 percentage points for each school year received, on average (the preferred results). Low-income students received the scholarship enhancement in a total of 2.5 school years, on average. Recall, a low-income student receiving the scholarship enhancement for 2.5 school years would receive \$6,250. The likelihood of graduating for these students would increase by 26.7 percentage points (10.7×2.5). For comparison, \$6,250 spent on the poorest student in the Alon (2011) study increases the likelihood of graduating within six years by roughly 38 percentage points. Also, \$6,250 spent on a low-income student in the Denning (2018) study increases the likelihood of graduating within four years by 16.1 percentage points.

Results show that grant aid increases the likelihood of graduating for low-income students only. Given that result, I examine, among graduates, whether or not grant aid decreased their time-to-degree. Table A2 presents the results of that analysis. The results are similar to the main findings on graduation—among merit-aid recipients, grant aid impacts low-income students most. For these students, grant aid increases their likelihood of graduating within six years by 3.7 percentage points per school year received, on average. Table A3 displays the results of the effects of grant aid on an alternative measure of college completion—the 'on-track to graduate' measure. The 'on-track to graduate' measure is a practical alternative to the graduation outcome variable, which does not vary within student. A student is considered on-track to graduate if, in any given term, they have accumulated enough credit hours to have earned at least 30 credit hours by the end of the school year. The results on the 'on-track to graduate' measure are similar to those on GPA and the likelihood of graduating—low-income, merit-aid recipients are most impacted. Specifically, grant aid increases the likelihood of being on-track to graduate by 14.7 percentage points for low-income students yet has no impact on high-income students, based on the preferred setup.

5 Further Examination

5.1 Robustness and Falsification Tests

Students in the sample are observed at all classification levels and remain within their initial STEM or non-STEM choice after the introduction of the program. These sample restrictions could bias the estimated treatment effect upward. Table A4 provides the effects of grant aid on GPA and the likelihood of graduating, including in the sample students that drop out of college before their senior year and students that opted out of STEM. Despite this inclusion, the differential achievement effects of grant aid on low-income students remains positive and statistically significant. Although the overall effects for these students are less precisely estimated and smaller in magnitude, with the effect on GPA being negative, the estimates are likely biased downward given the inclusion of students that would have opted out of STEM but, because of the financial incentive, do not. It is unclear which students are incentivized in this way. Nevertheless, the positive and statistically significant differential achievement effects of grant aid on low-income students provides further evidence that grant aid likely impacts the GPA and graduation prospects of these students most.

The financial incentive made possible via the scholarship enhancement program provided an exogenous, positive shock to the aid amount of recipients whose merit-aid recipient status and college major choice were not impacted by the program. Recall, students in the sample opted into a STEM or a non-STEM field prior to the introduction of the program, thus are not induced by the program with respect to their college major choice. Table A5 tests the possibility that the program induced students at or near the GPA cutoff for a merit-aid award (3.0) to improve their academic performance, thus impacting their merit-aid recipient status. If the effects of grant aid are solely driven by students whose GPA is at or near the GPA cutoff for a merit-aid award, it would be difficult to argue against the possibility that merit-aid recipient status is exogenous to the scholarship enhancement program. Low-income students below but near the GPA cutoff for a merit-aid award may be induced by the scholarship enhancement program to increase their GPA, thus explaining the differential achievement effect of grant aid on low-income students. For this analysis, a low GPA is one that is less than or equal to the median GPA in the sample (3.3). For GPA and the likelihood of graduating, the differential achievement effects of grant aid on low-income students remain positive and statistically significant for students with low and high GPAs, making it less likely that effects are solely driven by students whose merit-aid recipient status are impacted by the scholarship enhancement program. Aside from this analysis, it seems unlikely that students below but near the GPA cutoff for a merit-aid award would not have been induced by the already established state merit program to improve their GPA standing absent the scholarship enhancement program, assuming they were by the scholarship enhancement program.

Table A6 provides the effects of grant aid on GPA and the likelihood of graduating, estimating the differential effects of alternative income groups. In this analysis, I classify each student in the sample as one of the following: always Pell eligible with a zero EFC, always Pell eligible but not always having a zero EFC, sometimes Pell eligible, and never Pell eligible. For the GPA outcome, the differential effect of grant aid on students who are always Pell eligible with a zero EFC is positive and statistically significant. The overall effect of grant aid on GPA for these students is also positive, although imprecisely estimated. For all other students, overall effects of grant aid on GPA are negative, although imprecisely estimated. For the graduation outcome, the differential effect of grant aid on students who are always Pell eligible with a zero EFC is positive, although imprecisely estimated. Further, the overall effect of grant aid on these students is positive and statistically significant. For all other students, the effects of grant aid are smaller and mostly imprecisely estimated. Overall, the results suggest that students who are always Pell eligible with a zero EFC are most impacted by grant aid. This analysis provides further justification for classifying low-income students as those with a zero EFC.

Table A7 provides results from an analysis that examines the possibility that the main results are being driven by other program changes that may have impacted all students. In this analysis, I restrict the sample to only non-merit students and examine if statistically significant changes on achievement outcomes occur for these students after the introduction of the scholarship enhancement program. If other program changes occurred around the time that the scholarship enhancement program was introduced, significant effects on the achievement outcomes of non-merit students might be observed. The results of Table A7 do not provide strong evidence for this possibility. Estimated coefficients are mostly statistically insignificant. Even if such program changes existed, the triple-difference design ensures that other program effects are isolated from the effect of the scholarship enhancement program. Further, I replicate the analysis for the main results by randomly assigning majors as either STEM or non-STEM. In a separate placebo analysis, I randomly assign students as having a merit award or not. These exercises are repeated 1,000 times each and the cumulative distribution of the 1,000 placebo estimates is displayed in Figures A1 and A2 for the STEM and merit recipient placebo exercises, respectively. The vertical lines in each plot correspond to the actual coefficients reported in the main results. Across the c.d.f plots, actual coefficients tend to be uniquely more positive than the placebo estimates for low-income students. These results provide evidence that there is something unique about the actual scholarship recipients and STEM fields that contribute to the magnitude of the estimated effects in the main results.

5.2 Probing the Mechanism of the Differential Achievement Effects of Grant Aid by Income by Examining Work-Study Dollars Earned

Aside from examining if, and which, students benefit from grant aid, I also provide suggestive evidence for a possible mechanism that would explain the heterogeneous effects by income on achievement: time spent working.[16] Before proceeding to that analysis, I analyze if a one-to-one crowding-out effect occurs following the additional aid—is there an equal reduction in other non-work-related aid sources when a student receives the scholarship enhancement? Particularly, if the additional aid were completely offset by any non-work-related aid sources, then I would not expect a change in student work behavior. Panel A of Table 4 shows the results of this analysis. Based on columns (1) through (4), there does not appear to be a one-to-one crowding out effect of the additional aid, although students of both types do respond to the additional aid by reducing their total loan amount (column 1).[17]

Panel B of Table 4 displays the estimated effects of grant aid on work-related aid sources. Column (5) examines, among students with work-study, whether or not the effect of additional aid on work-study dollars earned is significantly different between low- and high-income students. The results demonstrate that the additional aid decreased work-study dollars earned for low-income students only, despite the fact that high-income students also participate in The Federal Work-Study Program (Scott-Clayton 2017). The results suggest that low-income students may have decreased their time spent working. I describe these

[16] I also consider changes in course loads as a possible mechanism for the heterogeneous effects by income on achievement. The positive effect of grant aid on the GPAs of low-income students might be driven by these students reducing their course load. To examine this possibility, I estimate the effects of grant aid on course hours carried. Table A8 displays the preferred results of that analysis. The results in Table A8 demonstrate that the increase in the GPAs of low-income students is not a result of these students reducing their course load.

[17] The per-term reduction in total non-work-related aid is not equal to the $1,250 additional aid amount received in a given term.

results as suggestive evidence that grant aid differentially effects work behavior for low- and high-income students since (1) I do not observe the working behavior of students who work off-campus, who make up the majority of students working while in college (Broton et al. 2016) and (2) I do not directly observe hours worked. Nevertheless, the results on work-study dollars earned, coupled with the results on achievement, help to validate the argument that low-income students are financially constrained and, as a result, are more likely to change their work behavior following the receipt of grant aid than high-income students.

6 Conclusion

Given the importance of a four-year degree, the college-completion gap between low- and high-income students helps to perpetuate the financial and health disparities observed among low- and high-income persons in our society. With the cost of college rising, many students are facing difficulties financing their education. Among them, low-income students face the most difficulties. These students are more likely to work while in school . This is concerning because studies have shown that working while in school harms students academically. States have stepped in to offer financial assistance to students going to college, with many of them shifting their focus away from need-based aid and towards merit-based aid. This shift has led to a compositional change in grant aid recipients, as high-income students began receiving new grant aid dollars, and also led to a national debate about which students should receive grant aid.

I examine if grant aid impacts achievement and whether or not low-income students are impacted most. I find that, for low-income merit-aid recipients, grant aid in a given year increases their likelihood of graduating by 10.7 percentage points and increases their GPA by 0.169 GPA points, on average. Further, the additional aid led to reductions in work-study dollars earned for low-income students, suggesting they may be responding to the additional aid by reducing their time spent working. Grant aid does not impact achievement outcomes for high-income students, even when considering time-to-degree.[18]

Policymakers should ensure that grant aid dollars are allocated efficiently—meaning students with the most to gain should receive disproportionately more than students with the least to gain. Given that grant aid mostly impacts, among merit-aid recipients, low-income students, policymakers should consider means-tested merit programs. Re-allocating more grant aid to these high-achieving, low-income students would help to close the college-completion gap between low- and high-income students. This policy recommendation is based on the assumption that policymakers perceive college completion as the primary motivation behind disbursing such funds.[19] Even if policymakers are primarily concerned about reducing the time-to-degree for students who would graduate without states' financial assistance, the evidence suggest that incorporating some need-based component within merit programs would be impactful.

[18] Although the results of my paper demonstrate that grant aid does not impact the GPAs or graduation prospects of high-income students, this paper does not conclude that these students aren't potentially impacted in other ways. For example, perhaps there are qualitative outcomes whereby grant aid impacts high-income students (i.e., graduating with honors). The extent to which such outcomes are important to policymakers should determine the degree to which the conclusions of this paper are used to guide policy decisions.

[19] Similarly, institutions of higher learning should also consider means-tested merit programs if their objective function closely mirrors that of state policymakers.

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Tables

Table 1: Summary Statistics for Sample

	Mean	Standard Deviation
Female	0.62	0.49
Black	0.20	0.40
Hispanic	0.02	0.14
Age	20.94	1.60
SAT Score	1114.58	155.59
Sophomore	0.30	0.46
Junior	0.31	0.46
Senior	0.40	0.49
Low Income (EFC = 0)	0.47	0.50
Post	0.67	0.47
STEM	0.33	0.47
Merit	0.56	0.50
Post $\times$ STEM $\times$ Merit	0.13	0.34
Observations	28,343	
Number of Unique Students	4,263	

Note: For summary statistics, data is at the student-term level.

Table 2: Effects of Grant Aid on GPA

	(1) No Controls	(2) With Controls	(3) Heterogeneity by Income	(4) + Heterogeneity by Skill Control
Post × STEM × Merit	0.052	0.037	-0.050	-0.038
	(0.050)	(0.041)	(0.057)	(0.068)
Post × STEM × Merit × Low Income			0.192**	0.207**
			(0.079)	(0.080)
Post × STEM × Merit × SAT Score $<$ Median				0.052
				(0.082)
Term	No	Yes	Yes	Yes
Level	No	Yes	Yes	Yes
Term × Level	No	Yes	Yes	Yes
Student Major	No	Yes	Yes	Yes
Campus Fixed Effects	No	Yes	Yes	Yes
Effect for Low-Income Students			0.142**	0.169**
P-Value			0.012	0.033
R-Squared	0.007	0.052	0.053	0.053
Observations	28,343	28,343	28,343	28,234

Standard errors in parentheses.

Standard errors are robust and clustered at the student level.

OLS estimates.

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

Note: The models include student fixed effects.

Table 3: Effects of Grant Aid on the Likelihood of Graduating

	(1) No Controls	(2) With Controls	(3) Heterogeneity by Income	(4) + Heterogeneity by Skill Control
Post × STEM × Merit	0.011	0.014	-0.008	0.022
	(0.021)	(0.016)	(0.022)	(0.040)
Post × STEM × Merit × Low Income			0.068**	0.085**
			(0.022)	(0.022)
Post × STEM × Merit × SAT Score < Median				0.057
				(0.028)
School Year Entered	No	Yes	Yes	Yes
Student Controls	No	Yes	Yes	Yes
Campus Fixed Effects	No	Yes	Yes	Yes
Effect for Low-Income Students			0.060**	0.107*
P-Value			0.037	0.085
R-Squared	0.010	0.132	0.133	0.134
Observations	4,263	4,250	4,250	4,250

Standard errors in parentheses.
Standard errors are robust.
OLS estimates.
* p<0.10, ** p<0.05, *** p<0.01

Table 4: Effects of Grant Aid on Other Aid Sources

	Panel A: Non-Work-Related Aid Sources				Panel B: Work-Related Aid Sources	
	(1)	(2)	(3)	(4)	(5)	(6)
	Loans	Other Scholarships	Grants	Total	Work-Study Dollars Earned if > 0	Student Has Work-Study?
Post $\times$ STEM $\times$ Merit	-696.649***	-104.724	-22.013	-823.385***	-66.331	0.014
	(186.383)	(69.419)	(82.195)	(196.614)	(281.533)	(0.022)
Post $\times$ STEM $\times$ Merit $\times$ Low Income	304.611	208.472	53.354	566.437*	-801.924*	-0.025
	(251.400)	(155.226)	(112.840)	(294.054)	(470.751)	(0.028)
Effect for Low Income Students	-392.038**	103.748	31.341	-256.949	-868.255**	-0.011
P-Value	0.026	0.472	0.694	0.267	0.022	0.569
R-Squared	0.214	0.061	0.202	0.268	0.252	0.023
Observations	28,343	28,343	28,343	28,343	1,214	28,343

Standard errors in parentheses.

Standard errors are robust and clustered at the student level.

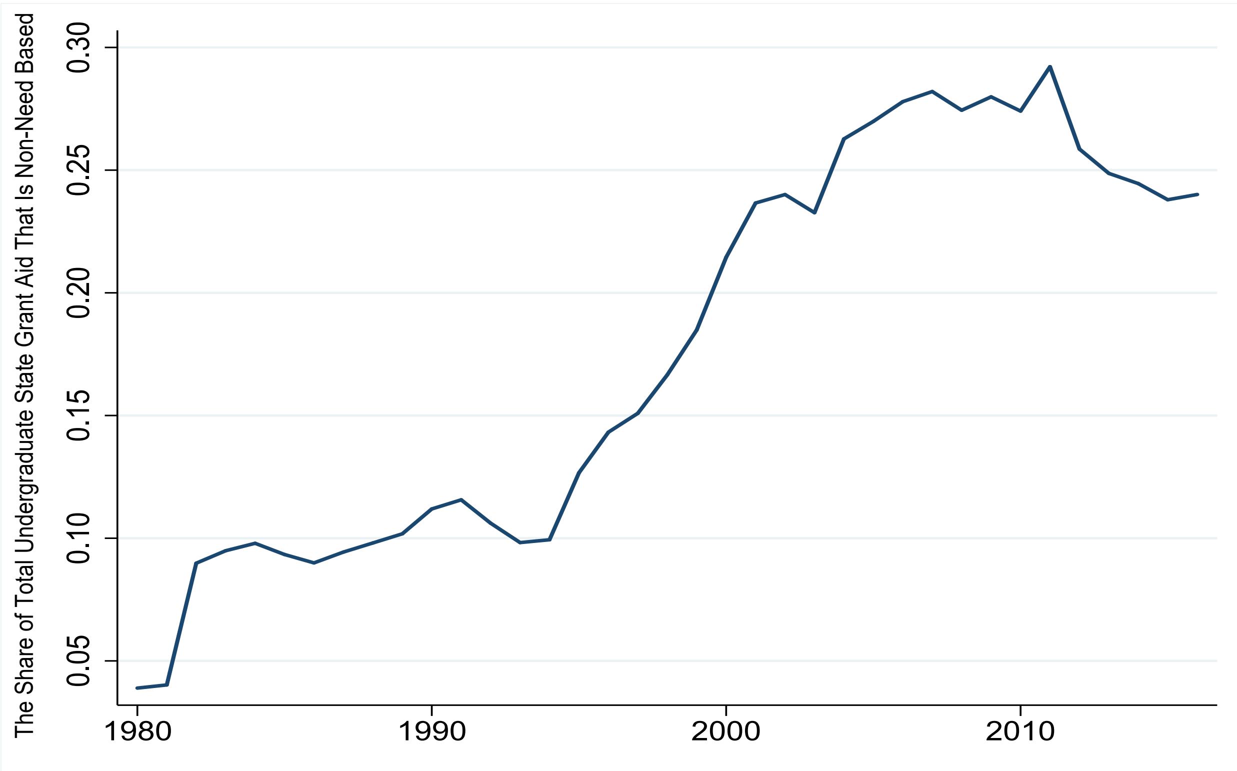
OLS estimates.

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

Note: The models include campus fixed effects, student fixed effects, student major, and the full interaction of term with student classification fixed effects. Column (6) shows the results of a linear probability model.

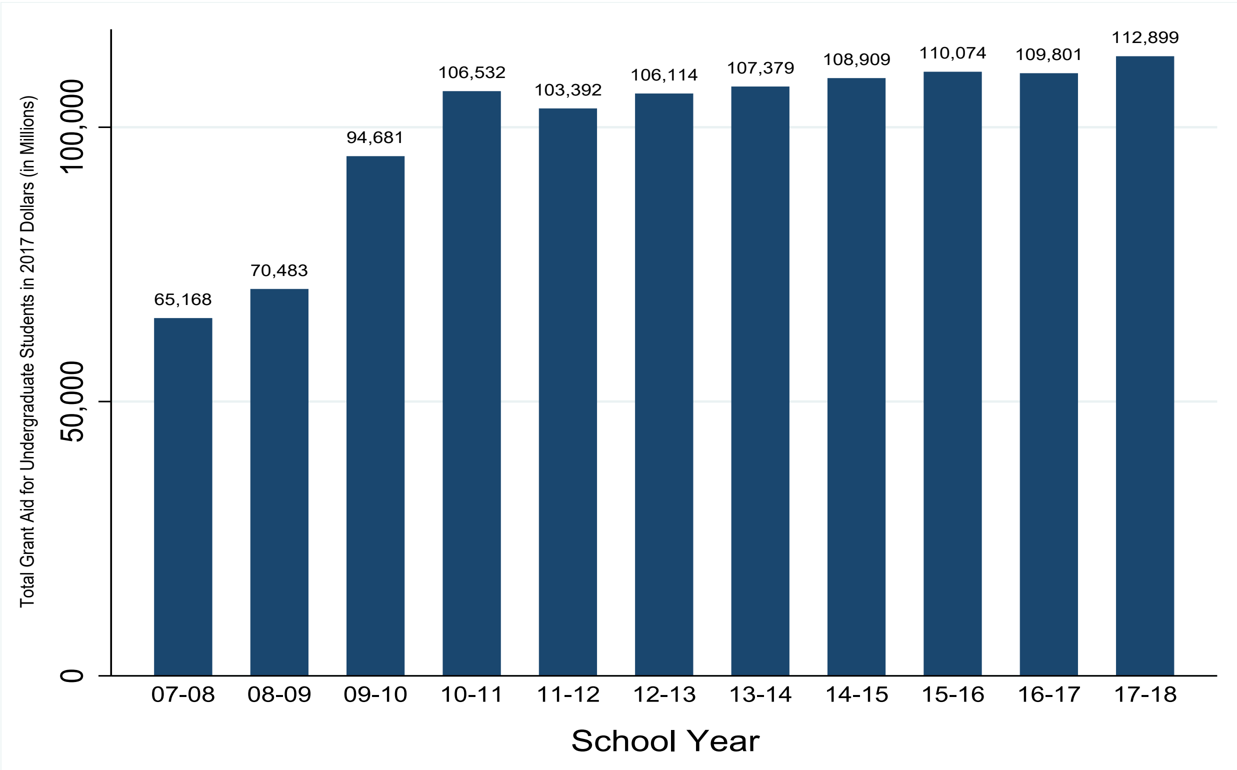
Figures

Figure 1: The Share of Total Undergraduate State Grant Aid That is Non-Need Based by Year



Note: Total undergraduate state grant aid does not include loans and work-related aid. *Source*: National Association of State Student Grant and Aid Programs.

Figure 2: Total Grant Aid for Undergraduate Students in 2017 Dollars (in Millions) by School Year



Note: Total grant aid does not include loans and work-related aid. Total amounts include grant aid from the federal government, state governments, and institutions. *Source*: National Association of State Student Grant and Aid Programs.

Appendix Tables

Table A1: Approved Programs for the Scholarship Enhancement

Biochemistry and Molecular Biology
Biological Sciences
Biomedical Engineering
Cardiovascular Technology
Chemical Engineering
Chemistry
Civil Engineering
Clinical Laboratory Science
Computational Science
Computer Engineering
Computer Information Systems
Computer Science
Electrical Engineering
Engineering Technology Management
Environmental Science
Exercise and Sport Science
Geology
Geophysics
Health Promotion
Industrial Mathematics
Industrial Process Engineering
Information Management and Systems
Information Science
Integrated Information Technology
Marine Science
Mathematics
Mathematics & Computer Science
Mechanical Engineering
Middle Level Education, Mathematics/Science
Nursing, BSN Completion(RN to BSN)
Nursing, BSN Generic (No RN)
Pharmaceutical Studies
Physics
Public Health
Secondary Teacher Education, Biology
Secondary Teacher Education, Chemistry
Secondary Teacher Education, Comprehensive Science
Secondary Teacher Education, Mathematics
Statistics

Source: South Carolina Commission on Higher Education.

Table A2: Effects of Grant Aid on the Likelihood of Graduating Within Six Years - Conditional on Graduating

	Preferred
Post × STEM × Merit	0.002
	(0.011)
Post × STEM × Merit × Low Income	0.050**
	(0.016)
Post × STEM × Merit × SAT Score < Median	-0.016***
	(0.002)
Effect for Low-Income Students	0.053***
P-Value	0.005
R-Squared	0.178
Observations	4,044

Standard errors in parentheses.

Standard errors are robust.

OLS estimates.

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

Note: The model includes campus fixed effects, fixed effects for the school year the student entered college, and student controls. The results shown are derived from a linear probability model.

Table A3: Effects of Grant Aid on the 'On-track to Graduate' Measure

	Preferred
Post × STEM × Merit	0.025
	(0.036)
Post × STEM × Merit × Low Income	0.117***
	(0.041)
Post × STEM × Merit × SAT Score < Median	0.004
	(0.042)
Effect for Low Income Students	0.142***
P-Value	0.000
R-Squared	0.514
Observations	28,031

Standard errors in parentheses.

Standard errors are robust and clustered at the student level.

OLS estimates.

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

Note: The model includes campus fixed effects, student fixed effects, student major, and the full interaction of term with student classification fixed effects. The results shown are derived from a linear probability model.

Table A4: Effects of Grant Aid on Achievement Outcomes - No Sample Restrictions

	(1) GPA	(2) Graduation
Post × STEM × Merit	-0.142***	-0.011
	(0.050)	(0.009)
Post × STEM × Merit × Low Income	0.098*	0.027**
	(0.052)	(0.008)
Post × STEM × Merit × SAT Score < Median	0.078	-0.001
	(0.053)	(0.019)
Effect for Low Income Students	-0.044	0.015
P-Value	0.310	0.266
R-Squared	0.047	0.182
Observations	72,233	11,784

Standard errors in parentheses.

Standard errors are robust.

OLS estimates.

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

Note: For column (1), the model includes campus fixed effects, student fixed effects, student major, and the full interaction of term with student classification fixed effects. For column (2), the model includes campus fixed effects, fixed effects for the school year the student entered college, and student controls. The graduation results shown are derived from a linear probability model.

Table A5: Effects of Grant Aid on Achievement Outcomes - Testing for the Incentive Effect

	Panel A: GPA		Panel B: Graduation	
	(1)	(2)	(3)	(4)
	Low GPA	High GPA	Low GPA	High GPA
Post × STEM × Merit	-0.019	-0.098*	-0.152**	0.018***
	(0.145)	(0.054)	(0.049)	(0.003)
Post × STEM × Merit × Low Income	0.313**	0.152**	0.185**	0.012**
	(0.148)	(0.063)	(0.047)	(0.004)
Post × STEM × Merit × SAT Score < Median	-0.043	-0.008	0.187***	0.034**
	(0.159)	(0.086)	(0.013)	(0.008)
Effect for Low Income Students	0.295	0.054	0.032	0.031***
P-Value	0.105	0.201	0.573	0.000
R-Squared	0.074	0.041	0.186	0.166
Observations	14,099	14,135	1,909	2,341

Standard errors in parentheses.
Standard errors are robust.
OLS estimates.
* p<0.10, ** p<0.05, *** p<0.01

Note: For columns (1) and (2), the models include campus fixed effects, student fixed effects, student major, and the full interaction of term with student classification fixed effects. For columns (3) and (4), the models include campus fixed effects, fixed effects for the school year the student entered college, and student controls. The graduation results shown are derived from a linear probability model.

Table A6: Effects of Grant Aid on Achievement Outcomes - Using Alternative Income Groups

	(1) GPA	(2) Graduation
Post × STEM × Merit	-0.098	0.046
	(0.108)	(0.049)
Post × STEM × Merit × Always Pell Eligible & Always Zero EFC	0.213**	0.002
	(0.094)	(0.031)
Post × STEM × Merit × Always Pell Eligible & Not Always Zero EFC	-0.005	-0.145*
	(0.122)	(0.055)
Post × STEM × Merit × Sometimes Pell Eligible	0.013	-0.073
	(0.104)	(0.043)
Post × STEM × Merit × SAT Score < Median	0.053	0.063
	(0.082)	(0.031)
Effect for Always-Pell-Eligible Students with Zero EFC	0.115	0.048*
P-Value	0.107	0.085
Effect for Always-Pell-Eligible Students without Zero EFC	-0.104	-0.099***
P-Value	0.383	0.002
Effect for Sometimes-Pell-Eligible Students	-0.086	-0.028
P-Value	0.258	0.119
R-Squared	0.054	0.139
Observations	28,234	4,250

Standard errors in parentheses.

Standard errors are robust.

OLS estimates.

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

Note: For column (1), the model includes campus fixed effects, student fixed effects, student major, and the full interaction of term with student classification fixed effects. For column (2), the model includes campus fixed effects, fixed effects for the school year the student entered college, and student controls. The graduation results shown are derived from a linear probability model.

Table A7: Falsification Tests

	Panel A: Non-Merit	
	(1)	(2)
	GPA	Graduation
Post × Stem	0.038	-0.017
	(0.087)	(0.012)
Post × Stem × Low Income	-0.064	0.006
	(0.094)	(0.009)
Post × Stem × SAT Score < Median	-0.200*	-0.032
	(0.114)	(0.034)
Effect for Low Income Students	-0.026	-0.011
P-Value	0.579	0.151
R-Squared	0.049	0.343
Observations	6,982	1,048

Standard errors in parentheses.
Standard errors are robust.
OLS estimates.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Note: For column (1), the model includes campus fixed effects, student fixed effects, student major, and the full interaction of term with student classification fixed effects. For column (2), the model includes campus fixed effects, fixed effects for the school year the student entered college, and student controls. The graduation results shown are derived from a linear probability model.

Table A8: Effects of Grant Aid on Course Hours Carried

	Preferred
Post × STEM × Merit	0.348
	(0.298)
Post × STEM × Merit × Low Income	-0.341
	(0.348)
Post × STEM × Merit × SAT Score < Median	0.300
	(0.343)
Effect for Low Income Students	0.007
P-Value	0.980
R-Squared	0.499
Observations	28,234

Standard errors in parentheses.

Standard errors are robust and clustered at the student level.

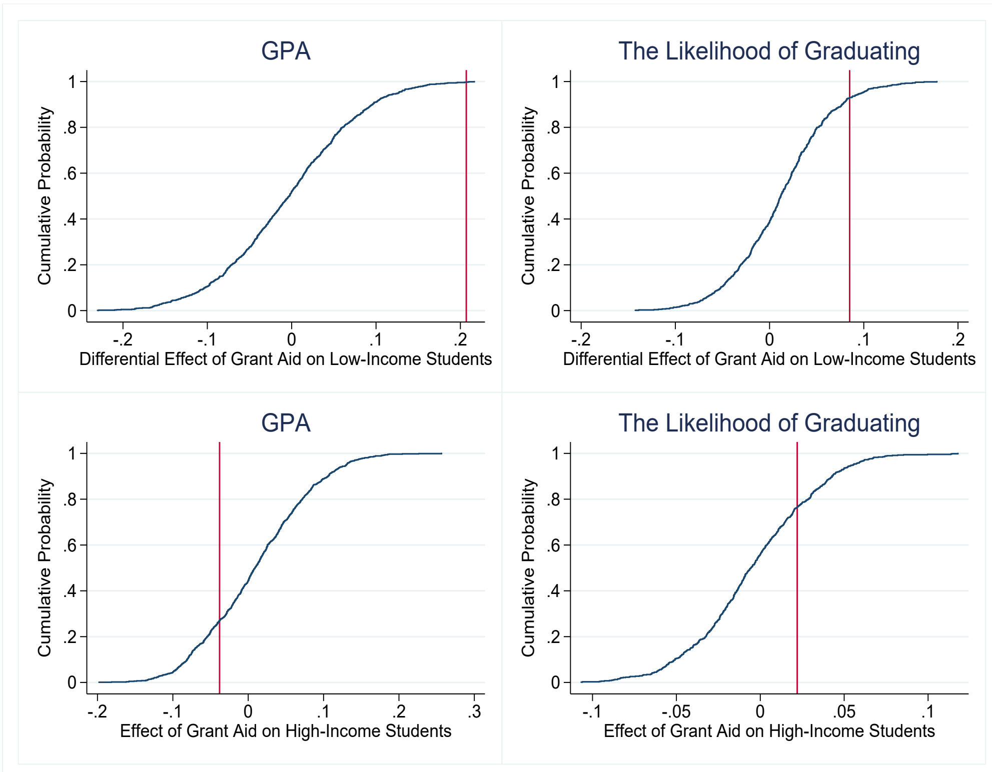
OLS estimates.

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

Note: The model includes campus fixed effects, student fixed effects, student major, and the full interaction of term with student classification fixed effects.

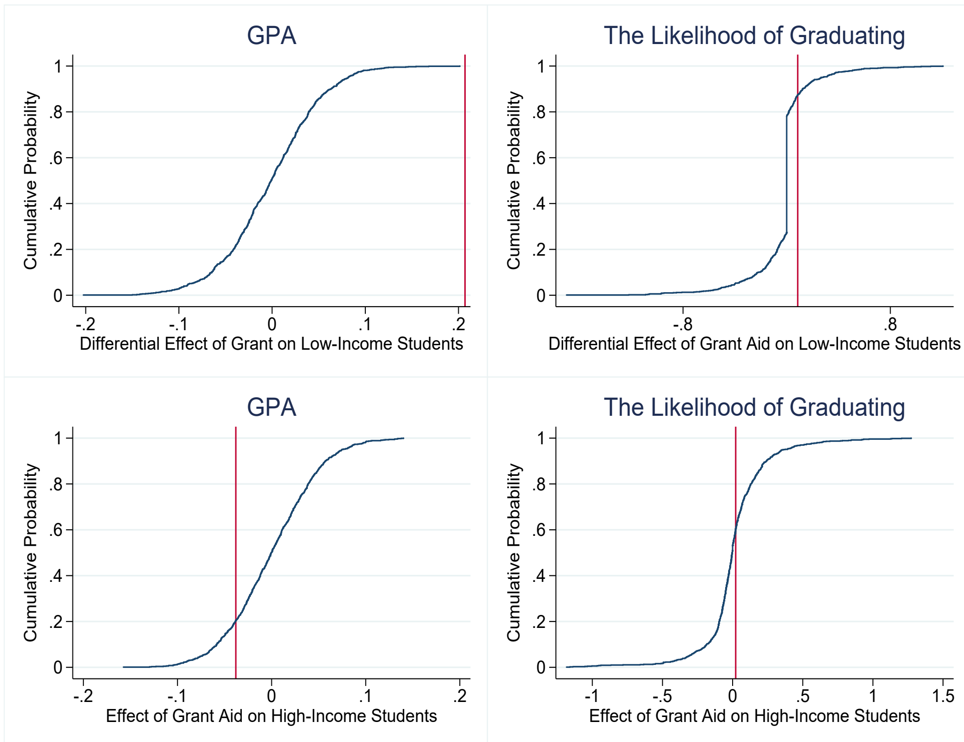
Appendix Figures

Figure A1: Cumulative Distribution of 1,000 Replication Estimates of the Effect of Grant Aid on Achievement, by Income Group - Randomly Assigning Majors as STEM



Note: The coefficients are estimated using the preferred setup. The vertical lines correspond to the estimated coefficients reported in the main results and, together with the cumulative distribution plot, displays the percentage of placebo estimates above or below the actual estimates of the effect of grant aid on the achievement outcomes. OLS estimates.

Figure A2: Cumulative Distribution of 1,000 Replication Estimates of the Effect of Grant Aid on Achievement, by Income Group - Randomly Assigning Merit Recipients



Note: The coefficients are estimated using the preferred setup. The vertical lines correspond to the estimated coefficients reported in the main results and, together with the cumulative distribution plot, displays the percentage of placebo estimates above or below the actual estimates of the effect of grant aid on the achievement outcomes. OLS estimates.