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The Impact of Merit Aid on STEM Major Choices: A Propensity Score Approach

Teng Zhao
Hangzhou Dianzi University

Lara Perez-Felkner
Shouping Hu
Florida State University

Limited literature has investigated the effects of state and institutional merit-based financial aid on student choice of science, technology, engineering, and mathematics (STEM) major fields, an unintended consequence with important implications. By leveraging nationally representative longitudinal data from the Beginning Postsecondary Students, we examined these effects—respectively and jointly—with logistic regressions (LR) and propensity score matching (PSM). Both the LR and PSM results showed that students who receive both state- and institution-awarded merit aid were more likely to major in STEM. For students who only received state-awarded merit aid, the PSM presented significant and positive effects while the LR did not. Institution-only merit aid had no statistically measurable effect. We discuss implications for research, policy, and practice for state- and institution-based financial aid.

Keywords: *merit aid, state policy, financial aid, STEM major, propensity score matching*

Science, technology, engineering, and mathematics (STEM) disciplines are typically perceived as highly challenging postsecondary majors (Lindemann et al., 2016). Approximately 52% of adults express that the "difficulty" of STEM disciplines deters youth from pursuing degrees in STEM fields (Kennedy et al., 2018). Accordingly, students interested in these disciplines may be concerned about potentially taking longer to graduate than their peers in other majors, making their education more costly. However, evidence shows students with STEM majors go on to earn about 26% more than those in non-STEM fields with similar levels of education (Graf et al., 2018).

There is then tension for students weighing the potentially prohibitive cost of majoring in STEM in the short-run versus the potentially high future earnings of a career in STEM in the long-run. The former may hinder students—particularly those from low-income backgrounds—from choosing STEM majors. Moreover, Hoxby and Turner (2015) found that high college costs deter low-income, high-achieving students' intentions to apply to selective colleges. Supposing such students are sensitive to costs, they could be averse to pursuing these majors. On the other hand, recent research has also indicated that low-income students are more career-oriented (Plasman et al., 2021), which could increase their probability of choosing STEM majors. Yet, this contradiction still has been understudied.

Financial aid, which helps college students cover higher education expenses, may thus encourage students' interest in "difficult" STEM fields to pursue STEM degrees and careers to achieve high future earnings. Various forms of financial aid (e.g., need-based, merit-based, loans, tax credits) may be provided to alleviate students' financial burdens (Dynarski & Scott-Clayton, 2013). Among these, merit-based awards are distributed to academically talented students (Dynarski, 2004) who may be well-prepared for the academic rigor of STEM coursework. However, students may also avoid STEM majors when it is necessary to maintain a high grade point average (GPA) in order to continue receiving merit-based aid (Hu, 2008). Thus, it is inconclusive whether merit-based aid has positive or negative impacts on individual students' STEM major choices.

In the past, merit-based aid has been disproportionately awarded to students from higher-income families (Baum & Schwartz, 1988; Heller, 2006). Family income—as an additional financial source—should be seriously taken into account when assessing the effects of financial aid on students' STEM major choices. Quadlin (2017) investigates the relationship between socioeconomic background and STEM major choice with respect to financial aid funding source categories (e.g., loans vs. grants vs. family aid) but not merit aid specifically; she illustrated that low-income students are more likely to choose non-STEM major fields where their projected future earnings are also high but they perceive better odds of successfully (and more easily) graduating. Individual- and school-level factors such as gender, race/ethnicity, and high school type also shape these patterns (Zhao & Perez-Felkner, 2022). The propensity score matching (PSM) technique may effectively reduce selection bias by counterfactually establishing *similar* treatment and control groups in terms of observable characteristics apart from the treatment condition, obtaining conditioned casual inferences with observational data (Guo & Fraser, 2014; Guo et al., 2020).

In the present study, we used nationally representative data from the Beginning Postsecondary Students (BPS) study to investigate the impact of merit-based aid on students' STEM major choices. Previous empirical studies have primarily focused on state-awarded merit aid (Sjoquist & Winters, 2015b; Zhang, 2011) and less on aid awarded by institutions along with state merit aid. In addition, most existing literature has examined the intended goals of merit aid, such as promoting college access and attainment (Delaney, 2011; Leeds & DesJardins, 2015), but few have investigated potential unintended consequences such as STEM major choice.

As an important indicator of STEM career pathways, postsecondary major choice has received considerable scholarly attention. This research tends to focus on individual (Perez-Felkner et al., 2017; Zhao & Perez-Felkner, 2022), family (Niu, 2017; Sovansophal, 2020), or school/college context (Bottia et al., 2020; Wang, 2013) perspectives. However, insufficient research has been done on influencing factors from a policy perspective, particularly regarding financial aid. Moreover, there are many players in the student aid game in the United States (McPherson & Schapiro, 1998), and actions from one player could shape decisions by other players. For example, state merit aid programs could influence institutional decisions in making financial aid decisions (McPherson & Schapiro, 1998), which in turn can influence student decisions toward or away from STEM majors.

Thus, it is instructive to examine how state- and institutional merit aid, separately and/or jointly, affect individual student decisions, such as the choice of STEM fields. To our knowledge, ours is the first national study to counterfactually set similar groups with and without receiving merit-based aid to simultaneously estimate the effects of both state and institutional awards on students' STEM major choices. We propose policy recommendations to inform stakeholders regarding whether merit aid can contribute to the cultivation of STEM talents.

Literature Review

Historical Policy Context of State and Institutional Merit-Based Aid

Beginning in the 1980s, the purchasing power of the federal need-based financial aid available to college students declined. States began to more heavily share the responsibility of funding students pursuing degrees through state financial aid programs with the emergence of state-based merit aid programs (St. John & Asker, 2003). Currently, there is no consensus on which state was the first to establish merit aid programs. Doyle (2006) and Heller (2004) treated Georgia as the first state to do so in 1993, while Sjoquist and Winters (2015a) and Orsuwan and Heck (2009) consider the Arkansas Academic Challenge Scholarship as the first in 1991. Ness and Noland (2007) argue that merit-based financial aid policy can be traced back to 1960, with the California Master Plan.

There are also inconsistencies across the literature regarding the number of states that have adopted such programs, which may be an issue with the definition (Zhang et al., 2013). For example, Doyle (2006) defined 15 states as broad-based merit aid states before 2006, while Hu et al. (2012) listed 16 states that had adopted merit aid programs before 2006. Sjoquist and Winters (2015a) categorized 9 states as "strong" merit aid states and 16 states as "weak" merit aid states before 2006. Over time, at least 30 states have adopted some type of merit aid, including 4 states that abolished it later (Frisvold & Pitts, 2018). Supplemental Table A1 provides the features of each state's merit aid programs. It is clear that the 1990s and early 2000s are the heyday of state merit aid programs, making that time period ideal for researchers to examine the impacts of such programs on various outcomes (Hu et al., 2012).

Institutional merit aid is directly distributed from a postsecondary institution as a grant. Institution-level financial aid also plays a critical role in helping students access postsecondary education in the United States (McPherson & Schapiro, 1998; St. John & Asker, 2003). According to Baum and Payea (2003), institutional grants had increased more than any other levels of aid in constant dollars from 1983 to 2003 at an approximately 122% increase, as compared to 120% in federal and 107% in state aid. Institutional merit aid has grown in its proportional share of institutional grants into a tool to increase enrollment and attract talented students (Baum & Schwartz, 1988).

The motivation for colleges and universities to award aid in terms of merit may be traced back to the National Defense Education Act of 1958, which was designed to cultivate talents and enhance the national defense (Baum & Schwartz, 1988). In the early 1980s, many moderately selective postsecondary institutions began to add merit aid into their student funding programs (Griffith, 2011). Merit aid was critiqued as unfair to needy students since the aid was more likely to be awarded to those academically prepared students from the middle and upper classes (Baum & Schwartz, 1988). Still, selective institutions gradually replaced "self-help" financial aid with grant aid in late 1990s to compete for academic talents (DesJardins et al., 2002). To date, some selective institutions only provide merit aid (U.S. News, 2022).

To our knowledge, there are no specific rules to constrain a student from receiving both state and institutional merit aid. State merit aid is typically aimed at retaining the brightest students in the state (Cohen-Vogel et al., 2008). Meanwhile, the goal of institutional merit aid is to attract the most talented students to the institution (Somers, 1995).

These two goals are not in conflict. Ness and Lips (2011) pointed out that flagship institutions in merit aid states were more likely to attract academically talented students than those flagship institutions in non-merit aid states since they could "top off" the state merit aid and distribute scholarship money to a wider range of students. In addition, Dynarski and Scott-Clayton (2013) pointed out that students are required to complete the Free Application for Federal Student Aid by many state and institutional aid programs, and then wait for their whole aid packages. Moreover, focusing on the effects of state merit aid on institution aid, Long (2004) studied the Georgia HOPE Scholarship and found it led to a significant reduction of institutional aid among private colleges. In sum, institutional and state merit aid may work in tandem as a set of student financial supports—potentially also enhanced by other forms of financial aid—they do not necessarily function independently of one another. Accordingly, we consider in this study how state and institutional aid affect students (separately and in combination), and control for other forms of grant, loan, and work-related financial aid.

Effects of Merit-Based Aid Programs

Past studies have examined the effects of merit aid programs on various higher education topics, such as access and enrollment (Heller, 2006; Zhang & Ness, 2010) or degree completion (Gurantz & Odle, 2022; Zhang, 2011). The results vary significantly to include both positive and negative findings. In terms of positive effects, Zhang and Ness (2010) found that 8 of 13 states' merit aid programs significantly prevented resident students from leaving their state for schooling; the largest reduction of student departures from the state was in Mississippi (27.8%), and the lowest reduction (9.0%) was in West Virginia. Similarly, Orsuwan and Heck (2009) found that states with merit aid programs lost fewer proportions of students to out-of-state colleges compared with states that did not have such programs. Cornwell et al. (2006) found that after Georgia implemented its "HOPE" merit aid program, the state increased its freshman enrollment by 5.9%.

With respect to degree completion, Zhang et al. (2013) investigated Florida's Bright Futures Scholarship and found that the degree production for women students at 4-year public research and doctoral institutions significantly increased; the overall 2-year associate degree production also increased by approximately 10% after adopting the program. Directly examining STEM degree completion, Zhang (2011) found that merit aid programs in both Georgia and Florida had a positive influence on STEM degree completion, with a 5% to 7% and 10% to 13% increase, respectively. The effect was further pronounced for women, who experienced a 7.6% and 14.1% increase, respectively. Other positive effects of merit aid have been identified, including contributions to college persistence and academic performance (Henry et al., 2004).

In terms of the negative effects of merit aid, Dynarski (2000) found that Georgia's HOPE program not only widened the college access gap between high- and low-income students but also the gap between White and Black students. Heller and Marin (2002) found that merit scholarships were being awarded disproportionately at the national level to certain socioeconomic groups, potentially increasing the gaps in college enrollment between advantaged and disadvantaged students and running counter to the goal of equality of educational opportunity (Coleman, 1968). Two years later, Heller and Marin (2004) pointed out that merit-based scholarships were unlikely to be awarded to minority and low-income students since they were less likely to meet the criteria for merit aid.

Taken together, these studies have examined both the positive and negative effects of merit aid on different outcomes, such as college access and degree attainment. Yet, few have investigated the effects of merit aid on students' STEM major choices as an unintended effect of the aid program. Even when outcomes in STEM fields were examined like in Zhang's study (2011), the data were aggregated and thus not analyzable at the individual student level. This makes it difficult to disentangle the effects of merit aid programs on the composition of student populations—which could affect the aggregate STEM outcomes at the state level—from the effects on individual choice of STEM fields.

We attempt to remedy this gap in the research literature by quasi-experimentally examining the impact of merit aid on major choice, using student-level data from BPS, a national longitudinal database. Thus, our study can explore whether state and institutional merit aid, separately or in combination, could affect student choice of STEM fields. Moreover, we can also provide evidence on the possible implications for the country beyond individual states' interest in STEM education.

Potential Relationship Between Merit-Based Aid and STEM Major Choices

Policy goals of state-level merit aid include promoting higher education access in the state and incentivizing students' academic excellence (Whatley, 2019). Previous studies have not only examined the intended consequences of merit aid, such as college access (Cornwell et al., 2006), but also unintended, indirect consequences, such as facilitating study abroad opportunities for students by assuming the aid money can function as financial incentives to affect individuals' decisions on choices of costly activities (Whatley, 2019). Selecting a STEM major—a choice that potentially increases college costs—may function similarly as an unintended consequence of implementing merit aid. Hu et al. (2012) suggest that there are only limited, indirect effects of merit aid on students' STEM major choices. As far as potential negative effects of merit aid, high school students may choose easier coursework in order to qualify for merit aid (Sjoquist & Winters, 2015a), which impedes their preparation for the academic rigor of STEM disciplines in college. College students may also need to maintain high GPA levels to retain their financial aid, motivating them to avoid STEM fields in favor of "easier" majors (Armstrong & Hamilton, 2013; Zhang, 2011).

With respect to potential positive effects, merit aid can also function as a subsidy for students seeking to major in "high-risk" (not easy to graduate) disciplines such as STEM (Delaney, 2007). In other words, merit aid may reduce students' financial concerns over STEM coursework, delaying their graduations and thus increasing college costs, which in turn increases their likelihood of declaring a STEM major. The level of compensation in the field also influences students' college major choices (Malgwi et al., 2005). Melguizo and Wolniak (2012) found that early career earnings are associated with certain college majors, whereas STEM majors earn significantly more than non-STEM majors. Taken together, students' probability of declaring a STEM major is likely to increase if they perceive (a) high potential earnings in a future STEM career and (b) merit aid as a resource for overcoming financial obstacles in completing a STEM degree.

Methods

Data Source

The nationally representative BPS restricted-use database was used for this study. This dataset is particularly well-suited to this work because it not only contains U.S. students' declared college majors and financial aid information but also provides comprehensive pre-postsecondary characteristics of students, enabling us to counterfactually establish similar groups in terms of these observable characteristics using PSM. There are four BPS cohorts at present: 1990/1994, 1996/2001, 2004/2009, and 2012/2017.[1]

We selected the second-most recent (2004/2009) cohort because the policy window is clearest during this period. Considering policy implementation lags, students enrolling by 2003 ought to have *actually* received the aid since the majority of states adopted programs in 1997. More specifically, the adoption pattern of broad-based state merit aid[2] before 2005 is clearer than the most recent cohort (2012/2017). In addition, in the late 1990s and early 2000s, merit aid received substantial policy attention, as displayed in Supplemental Table A1. Meanwhile, mathematics and science education were key features of the education policy agenda (e.g., No Child Left Behind) during this window (Marx & Harris, 2006). The fact that merit aid and STEM education were coincidentally in the spotlight at the same period makes the cohort of 04/09 particularly appropriate for the present study.

By the 2010s, following the Great Recession, merit aid policies and implementation were in transition. Some states (e.g., Maryland, Michigan) had by then closed or changed their programs, shrinking the number of eligible states to include in our analyses (and inherently also shrinking our analytic sample). This is important given the national focus of our study, with states ranging by region, population size, college-going and workforce climates, and other important considerations. As time goes on, state merit aid may add new criteria, especially among those states that abolished merit aid but re-adopted it later. In addition, well-recognized studies such as Doyle (2006) use the states studied here, which are distinct from those in the 2012/2017 period. Thus, we decided to expand the earlier studies by adopting their definition of broad-based state merit aid and choose BPS:2004/2009 as our analytical focus. To add additional insight and as a robustness check, we conducted a supplemental analysis of these data with the newer 2012/2017 cohort, and report similar patterns in our sensitivity analysis discussion.

In the present study, there were no specific policies limiting the amount of merit aid that one student can receive: a student could receive both state- and institutionally awarded merit aid. BPS:2004/2009 sorted students' merit aid information by type (state or institutional), which provided us a unique opportunity to construct three analytic samples: students receiving both state and institutional merit aid, students only receiving state merit aid, and students only receiving institutional merit aid.

Analytic Sample

We focused here on the 15 states with broad-based merit aid, as identified by Doyle (2006).[3]

These 15 focal states are Alaska, Delaware, Florida, Georgia, Kentucky, Louisiana, Michigan, Mississippi, Missouri, Nevada, New Mexico, South Carolina, West Virginia, California, and Illinois. Supplemental Table A1 displays all states with merit aid programs, inclusive of those which we (and Doyle, 2006) deemed ineligible for the reasons explained below.

We selected states for inclusion in the final analytic sample based on two criteria. First, we limited the set to states that adopted broad-based merit aid programs before 2004, as the 04/09 cohort first enrolled in colleges and universities from 2003 to 2004 academic year. This eliminated states like Massachusetts and North Carolina, which first implemented merit aid in 2005. Second, we filtered states as per the policy window between adoption and actual implementation by leveraging the data from National Association of State Student Grant and Aid Programs (NASSGAP) to confirm that they had already distributed merit-based aid to students.[4] For example, West Virginia, which adopted the program in 2002, *actually* distributed aid to students. Tennessee, conversely, adopted the program in 2003, but no data were found in the NASSGAP annual survey, suggesting that Tennessean students may not have actually received merit aid that year; thus, we excluded the state from our analytic sample. California and Illinois adopted state merit aid policies, and each had a relatively large amount of state merit aid distribution in NASSGAP data. We, therefore, include these states in our analysis.

Table 1 shows the percentage of students' making STEM major choices by the type of merit aid received. Among students who received both state and institutional merit aid, 53.5% chose STEM majors, while 46.5% chose non-STEM majors. Looking at the state-only merit aid group and the institutional-only merit aid group, both groups consisted of 45.1% of STEM students and 54.9% of non-STEM students. This shows that students who received both state and institutional merit aid have a higher percentage of majoring in STEM fields. In addition, 45.2% of students who did not receive either type of merit aid entered STEM fields. The total analytic sample includes 2,310 students attending college in these 15 states. To comply with National Center for Education Statistics (NCES) restricted-data use limitations, we round our reporting of these and subsequent descriptive figures to the nearest tenth for means and standard deviations and to the nearest 10 for respondent numbers (*N*s).

Variables of Interest

Dependent Variable. The outcome variable in this study was students' STEM major choices, captured in the BPS dataset as students' major selections during their first year of postsecondary enrollment. We coded STEM major selections as "1" and "0" for otherwise, based on the Department of Education's Classification of Instructional Program 2010 categories. More specifically, these fields include life sciences, physical sciences, mathematics, computer/information sciences, social/behavioral sciences, engineering technologies, health, vocational/technical, and other technical/professional sciences.

Treatment Variable. The treatment condition (binary indicator) captures whether students received merit aid. Our analysis of BPS data shows the amount of merit aid received by students from both sources (i.e., states and institutions). We coded amounts larger than zero as "1" and "0" otherwise for both types of merit aid. Further, we classified students as "both" if students' state and institutional merit aid conditions were both equal to "1"; "state-only" if receiving "1" in state merit aid and "0" in institutional merit aid, "institution-only" if receiving "0" in state merit aid and "1" in institutional merit aid; and "none" if receiving both "0" in state and institutional merit aid, as shown in Table 1. We capture dollar amounts from other forms of financial aid in the matching model as well, as noted below.

Matching Variables. We also developed a set of matching variables to calculate the propensity score and determine assignments for the treatment or control group. We sorted the data into six categories: (a) gender and race, (b) other student characteristics, (c) high school academic preparation, (d) family characteristics, (e) high school characteristics, and (f) other financial aid.

Gender and race have been examined by many researchers as they influence students' STEM major choices (Perez-Felkner et al., 2012).

TABLE 1

STEM Field Participation for the Analytic Sample, by Types of Merit Aid Received

	Types of merit aid			
Variables	Both	State-only	Institution-only	None
STEM	90	160	160	650
%	53.5	45.1	45.1	45.2
Non-STEM	80	190	200	780
%	46.5	54.9	54.9	54.8
Total, *N*	170	350	360	1,430

Source. U.S. Department of Education, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS:2004/2009), First Survey, 2004.
*Note. N*s were rounded to the nearest 10, and percentages were rounded to the nearest 10th to comply with the NCES restricted-data regulations. STEM = science, technology, engineering, and mathematics.

Other student characteristics included age (Sjoquist & Winters, 2015b), student residential status and immigrant status (Flores, 2010), and enrollment status (Heller, 2004). These other characteristics are likely to influence students' selection for merit aid due to the complicated qualification criteria. *High school academic preparation* included high school GPA and completion of key high school course sequences (Park, 2015), which indicate whether students qualified for merit aid based on their academic performance. These qualities also may influence students' STEM major choices (Moakler & Kim, 2014). *Family characteristics* consisted of parental education, family size, and family income level. According to Bettinger (2004), researchers must comprehensively control for family characteristics when investigating effects of financial aid. *High school characteristics*, such as school type (Zhao & Perez-Felkner, 2022), are also associated with STEM major choices. *Other financial aid* was operationalized here to include other grants, loans, work-study, and financial aid application records. It is necessary to control for other possible financial aid to isolate and determine the precise effects of merit aid, which may be awarded in tandem with additional forms of aid.

Analytic Strategies

Logistic Regression. All the analyses in the present study were performed in Stata 16 (StataCorp LLC, Texas, the United States). We first used logistic regression as a benchmark for comparison against the PSM results. The dependent variable, STEM major choice, is a dichotomous variable: the student is coded as "1" if they choose a STEM major and otherwise as "0." The primary independent variable was whether a student received any form of merit aid. The aforementioned student-, family-, and school-level characteristics were also controlled. However, the estimated coefficient of merit aid is likely to be biased due to endogeneity, where merit-based aid may correlate with the error term in the model predicting STEM major choice. This would prevent us from drawing precise causal inferences (Li, 2012). The "true" effects of merit-based aid ought to be captured by merit aid recipients' STEM major decision-making as compared to their decisions had they not received this aid. However, this counter factuality cannot be addressed in the logistic regression model.

Counterfactual Framework. Educational effectiveness research attempts to generate causal inferences, such as whether postsecondary outcomes are caused by certain factors (Gustafsson, 2013). We sought to understand the effects of merit aid on students' STEM major choices. The naïve estimator was students who received merit aid versus those who did not. However, the other factors discussed above as matching variables may also affect students' STEM major choices. For example, students who receive merit aid may show better academic performance, come from wealthier families, and be more likely to have parents working in STEM occupations. Therefore, a simple comparison between those students receiving and not receiving merit aid would overestimate the effect of merit aid on students' STEM major choices. As such, the "true" effect of merit-based aid is difficult to capture.

To address this bias, a counterfactual analysis was set up for a group of students with similar observable characteristics, including both receiving and not receiving merit aid (Flores & Park, 2015; Rosenbaum & Rubin, 1983). The counterfactual analysis allowed us to observe STEM major choices for students who simultaneously did and did not receive merit aid (Park, 2015). The primary statistical interest was the average treatment effect on the treated (ATT) (Olitsky, 2014). We first established the treatment group's outcome as y_1, while the control group's outcome was y_0. Students having received merit aid were denoted as $z=1$ and otherwise as $z=0$. As mentioned above, other observable factors (denoted as s) may also affect students' STEM major choices. Accordingly, ATT was calculated as follows:

$$\begin{aligned}\text{ATT} &= E(y_1 - y_0 \,|\, s, z=1)\\ &= E(y_1 \,|\, s, z=1) - E(y_0 | s, z=1).\end{aligned}$$

Merit aid recipients' STEM major choices, $E(y_1 \,|\, s, z=1)$, was determined from the BPS data. However, the counterfactual outcome, $E(y_0 \,|\, s, z=1)$, cannot be directly acquired because students cannot simultaneously receive and not receive merit aid. PSM was conducted to resolve this. We identified "similar" students $E(y_0 \,|\, s, z=0)$ and randomized them into the control and treatment groups based on observable characteristics (Park, 2015). The average treatment effect (ATE) was calculated as follows:

$$\text{ATE} = E(\Delta = y_1 - y_0).$$

According to Guo and Fraser (2014), ATE estimates the effect of a given treatment across an entire sample. In our case, it measured the mean difference in majoring in STEM fields between merit aid recipients and non-merit aid recipients in a manner comparable to the logistic regression's coefficients (Olitsky, 2014). ATT measured the average difference only in the treated sample. We also measured the mean difference in majoring in STEM fields between merit aid recipients and their major choices if they did not receive merit aid. ATT was a better fit than ATE because it captures the "true" treatment effects of merit aid on major choices—students in the treated group *actually* experienced the treatment (i.e., received merit aid).

PSM Technique

PSM can be used to estimate both ATT and ATE values. We operated the PSM technique in two steps (Morgan et al., 2010). In Step 1, we applied a probit regression model to calculate students' propensity for receiving the treatment (i.e., merit aid). The propensity score was calculated by the formula below (Rosenbaum & Rubin, 1983):

$$p = \Pr\left(z = 1|s\right) = E\left(z|s\right) < 1,$$

where p is the probability or propensity score that a student would receive merit aid in terms of a set of observable variables (s), such that $p < 1$ for all s (Flores & Park, 2015).

In Step 2, we used the obtained propensity scores to match "similar" students who received merit aid and those who did not. Our interest was to find "similar" students through the matching process using a series of key covariates (observable variables) and then to examine the impact of merit aid only focusing on these matched students to acquire the "true" effects. We made the following assumption in the matching process (Smith & Todd, 2001):

$$E(y_0 \,|\, p, z=1) = E(y_0 \,|\, p, z=0).$$

We sought to statistically compare students' STEM major choices from the treatment and control groups conditional on a common probability (propensity) for being placed into the treatment group, which is defined by p (Park, 2015). The impact of merit aid, denoted as α, is calculated as follows (Smith & Todd, 2001):

$$\begin{aligned}\alpha &= E(y_1 - y_0 \,|\, z=1)\\ &= E(y_1 \,|\, z=1) - E(y_0 \,|\, z=1).\end{aligned}$$

Based on the double expectation formula and the matching process assumption, $E(y_0 \mid z=1)$ is

$$E(y|z=1) = \int_0^1 E(y|z=1,p) f(p|z=1)\,dp = E_{p|z=1}(E_y(y \mid z=1,p)).$$

Therefore, the formula for calculating the impact of merit aid is (Smith & Todd, 2001)

$$\alpha = E(y_1 \mid z=1) - E_{p|z=1}(E_y(y \mid z=0,p)).$$

The average effect of merit aid is then the sum of each pair of matched students' differences in STEM major choices divided by the number of pairs *n*. The mean impact of merit-based aid is thus given by

$$\alpha_m = \frac{1}{n}\sum_{i \in I1 \cap Sp}^{n} \left(y_{1i} - y_{0j}\right),$$

where y_{1i} denotes a treatment group student's outcome, y_{0j} is the matched control group student's outcome, I_1 represents students in the treatment group and S_p is the region of common support, which shows the range of propensity scores between treated and untreated students.

With reference to the literature (Flores & Park, 2015; Olitsky, 2014), we also implemented the nearest neighbor matching technique, defined as $\min_j \|p_i - p_j\|$ (Smith & Todd, 2001). This algorithm is also known as one-to-one matching (Park, 2015). We matched one student in the treatment group to one student in the control group based on how close these two students' propensity scores were (i.e., a specified caliper). We chose a commonly used caliper, $0.25\,\sigma_p$. In other words, we selected a merit aid student from the sample, and then found a non-merit aid student who had a minimum propensity difference within a caliper width of 0.25 standard deviations of the calculated propensity score (Park, 2015). If we could not find a matched student for the treated student, then the treated student was removed from the analysis.

Sensitivity Analysis

Alternative Dataset. As explained above, the BPS:2004/2009 cohort is ideal for studying merit aid effects. As an additional check, we conducted the full analysis with the newest BPS cohort, which began college in 2012. This BPS:2012/2017 analysis included nearly the same states; two were excluded from eligibility because their states had abolished merit aid and not brought it back during the period when these more recent college students were applying for financial aid and enrolled in school. Supplemental Table A2 shows that the percentage of students in the active merit aid states were less likely to attain merit aid from their institutions, states, or both, as compared to students in the BPS:2004/2009 cohort: 73.7% had *no* merit aid in 2012, as compared to 62.0% in 2004. Supplemental Table A3 indicates that students' choice of STEM majors is lower among merit aid recipients in the newer cohort, even when assessing this descriptive pattern among alternative STEM definitions. This further supports our later finding that state merit aid has significantly positive effects on students' STEM major choices because merit aid, particularly at the state level, has been looked at more critically after the Great Recession (Ingle & Ratliff, 2015). The increase in eligibility of criteria may lower students' STEM major choices due to increased risks; meanwhile, the decrease in generosity may reduce the subsidy effects of merit aid on students' STEM major choices.

Supplemental Table A4 shows the probit results for students receiving state, institutional, and both forms of merit aid, respectively. Overall, the relationships and overall model strength are similar across cohorts for each model; when comparing the BPS:2004/2009 results, we report in the main text with the results reported in Supplemental Table A4. This enhances our confidence in the design and its appropriateness for studying the impact of merit aid on postsecondary students' STEM major choices while adjusting for their propensity to attain merit aid from these sources.

Rosenbaum Bounds. PSM is operated by using observable characteristics to match individuals. However, there may still exist certain unobservable characteristics that also affect the treatment's outcomes, or the placement of either the treatment or control group, which would bias the estimated effects of the treatment. A high bias emerges if only a rough set of observable variables is used (Heckman et al., 1998). We conducted a robustness check to ensure this did not happen in our case. Specifically, the Rosenbaum Bounds (RB) sensitivity analysis is a recommended robustness check after conducting PSM (Olitsky, 2014). RB helps to determine whether "hidden bias" significantly influences results; it reveals how large the unobservable variables' effects on the odds of treatment must be in order to make treatment effect statistically insignificant (Olitsky, 2014). Put simply, this analysis determines whether the matching is sensitive to any "hidden biases" caused by these unobserved characteristics (Guo & Fraser, 2014). Together, these analyses aim to robustly assess the impacts of merit aid on students' STEM major choices.

Results

Descriptive Analysis Preceding Propensity Matching

Table 2 provides descriptive statistics of the intended variable for each analytic sample. Fewer men than women received either solely state (41% male) or solely institutional (38% male) merit aid. Men and women received both state and institutional merit aid at similar rates (49% vs. 51%). We identified racial differences by merit aid receipt category. Specifically, among students receiving both state and institutional merit aid, 82% were White. Among state-only and institutional-only aid recipients, 69% and 71% were White, respectively.

Many states require that students must be residents of that state to qualify for state-awarded merit aid, as the intent is to retain the state's best students for college and beyond. Conversely, institutional merit aid may be awarded specifically to attract talent from other states (Zhang & Ness, 2010). All "both" group students and 99% of the state-only-group students enrolled in postsecondary institutions in the same states as their residence, while only 67% of students did so in the institutional-only aid group.

We also found that students in the "both" group had higher mean high school preparation variables than those in the state- and institutional-only groups. Also, students receiving both types of merit aid, on average, had higher rates of receiving other financial aid through work-study than the other two groups.

Matching Results

Table 3 shows the probit results of the final matching model.[5] We calculated predicted probabilities for students receiving merit aid based on the final set of matching variables. For example, in both groups, Latino male students with high school GPAs ranging from 3.0 to 4.0 and whose parents had at least a 4-year college degree (holding other variables constant) showed a predicted 23.6% probability of receiving both state and institutional merit aid. However, a Black student with these same characteristics only had a predicted 16.9% probability of receiving both types of aid.[6]

After generating the propensity score for every student in each group of the analytic sample, we conducted a balanced assessment. Table 4 provides the *t* statistics for differences in means across all matching covariates for the matched and unmatched groups. No statistically significant difference was identified between the three matched groups on these matching covariates. Most variables for unmatched groups were statistically significantly different at the .001 level, as shown in Table 4. This suggests that the matching processes were effective in balancing the treatment and control groups of students (Park, 2015).

Additionally, we created kernel density plots of propensity scores for the treatment and control groups for each sample. Figure 1 shows a substantial number of common supports for each sample—meaning that several "similar" students were found in the treatment and control groups (Flores & Park, 2015), which further suggests that our matching process was adequate.

Treatment Effect Results

Table 5 shows the treatment effects of merit aid on students' STEM major choices, including logistic regression (LR) results, ATEs, and ATT for each analytic sample in the "both," state-only, and institutional-only groups.

TABLE 2

Descriptive Summary Statistics for All of the Initial Matching Variables

	Both (N=170)		State-only (N=350)		Institution-only (N=360)	
Variables	Mean	*SD*	Mean	*SD*	Mean	*SD*
Primary variable of interest						
STEM major choice	0.50	0.50	0.50	0.50	0.50	0.50
Student-level						
Gender and race						
Male	0.50	0.50	0.40	0.49	0.40	0.48
White	0.80	0.39	0.70	0.46	0.70	0.45
Black	0.10	0.24	0.20	0.39	0.10	0.34
Latino	0.10	0.21	0.10	0.21	0.10	0.26
Asian	0.10	0.25	0.00	0.18	0.00	0.19
Other identities	0.00	0.11	0.10	0.23	0.00	0.21
Other characteristics						
Age	18.30	0.60	18.50	0.78	18.40	0.66
Residence	1.00	0.00	1.00	0.08	0.70	0.47
Immigrant status	0.90	0.35	0.90	0.35	0.90	0.36
Enrollment intensity	1.20	0.60	1.30	0.70	1.20	0.61
High school academic preparation						
HS GPA 3.0–4.0	1.00	0.21	0.80	0.37	0.80	0.36
2.0–2.9	0.10	0.21	0.20	0.36	0.10	0.35
<2.0	0.00	0.00	0.00	0.08	0.00	0.13
English course-taking	3.80	0.54	3.80	0.44	3.80	0.54
Foreign language course-taking	2.50	1.02	2.30	1.00	2.60	1.14
Math course-taking	3.90	0.39	3.60	0.84	3.60	0.83
Science course-taking	3.40	0.80	3.40	0.75	3.30	0.82
Social science course-taking	3.30	0.76	3.40	0.76	3.30	0.76
Family-level						
Parental education						
4-Year college degree	0.60	0.50	0.50	0.50	0.60	0.49
Family size	4.20	1.25	4.00	1.17	4.10	1.19
Live alone	0.20	0.41	0.10	0.35	0.20	0.41
Family income	72,821.10	51,269.04	69,124.90	47,317.89	81,358.50	60,041.97
High school-level						
School types						
Public	0.90	0.34	0.90	0.27	0.90	0.35
Private	0.10	0.34	0.10	0.27	0.10	0.35
Financial aid						
Other grant	3,281.40	3,806.82	1,793.80	3,301.63	3,447.50	4,729.15
Loan	2,010.20	2,948.21	1,081.50	2,190.52	2,645.30	3,609.10
Work-study	473.30	987.98	172.80	663.63	372.60	814.79
Other type	774.80	2,734.54	627.50	2,106.53	1,430.70	4,153.57
Application record	0.90	0.30	0.80	0.41	0.90	0.34

*Note. N*s were rounded to the nearest 10, and means were rounded to the nearest 10th to comply with the NCES restricted-data regulations. STEM = science, technology, engineering, and mathematics.
Source. U.S. Department of Education, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS:2004/2009), First Survey, 2004.

Only the "both" group shows a statistically significant effect of merit aid on students' STEM major choices as per the LR results. Students who received both state and institutional merit aid were 1.48 times more likely to major in STEM fields, holding other variables constant. According to the ATE results, only the state-only merit aid group showed a significant effect of

TABLE 3

Probit Results of a Student's Likelihood of Receiving Merit Aid

	Both		State-only		Institution-only	
Variables	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*
Gender and race						
Male	0.17	0.10	0.03	0.08	−0.12	0.07
Asian	−0.13	0.24	−0.34	0.21	−0.24	0.20
Black	−0.85***	0.19	−0.06	0.10	−0.29**	0.11
Latino	−0.59**	0.22	−0.56***	0.16	−0.21	0.14
Others	−1.09**	0.35	−0.11	0.16	−0.22	0.17
White	—	—	—	—	—	—
Other characteristics						
Age	−0.17*	0.08	−0.01	0.04	−0.09	0.05
Residence	—	—	1.64***	0.26	−0.38***	0.09
Immigrant status	0.44*	0.17	0.37**	0.12	0.29**	0.11
Enrollment intensity	−0.20*	0.08	−0.05	0.05	−0.11	0.06
High school academic preparation						
HS GPA 3.0–4.0	0.91***	0.19	0.72*	0.31	0.17	0.25
2.0–2.9	—	—	0.28	0.32	−0.15	0.25
<2.0	—	—	—	—	—	—
Foreign language course-taking	−0.04	0.05	−0.02	0.04	−0.01	0.03
Mathematics course-taking	0.54***	0.11	0.18***	0.04	0.09*	0.04
Family characteristics						
Parental education (4-year)	0.15	0.11	0.10	0.08	0.21**	0.08
Family income	−0.01	0.01	−0.01	0.01	0.01	0.01
Financial aid						
Other grant	0.00	0.01	−0.03**	0.01	0.01	0.01
Loan	−0.02	0.02	−0.07***	0.02	0.01	0.01
Work-study	0.31***	0.07	0.08	0.06	0.13**	0.05
Application record	0.63***	0.15	0.31***	0.09	0.40***	0.10
Constant	−1.28	−1.56	−3.52***	1.00	0.27	1.00
LR chi-square	232.41***		242.55***		186.60***	
Pseudo R^2	0.23		0.14		0.10	
N	1,350		1,780		1,790	

Note. White and GPA <2.0 were omitted because they are the reference groups. Residence and 2.0 to 2.9 were omitted in the "both" group because of no/little variation in these two variables. Family income was divided by 10,000. Other grant, loan, and work-study were divided by 1,000 for ease of interpretation. LR = logistic regressions.
Source. U.S. Department of Education, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS:2004/2009), First Survey, 2004.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

merit aid on students' STEM major choices; students receiving state-only merit aid were 11.2% more likely to major in STEM fields. ATT results indicated significant and positive effects of merit aid on state-only and "both" groups. For the "both" group, the effect of merit aid manifests as a 10.9% increase in the probability of choosing STEM majors; for the state-only group, the effect is 7.5%. We found no significant results in any of the three statistical estimations in the institution-only group. Importantly, ATE and ATT show statistically significant differences in the state-only group, while LR result does not. It should be noted that LR estimates cannot capture the "true" treatment effect, STEM major choice that a merit aid recipient would have made had they not

TABLE 4

Balance Assessment: T-Test for Differences in Means for Matching Covariates

	Both				State-only				Institution-only			
	Unmatched		Matched		Unmatched		Matched		Unmatched		Matched	
Variables	T	C	T	C	T	C	T	C	T	C	T	C
Gender and race												
Male	0.49	0.41	0.47	0.50	0.41	0.43	0.41	0.41	0.38	0.43	0.38	0.43
White												
Black	0.06	0.18***	0.06	0.05	0.18	0.18	0.18	0.16	0.13	0.18*	0.13	0.16
Latino	0.05	0.16***	0.05	0.04	0.05	0.14***	0.05	0.05	0.08	0.14***	0.08	0.07
Asian	0.06	0.07	0.07	0.09	0.03	0.06*	0.03	0.03	0.04	0.06	0.04	0.03
Others	0.01	0.06**	0.01	0.01	0.05	0.06	0.05	0.07	0.04	0.06	0.05	0.06
Other characteristics												
Age	18.32	18.52**	18.32	18.32	18.48	18.52	18.48	18.44	18.36	18.52***	18.36	18.31
Residence	1.00	1.00	1.00	1.00	0.99	0.85***	0.99	0.99	0.67	0.85***	0.67	0.69
Immigrant status	0.86	0.70***	0.85	0.84	0.86	0.72***	0.86	0.86	0.85	0.72***	0.84	0.84
Enrollment intensity	1.21	1.36**	1.19	1.17	1.31	1.34	1.31	1.36	1.21	1.34**	1.21	1.18
High school academic preparation												
HS GPA 3.0–4.0	0.95	0.70***	0.95	0.96	0.84	0.69***	0.84	0.84	0.84	0.69***	0.84	0.87
2.0–2.9	0.05	0.30***	0.05	0.04	0.15	0.28***	0.15	0.15	0.14	0.28***	0.14	0.12
<2.0	0.00	0.00	0.00	0.00	0.01	0.03**	0.01	0.01	0.02	0.03	0.02	0.02
Foreign language course-taking	2.51	2.31*	2.53	2.56	2.34	2.35	2.34	2.37	2.56	2.35**	2.56	2.48
Math course-taking	3.85	3.27***	3.84	3.81	3.60	3.30***	3.60	3.61	3.62	3.30***	3.62	3.60
Family characteristics												
Parental education (4-year)	0.55	0.41***	0.55	0.59	0.49	0.44	0.49	0.51	0.59	0.44***	0.59	0.58
Family income	7.28	6.44	7.27	7.69	6.91	6.78	6.91	6.85	8.14	6.78***	8.12	8.31
Financial aid												
Other grant	3.28	2.59*	3.31	2.86	1.79	2.70***	1.79	1.79	3.45	2.70**	3.43	3.55
Loan	2.01	1.83	2.04	2.05	1.08	1.95***	1.08	1.22	2.65	1.95***	2.65	2.60
Work-study	0.47	0.17***	0.37	0.38	0.17	0.18	0.17	0.17	0.37	0.18***	0.36	0.36
Application record	0.9	0.74***	0.90	0.87	0.79	0.74*	0.79	0.80	0.87	0.74***	0.86	0.87

Note. White and <2.0 were omitted because they are the reference groups. Residence and 2.0 to 2.9 were omitted in the "both" group because of no/little variation in these two variables. Family income was divided by 10,000; Other grants, loans, and work-study were divided by 1,000 for ease of interpretation. T = treatment group; C = control group.

Source. U.S. Department of Education, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS:2004/2009), First Survey, 2004.

$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

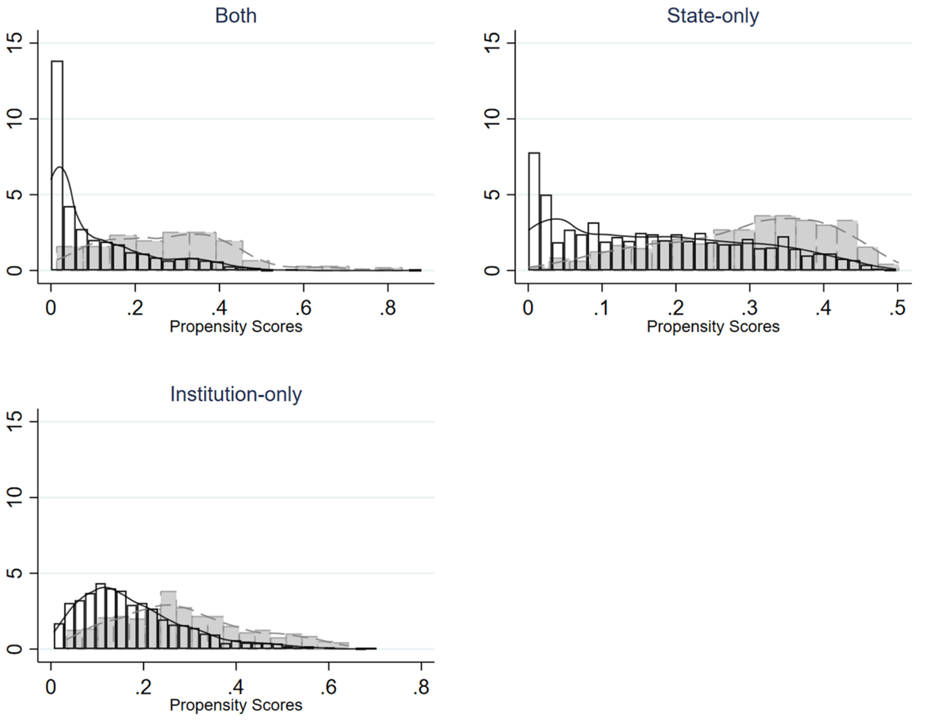

FIGURE 1. *Kernel density plots of propensity scores for the treatment and control groups after the match by analytic sample.*
Note. Dashed histogram represents the treatment group (merit aid recipients), while the solid histogram represents the control group (similar non-aid recipients).
Source. U.S. Department of Education, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS:2004/2009), First Survey, 2004.

TABLE 5
Treatment Effects for Merit Aid on STEM Major Choices

	Both			State-only			Institution-only		
Statistics	LR	ATE	ATT	LR	ATE	ATT	LR	ATE	ATT
Effect	.396*	0.145	0.109*	.22	0.112**	0.075*	.012	0.003	−0.017
SE	.184	0.085	0.055	.135	0.037	0.037	.132	0.036	0.038
N	1,600	1,330	170	1,780	1,770	350	1,790	1,780	350

Note. ATE = average treatment effect; ATT = average treatment effect on the treated; LR = logistic regression.
Source. U.S. Department of Education, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS:2004/2009), First Survey, 2004.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

received merit aid. In contrast, it may overstate this effect. Given the importance of minimizing this bias, PSM is thus preferred.

Sensitivity Analysis Results

Table 6 shows the results of our RB sensitivity analysis. Critical *p*-values were determined to check the point at which the results became insignificant, that is, the point at which the effect begins to be sensitive to hidden bias (Guo & Fraser, 2014). We used Wilcoxon's signed rank test to operate the RB process. The results indicated that the effect of merit aid became sensitive to hidden bias at $\Gamma = 1.08$ in the "both" group and $\Gamma = 1.05$ in the state-only group.

TABLE 6

Sensitivity Analysis (Hidden Bias): Range of the Significance Levels for Wilcoxon's Signed Rank Test

	Both		State-only		Institution-only	
Γ	Min	Max	Min	Max	Min	Max
1	0.025	0.025	0.026	0.026	0.324	0.324
1.01	0.022	0.028	0.022	0.031	0.347	0.301
1.02	0.020	0.031	0.019	0.036	0.372	0.278
1.03	0.018	0.034	0.016	0.041	0.396	0.257
1.04	0.016	0.037	0.014	0.047	0.421	0.237
1.05	0.014	0.041	0.012	**0.054**	0.445	0.218
1.06	0.013	0.045	0.010	0.061	0.470	0.201
1.07	0.011	0.049	0.008	0.069	0.494	0.184
1.08	0.010	**0.053**	0.007	0.077	0.519	0.168
1.09	0.009	0.058	0.006	0.087	0.543	0.153
1.1	0.008	0.063	0.005	0.097	0.566	0.139
1.2	0.002	0.128	0.001	0.235	0.770	0.049

Note. The minimum value of Γ is 1. *p* critical is Max for both and state-only models and *p* critical is Min for the institution-only model. In the institution-only model, the ATT is negative. See details in DiPrete and Gangl (2004). The effect becomes insignificant at the .05 level beginning at the bolded value.
Source. U.S. Department of Education, National Center for Education Statistics, Beginning Postsecondary Students Longitudinal Study (BPS:2004/2009), First Survey, 2004.

According to Guo and Fraser (2014), 1.08 is a small Γ value. To this effect, the impact of merit aid on students' STEM major choices is sensitive to hidden bias. However, effects that remain statistically significant at higher levels of Γ are less likely to be influenced by hidden bias (Olitsky, 2014). Our results showed the range of Γ at the significant level extended from 1 to 1.08 for the "both" group and from 1.0 to 1.05 for the state-only group, suggesting that the ATT in the "both" group was more robust to unobserved selection variables than the ATT in the state-only group.

Discussion

Implications for Research, Policy, and Practice

In this study, we sought to determine the effects of state and institutional merit aid, separately or in combination, on students' STEM major choices. Few researchers have examined whether this type of financial aid has any effect on leading students to STEM fields in a national study (Hu et al., 2012). To our knowledge, this is the first national study investigating the separate and combined effects of state and institutional merit aid on students' postsecondary STEM major choice.

Our ATT results show that state merit aid has a positive effect on students' STEM major choices, using students as the unit of analysis at the national level. Delaney (2007) suggested merit aid as a subsidy may motivate students to pursue "hard" majors, including STEM. We agree that additional funding may reduce students' college financial burden, thus encouraging them to pursue "high-risk" but "high payback" majors in STEM. Students who received both state-awarded and institution-awarded merit aid were more likely to choose STEM majors than those who received only one type of aid. By increasing the number of subsidies and reducing the amount paid by students' own financial sources, such a transfer of financial risk from students to governments (state, federal) and/or postsecondary institutions may increase students' willingness to pursue STEM majors and, in turn, careers in these fields.

We did not find any significant impact of institutional-only merit aid on students' STEM major choices. However, we did find a negative ATT trend in this group. Institutional merit aid is a tool for colleges and universities to compete for high-performing students, as discussed above (Baum & Schwartz, 1988). In general, institutional merit aid programs have stricter qualification criteria than state merit aid programs (Ness & Lips, 2011). Further, as Zhang (2011) argued, students may avoid “hard” majors to maintain their high GPA to continually qualify for or renew their merit aid. That is, the subsidies of institutional merit aid to help students take risks in choosing STEM fields may be cancelled out by the avoidance of STEM fields due to higher qualification requirements for institutional merit aid and student concerns about stricter grading practices in STEM fields (Hu et al., 2012). This may explain our observation of a negative but insignificant effect of institutional merit aid on students’ STEM major choices.

In the research literature on merit-based aid, much has focused on the state level (Cummings et al., 2022; Domina, 2014). There has been less attention to the institutional level (Gross et al., 2015; Johnson, 2022). Even fewer studies have attended to the unintended consequence studied here: STEM major choices (Sjoquist & Winters, 2015b).

Specifically, our study contributes to the research base in three ways. First, while previous literature assessed as a naïve estimator of whether students are exposed to state merit aid or not (Leeds & DesJardins, 2015; Zhang, 2011), we directly and simultaneously assess state and institutional merit-based aid’s effects. We directly utilize the amount of merit aid received by students in the BPS: The naïve estimator is students who *actually* received merit aid versus those who did not. Second, most existing literature has examined the intended goals of merit aid, such as promoting college access and attainment (Delaney, 2011; Gurantz & Odle, 2022; Leeds & DesJardins, 2015), stemming brain drain (Zhang & Ness, 2010), and incentivizing academic excellence and achievements (Domina, 2014). Few have investigated the unintended consequences (e.g., Whatley, 2019). This study expands our understanding of the unintended effects of merit aid, with a focus on STEM, and distinguishes itself from Sjoquist and Winters (2015b) through use of distinct nationally representative data and methodologies. Third, research on students’ STEM major choices has been studied extensively from student, family, and institutional perspectives (Niu, 2017; Perez-Felkner et al., 2017; Wang, 2013); fewer studies have taken a policy perspective. Our study adds insights into how policy plays roles in students’ college access decisions, with a focus on STEM fields.

With respect to policy and practice, our findings have implications for state policymakers as state-awarded merit-based aid policy does positively impact students’ STEM major choices. States with merit aid policies could continue to implement such policies to increase the likelihood of students choosing STEM majors. States that have not implemented such policies may do well to consider merit aid in order to compete for STEM talents and to develop their local economies. One related concern was that state merit aid programs may benefit states implementing such programs on STEM outcomes in their own colleges and universities for individual students, perhaps negatively affecting STEM outcomes nationally (Hu et al., 2012). The results from our current study suggest that merit aid could enhance students’ choice of STEM fields in these states, or at a minimum, do not seem to hurt students’ choice of STEM fields nationally.

For postsecondary institution administrators, our results suggest that only providing general institutional merit aid is insufficient to recruit excellent students into STEM disciplines; explanations to date vary by students’ socioeconomic status. Researchers have found that institutional merit aid recipients tend to be higher-income students (Griffith, 2011; Gross et al., 2015). However, economically advantaged students typically pursue majors in fields such as business (Astin, 1993) and liberal arts fields (Hu & Wu, 2019) rather than STEM majors. Distinctly, lower-income, high-achieving students who are academically well-positioned to obtain institutional merit aid may avoid applying to selective colleges out of concern for college costs (Hoxby & Turner, 2015). Hoxby and Turner (2013) suggest interventions such as the Expanding College Opportunities project to bridge information gaps around application guidance, net costs, and fee waivers and, in turn, increase students’ chances of choosing selective colleges. Somewhat similarly, we argue that framing STEM majors as “difficult” majors could hinder their pathways to

STEM disciplines and increase their costs (see also Zhao & Perez-Felkner, 2022). Thus, informational interventions could be delivered to students alongside institutional merit aid to raise students' likelihood of choosing STEM majors.

Limitations and Future Research Directions

Scope: Merit Aid Sources and National Focus. Our study attended to merit aid and its sources. Future researchers might focus more narrowly on state or institutional merit aid programs (using their respective data) to further examine whether students' STEM major choices are causally explained by the availability of merit aid. Further, to better understand to what degree merit aid contributes to STEM major declaration, future research could more directly examine the effects of the *amount* of merit aid on STEM major choices. Notably, it remains unclear how merit aid affects students' STEM persistence: merit aid may be regarded as either financial incentives when functioning as price subsidies or disincentives due to college grading policies (Hu et al., 2012). This is worth exploring in future research and would deepen our understanding of the effects of merit aid programs on various STEM outcomes.

In this study, we combined data for different states' and institutions' merit aid programs to estimate the effects of state and institutional merit aid on students' STEM major choices. The combination enhanced the statistical power of the estimates for our purposes. This is an important limitation, as states (as well as individual institutions) have distinct criteria for awarding merit aid. In addition, if merit aid is treated as a treatment/intervention, then it is arguably preferable to examine separately the effects of each merit aid program. Nevertheless, the findings from this study suggest that, even in a national context where many states and institutions adopted merit aid programs, a student's choice of STEM fields was not negatively affected when all the associated incentives and disincentives were considered.

Design Considerations: Quasi-Experimental Approaches and Sensitivity Analyses. Though BPS is a comprehensive, nationally representative study with limited missing data, the total number of merit aid recipients contained therein is relatively small. After, we sorted the aid recipients only from 15 states and then again into 3 analytic samples: state-only, institution-only, and both. Our PSM design balances the loss of statistical power with the intended precision of our quasi-experimental analysis. Future researchers might alternatively explore the longitudinal effects of specific merit aid programs on students' STEM major choices with other quasi-experimental designs such as difference-in-difference, that is, comparing the differences of merit aid recipients and non-aid recipients before and after the program. Regression discontinuity also may be applicable if assessing the impacts of merit aid funding for recipients and who would be just above and below the cutoff point of receiving aid.

In addition, the Γ value we used in our sensitivity analysis could be larger. Guo and Fraser (2014) suggested that researchers may reconsider the set of matching variables if Γ is small, as this means the model is very sensitive to hidden selection bias. There is no clear cutoff value of Γ provided by the literature, however, which makes it hard to assess conclusively. Future researchers could construct a more robust set of matching variables to enhance the model's sensitivity.

Disaggregating Effects of Merit Aid. Finally, while focusing on STEM major choices of merit aid recipients versus non-aid recipients, gender and race disparities in this effect are also worth exploring. Gender inequalities continue to exist in education (Buchmann et al., 2008), including in some STEM postsecondary fields like computing and engineering (Chen et al., 2023; Lindemann et al., 2016). Among merit-aid recipients, women recipients may still be less likely to declare STEM majors. Therefore, an analysis to dig deeper into the postsecondary trajectories of women versus men recipients and women versus men non-recipients could shed further light on gender disparities in the effect of merit aid on postsecondary and workforce outcomes, including STEM majors and careers.

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ORCID iDs

Teng Zhao https://orcid.org/0000-0003-3726-8134
Lara Perez-Felkner https://orcid.org/0000-0002-3451-8524
Shouping Hu https://orcid.org/0000-0003-1766-6629

Notes

1. Detailed information about these national cohorts is available on their associated federal websites, as is information about how to request restricted-data use access licenses. Statistical code or other documentation used in this study is available by request to the authors.

2. See details in Doyle's (2006), Note 1.

3. They are Alaska, Delaware, Florida, Georgia, Kentucky, Louisiana, Massachusetts, Michigan, Mississippi, Missouri, Nevada, New Mexico, South Carolina, Tennessee, and West Virginia.

4. NASSGAP only provides the data from 2003 to 2016 in its State Data Quick Check.

5. Regarding matching balance assessments, we conducted a series of *t*-tests to estimate whether the treatment group and control group were sufficiently well-balanced. In the initial balance check, years of high school English, science, and social science spent did not appear to make a significant difference before and after matching ($p < .05$). Therefore, we removed these variables from the matching model. We additionally checked the values of % bias provided by balance assessment results to further establish the final set of matching variables.

6. This was calculated by the cumulative distribution function of the standard normal distribution using the Stata normal command.

References

Armstrong, E. A., & Hamilton, L. T. (2013). *Paying for the party: How college maintains inequality*. Harvard University Press.

Astin, A. W. (1993). *What matters in college? Four critical years revisited*. Jossey-Bass/Wiley.

Baum, S., & Payea, K. (2003). *Trends in student aid, 2003*. The College Board.

Baum, S. R., & Schwartz, S. (1988). Merit aid to college students. *Economics of Education Review*, *7*(1), 127–134. https://doi.org/10.1016/0272-7757(88)90077-5

Bettinger, E. (2004). How financial aid affects persistence. In C. M. Hoxby (Ed.), *College choices: The economics of where to go, when to go, and how to pay for it* (pp. 207–238). University of Chicago Press.

Bottia, M. C., Stearns, E., Mickelson, R. A., Moller, S., & Jamil, C. (2020). The importance of community colleges in students' choice to major in STEM. *The Journal of Higher Education*, *91*(7), 1116–1148. https://doi.org/10.1080/00221546.2020.1742032

Buchmann, C., DiPrete, T. A., & McDaniel, A. (2008). Gender inequalities in education. *Annual Review of Sociology*, *34*(1), 319–337. https://doi.org/10.1146/annurev.soc.34.040507.134719

Chen, J., Perez-Felkner, L., Nhien, C., Hu, S., Erichsen, K., & Li, Y. (2023). Gender differences in motivational and curricular pathways towards postsecondary computing majors. *Research in Higher Education*. https://doi.org/10.1007/s11162-023-09751-w

Cohen-Vogel, L., Ingle, K., Albee, A., & Spence, M. (2008). The "spread" of merit-based college aid: Politics, policy consortia and interstate competition. *Educational Policy*, *22*(3), 339–362. https://doi.org/10.1177/0895904807307059

Coleman, J. S. (1968). Equality of educational opportunity. *Equity & Excellence in Education*, *6*(5), 19–28. https://doi.org/10.1080/0020486680060504

Cornwell, C., Mustard, D. B., & Sridhar, D. J. (2006). The enrollment effects of merit-based financial aid: Evidence from georgia's hope program. *Journal of Labor Economics*, *24*(4), 761–786. https://doi.org/10.1086/506485

Cummings, K. M., Deane, K. C., McCall, B. P., & DesJardins, S. L. (2022). Exploring race and income heterogeneity in the effects of state merit aid loss among four-year college entrants. *The*

Journal of Higher Education, *93*(6), 873–900. https://doi.org/10.1080/00221546.2022.2042155

Delaney, J. A. (2007). *The academic consequences of state merit aid: The case of Kentucky*. Stanford University.

Delaney, J. A. (2011). State merit-based aid and enrolling in graduate study: Evidence from the scholarship. *Journal of Student Financial Aid*, *41*(2), 6–21. https://doi.org/10.55504/0884-9153.1019

DesJardins, S. L., Ahlburg, D. A., & McCall, B. P. (2002). Simulating the longitudinal effects of changes in financial aid on student departure from college. *The Journal of Human Resources*, *37*(3), 653–679. https://doi.org/10.2307/3069685

DiPrete, T. A., & Gangl, M. (2004). Assessing bias in the estimation of causal effects: Rosenbaum bounds on matching estimators and instrumental variables estimation with imperfect instruments. *Sociological Methodology*, *34*(1), 271–310. https://doi.org/10.1111/j.0081-1750.2004.00154.x

Domina, T. (2014). Does merit aid program design matter? A cross-cohort analysis. *Research in Higher Education*, *55*(1), 1–26. https://doi.org/10.1007/s11162-013-9302-y

Doyle, W. R. (2006). Adoption of merit-based student grant programs: An event history analysis. *Educational Evaluation and Policy Analysis*, *28*(3), 259–285. https://doi.org/10.3102/01623737028003259

Dynarski, S. (2000). Hope for whom? Financial aid for the middle class and its impact on college attendance. *National Tax Journal*, *53*(3.2), 629–661. https://doi.org/10.17310/ntj.2000.3S.02

Dynarski, S. (2004). The new merit aid. In C. M. Hoxby (Ed.), *College choices: The economics of where to go, when to go, and how to pay for it*. University of Chicago Press.

Dynarski, S., & Scott-Clayton, J. (2013). Financial aid policy: Lessons from research. *Future Child*, *23*(1), 67–91. https://doi.org/10.1353/foc.2013.0002

Flores, S. M. (2010). State DREAM acts: The effect of in-state resident tuition policies and undocumented Latino students. *Review of Higher Education*, *33*(2), 239–283. https://doi.org/10.1353/rhe.0.0134

Flores, S. M., & Park, T. J. (2015). The effect of enrolling in a minority-serving institution for Black and Hispanic students in Texas. *Research in Higher Education*, *56*(3), 247–278. https://doi.org/10.1007/s11162-014-9342-y

Frisvold, D. E., & Pitts, M. (2018). *State merit aid programs and youth labor market attachment*. (Working Paper No. W24662). National Bureau of Economic Research.

Graf, N., Fry, R., & Funk, C. (2018). *7 facts about the STEM workforce*. Fact Tank. http://www.pewresearch.org/fact-tank/2018/01/09/7-facts-about-the-stem-workforce/

Griffith, A. L. (2011). Keeping up with the Joneses: Institutional changes following the adoption of a merit aid policy. *Economics of Education Review*, *30*(5), 1022–1033. https://doi.org/10.1016/j.econedurev.2011.05.003

Gross, J. P., Hossler, D., Ziskin, M., & Berry, M. S. (2015). Institutional merit-based aid and student departure: A longitudinal analysis. *The Review of Higher Education*, *38*(2), 221–250. https://doi.org/10.1353/rhe.2015.0002

Guo, S., Fraser, M., & Chen, Q. (2020). Propensity score analysis: Recent debate and discussion. *Journal of the Society for Social Work and Research*, *11*(3), 463–482. https://doi.org/10.1086/711393

Guo, S., & Fraser, M. W. (2014). *Propensity score analysis: Statistical methods and applications* (2nd ed.). Sage.

Gurantz, O., & Odle, T. K. (2022). The impact of merit aid on college choice and degree attainment: Reexamining Florida's Bright Futures program. *Educational Evaluation and Policy Analysis*, *44*(1), 79–104. https://doi.org/10.3102/01623737211030489

Gustafsson, J.-E. (2013). Causal inference in educational effectiveness research: A comparison of three methods to investigate effects of homework on student achievement. *School Effectiveness and School Improvement*, *24*(3), 275–295. https://doi.org/10.1080/09243453.2013.806334

Heckman, J., Ichimura, H., Smith, J., & Todd, P. (1998). Characterizing selection bias using experimental data. *Econometrica*, *66*(5), 1017–1098. https://doi.org/10.2307/2999630

Heller, D. E. (2004). State merit scholarship programs: An overview. In D. E. Heller & P. Marin (Eds.), *State merit scholarship program and racial inequality* (pp. 13–22). The Civil Rights Project at Harvard University.

Heller, D. E. (2006). Merit aid and college access. In *Symposium on the consequences of merit-based student aid*. University of Wisconsin-Madison, Madison.

Heller, D. E., & Marin, P. (2002). *Who should we help? The negative social consequences of merit scholarships*. The Civil Rights Project at Harvard Univesity.

Heller, D. E., & Marin, P. (2004). *State merit scholarship program and racial inequality*. The Civil Rights Project at Harvard Univesity.

Henry, G. T., Rubenstein, R., & Bugler, D. T. (2004). Is hope enough? Impacts of receiving and losing merit-based financial aid. *Educational Policy*, *18*(5), 686–709. https://doi.org/10.1177/0895904804269098

Hoxby, C. M., & Turner, S. (2013, June). *Informing students about their college options: A proposal* *for broadening the expanding college opportunities project* (Discussion Paper 2013-03). The Hamilton Project.

Hoxby, C. M., & Turner, S. (2015). What high-achieving low-income students know about college. *American Economic Review*, *105*(5), 514–517. https://doi.org/10.1257/aer.p20151027

Hu, A., & Wu, X. (2019). Science or liberal arts? Cultural capital and college major choice in China. *The British Journal of Sociology*, *70*(1), 190–213. https://doi.org/10.1111/1468-4446.12342

Hu, S. (2008). *Merit-based aid and student enrollment in baccalaureate degree programs in science and engineering: An examination of Florida's Bright Futures program*. The Annual Forum of the Association for Institutional Research.

Hu, S., Trengove, M., & Zhang, L. (2012). Toward a greater understanding of the effects of state merit aid programs: Examining existing evidence and exploring future research direction. In J. C. Smart & M. B. Paulsen (Eds.), *Higher education: Handbook of theory and research* (*Vol. 27*, pp. 291–334). Springer Netherlands. https://doi.org/10.1007/978-94-007-2950-6_6

Ingle, W. K., & Ratliff, J. R. (2015). Then and now: An analysis of broad-based merit aid initial eligibility policies after twenty years. *Kentucky Journal of Higher Education Policy and Practice*, *3*(2), 3.

Johnson, I. (2022). Merit aid and retention: Mediation and moderation. *Research in Higher Education*, *63*(4), 713–739. https://doi.org/10.1007/s11162-021-09661-9

Kennedy, B., Hefferon, M., & Funk, C. (2018). *Half of Americans think young people don't pursue STEM because it is too hard*. Fact Tank. http://www.pewresearch.org/fact-tank/2018/01/17/half-of-americans-think-young-people-dont-pursue-stem-because-it-is-too-hard/

Leeds, D. M., & DesJardins, S. L. (2015). The effect of merit aid on enrollment: A regression discontinuity analysis of Iowa's National Scholars Award. *Research in Higher Education*, *56*(5), 471–495. https://doi.org/10.1007/s11162-014-9359-2

Li, M. (2012). Using the propensity score method to estimate causal effects: A review and practical guide. *Organizational Research Methods*, *16*(2), 188–226. https://doi.org/10.1177/1094428112447816

Lindemann, D., Britton, D., & Zundl, E. (2016). "I don't know why they make it so hard here": Institutional factors and undergraduate women's STEM participation. *International Journal of Gender, Science and Technology*, *8*(2), 221–241. https://genderandset.open.ac.uk/index.php/genderandset/article/view/435

Long, B. T. (2004). How do financial aid policies affect colleges?: The institutional impact of the Georgia HOPE scholarship. *Journal of Human Resources*, *39*(4), 1045–1066. https://doi.org/10.2307/3559038

Malgwi, C. A., Howe, M. A., & Burnaby, P. A. (2005). Influences on students' choice of college major. *Journal of Education for Business*, *80*(5), 275–282. https://doi.org/10.3200/JOEB.80.5.275-282

Marx, R. W., & Harris, C. J. (2006). No Child Left Behind and science education: Opportunities, challenges, and risks. *The Elementary School Journal*, *106*(5), 467–478. https://doi.org/10.1086/505441

McPherson, M. S., & Schapiro, M. O. (1998). *The stduent aid game: Meeting need and rewarding talent in American higher education*. Princeton University Press.

Melguizo, T., & Wolniak, G. C. (2012). The earnings benefits of majoring in STEM fields among high achieving minority students. *Research in Higher Education*, *53*(4), 383–405. https://doi.org/10.1007/s11162-011-9238-z

Moakler, M. W., & Kim, M. M. (2014). College major choice in STEM: Revisiting confidence and demographic factors. *Career Development Quarterly*, *62*(2), 128–142. https://doi.org/10.1002/j.2161-0045.2014.00075.x

Morgan, P. L., Frisco, M., Farkas, G., & Hibel, J. (2010). A propensity score matching analysis of the effects of special education services. *The Journal of Special Education*, *43*(4), 236–254. https://doi.org/10.1177/0022466908323007

Ness, E. C., & Lips, A. J. (2011). Marketing merit aid: The response of flagship campuses to state merit aid programs. *Journal of Student Financial Aid*, *41*(1), 4–17. https://doi.org/10.55504/0884-9153.1015

Ness, E. C., & Noland, B. E. (2007). Targeted merit aid: Implications of the Tennessee education lottery scholarship program. *Journal of Student Financial Aid*, *37*(1), 7–17. https://doi.org/10.55504/0884-9153.1074

Niu, L. (2017). Family socioeconomic status and choice of STEM major in college: An analysis of a national sample. *College Student Journal*, *51*(2), 298–312.

Olitsky, N. H. (2014). How do academic achievement and gender affect the earnings of stem majors? A propensity score matching approach. *Research in Higher Education*, *55*(3), 245–271. https://doi.org/10.1007/s11162-013-9310-y

Orsuwan, M., & Heck, R. H. (2009). Merit-based student aid and freshman interstate college migration: Testing a dynamic model of policy change. *Research in Higher Education*, *50*(1), 24–51. https://doi.org/10.1007/s11162-008-9108-5

Park, T. J. (2015). The impact of full-time enrollment in the first semester on community college transfer rates: New evidence from texas with pre-college determinants. *Teachers College Record*, *117*(12), 1–34. https://doi.org/10.1177/016146811511701207

Perez-Felkner, L., McDonald, S.-K., Schneider, B., & Grogan, E. (2012). Female and male adolescents' subjective orientations to mathematics and the influence of those orientations on postsecondary majors. *Developmental Psychology*, *48*(6), 1658–1673. https://doi.org/10.1037/a0027020

Perez-Felkner, L., Nix, S., & Thomas, K. (2017). Gendered pathways: How mathematics ability beliefs shape secondary and postsecondary course and degree field choices. *Frontiers in Psychology*, *8*, 386. https://doi.org/10.3389/fpsyg.2017.00386

Plasman, J. S., Gottfried, M. A., & Klasik, D. J. (2021). Do career-engaging courses engage low-income students?. *AERA Open*, *7*(1), 1–17. https://doi.org/10.1177/23328584211053324

Quadlin, N. (2017). Funding sources, family income, and fields of study in college. *Social Forces*, *96*(1), 91–120. https://doi.org/10.1093/sf/sox042

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55. https://doi.org/10.1093/biomet/70.1.41

Sjoquist, D. L., & Winters, J. V. (2015a). State merit-based financial aid programs and college attainment. *Journal of Regional Science*, *55*(3), 364–390. https://doi.org/10.1111/jors.12161

Sjoquist, D. L., & Winters, J. V. (2015b). State merit aid programs and college major: A focus on stem. *Journal of Labor Economics*, *33*(4), 973–1006. https://doi.org/10.1086/681108

Smith, J. A., & Todd, P. E. (2001). Reconciling conflicting evidence on the performance of propensity-score matching methods. *American Economic Review*, *91*(2), 112–118. https://doi.org/10.1257/aer.91.2.112

Somers, P. (1995). A comprehensive model for examining the impact of financial aid on enrollment and persistence. *Journal of Student Financial Aid*, *25*(1), 13–27. https://doi.org/10.55504/0884-9153.1133

Sovansophal, K. (2020). Family socioeconomic status and students' choice of STEM majors: Evidence from higher education of Cambodia. *International Journal of Comparative Education and Development*, *22*(1), 49–65. https://doi.org/10.1108/IJCED-03-2019-0025

St. John, E. P., & Asker, E. H. (2003). *Refinancing the college dream: Access, equal opportunity, and justice for taxpayers*. JHU Press.

U.S. News. (2022). *Most students receiving merit aid*. U.S. News and World Report. https://www.usnews.com/best-colleges/rankings/most-merit-aid

Wang, X. (2013). Why students choose STEM majors: Motivation, high school learning, and postsecondary context of support. *American Educational Research Journal*, *50*(5), 1081–1121. https://doi.org/10.3102/0002831213488622

Whatley, M. (2019). Study abroad participation: An unintended consequence of state merit-aid programs? *Research in Higher Education*, *60*(7), 905–930. https://doi.org/10.1007/s11162-018-09540-w

Zhang, L. (2011). Does merit-based aid affect degree production in STEM fields? Evidence from Georgia and Florida. *The Journal of Higher Education*, *82*(4), 389–415. https://doi.org/10.1080/00221546.2011.11777210

Zhang, L., Hu, S., & Sensenig, V. (2013). The effect of Florida's bright futures program on college enrollment and degree production: An aggregated-level analysis. *Research in Higher Education*, *54*(7), 746–764. https://doi.org/10.1007/s11162-013-9293-8

Zhang, L., & Ness, E. C. (2010). Does state merit-based aid STEM brain drain? *Educational Evaluation and Policy Analysis*, *32*(2), 143–165. https://doi.org/10.3102/0162373709359683

Zhao, T., & Perez-Felkner, L. (2022). Perceived abilities or academic interests? Longitudinal high school science and mathematics effects on postsecondary STEM outcomes by gender and race. *International Journal of STEM Education*, *9*, 42. https://doi.org/10.1186/s40594-022-00356-w

TENG ZHAO, PhD, is an associate professor of higher education and public policy at Hangzhou Dianzi University. His research focuses on using data-driven approaches to examine issues related to student success and educational policy.

LARA PEREZ-FELKNER, PhD, is a professor of higher education and sociology at Florida State University. Her research focuses on the mechanisms that shape gender, racial/ethnic, and socioeconomic disparities in postsecondary pathways to educational attainment and scientific careers.

SHOUPING HU, PhD, is the Louis W. and Elizabeth N. Bender Endowed Professor of Higher Education at Florida State University. His research interests examine issues related to postsecondary readiness, outcomes, and success.

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