NBER WORKING PAPER SERIES

THE ECONOMICS OF ENCOURAGEMENT: CAN A SIMPLE EMAIL SHAPE MAJOR CHOICE?

Olivia Edwards
Jonathan Meer

Working Paper 33676
http://www.nber.org/papers/w33676

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
April 2025

We are grateful for support from Kurt Felpel, Steve Wiggins, and the Texas A\&M University Office of the Registrar. We benefited from comments from Danila Serra and seminar participants at the University of Michigan and Drexel University. We obtained approval from Texas A\&M University's Institutional Review Board for the retrospective analysis of student data used in this study. (IRB: 2024-0645) The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

The Economics of Encouragement: Can A Simple Email Shape Major Choice?
Olivia Edwards and Jonathan Meer
NBER Working Paper No. 33676
April 2025
JEL No. I21, I24

ABSTRACT

We examine the impact of encouragement emails sent to high-performing students in a principles of microeconomics course at a large state university, aimed at motivating them to take additional economics courses and consider an economics major or minor. Using a regression discontinuity design, we find some evidence of an increase in the likelihood of enrolling in intermediate microeconomics, especially for first-generation college students and underrepresented minorities, but limited effects on major switching or declaring an economics minor. Our findings suggest sustained interventions may be necessary to produce lasting effects

Olivia Edwards
Texas A&M University
olivia.edwards@tamu.edu

Jonathan Meer
Texas A&M University
Department of Economics
TAMU 4228
College Station, TX 77843
and NBER
jmeer@econmail.tamu.edu

1 Introduction

A student's college major choice directly impacts their future earning potential and career opportunities (Altonji et al., 2016; Altonji and Zimmerman, 2018; Andrews et al., 2022; Arcidiacono, 2004; Hastings et al., 2013; Kirkebøen et al., 2016). But incoming students are often unaware of their options and the outcomes thereof (Buckles, 2019; Patnaik et al., 2020). And when perceptions of a field of study differ by race or gender, significant disparities in representation can emerge. In economics, women and minorities are underrepresented relative to their share of college students, with these gaps persisting over long periods (Bayer and Rouse, 2016; Lundberg and Stearns, 2019). Recent initiatives targeting college students to increase diversity in the field have had mixed results (Allgood et al., 2015; Avilova and Goldin, 2018; Bayer et al., 2019; Chambers et al., 2021; Li, 2018; Porter and Serra, 2020; Pugatch and Schroeder, 2021).

We examine the effect of a light-touch intervention in a large, asynchronous principles of microeconomics course at Texas A&M University (TAMU) taught by the same two professors between 2017 and 2021 and then solely by one of those professors thereafter. Several days after final grades were posted in each semester, students who had performed well in the course – generally around the top ten percent – received an email from the professor praising their performance and encouraging them to take more economics courses and considering majoring or minoring in economics if they were not already doing so. Anecdotally, many students respond positively to this email. But the size of the class – with over 10,000 students in the sample – the consistent delivery of similar material by the same faculty, and the nature of the cutoff allows for a more rigorous analysis using a regression discontinuity design.

Beliefs about one's own ability relative to others in the field can influence this choice, and providing students with information about their relative ability helps them update their beliefs and make more informed decisions (Wiswall and Zafar, 2015). Risk aversion and preferences for competition also play a role, with research suggesting that gender differences in these attributes can explain part of the gender gap in major choice (Buser et al., 2014; Patnaik et al., 2020; Flory et al., 2015).

Those with whom students interact can also influence these choices. College counselors have a substantial impact on students' decisions regarding their majors and overall educational paths (Barr and Castleman, 2021; Canaan et al., 2022; Castleman et al., 2024). High school counselors also play a role in a student's major choice, particularly in settings where a student must declare a major before enrolling (Gentry et al., 2023).

The impact of professors on students' academic decisions is less clear. Some studies suggest that professors can positively influence students' engagement and retention in their chosen fields, but the evidence is mixed (Carrell and Kurlaender, 2023). This suggests that while professors can be important motivators, their influence may vary depending on the context and the specific student population.

We find limited impact of our intervention on the full sample of students. There is suggestive evidence of an increase in the likelihood of taking intermediate microeconomics, but little effect on majoring or minoring in economics – outcomes which involve a significantly larger change in the student's plans. The relatively low baseline rates and noisiness of these latter outcomes leaves us underpowered to detect reasonably-sized effects, though the results are generally noisy and few meaningful patterns emerge.

In addition, we use demographic data from the Office of the Registrar to examine heterogeneity by gender, minority status, and being a first-generation college student.[1] There is evidence that first-generation and underrepresented students are more likely to take interme-

[1] Stansbury and Schultz (2023) show that economics is the least socioeconomically diverse academic discipline among Ph.D. recipients. The gap is dramatic among undergraduates as well, with 42 percent of all US-born bachelors recipients having a parent who does not have a bachelors degree, as compared to just 21 percent among US-born economics bachelors recipients.

diate microeconomics in response to the encouragement email. There are no meaningful differences by gender, nor by whether students performed relatively better on the synchronous, in-person exams, conditional on earning the same score in the class.

Ideally, a successful intervention will be low-cost but high-impact with persistent effects. Light-touch interventions have varied in effectiveness when influencing college students' academic outcomes. Some studies found that these approaches did not significantly impact students' academic performance or engagement (Oreopoulos and Petronijevic, 2019, 2023). However, other research has demonstrated that well-designed, minimal interventions can positively influence students' academic decisions and successes (Bedard et al., 2021; Gomez-Vasquez and Serra, 2025; Porter and Serra, 2020). Further, the effectiveness of similar programs can vary significantly across institutions. For instance, Andrews et al. (2016) found that programs aimed at recruiting and enrolling high-ability, low-income students had substantial effects at the University of Texas but none at Texas A&M University. This suggests that institutional context is a critical factor in the success of such interventions. These findings suggest that the effectiveness of light-touch interventions depends on their design and implementation, emphasizing the need for consideration of the specific student population when developing such strategies.

This is a very large online course, and the results may very well differ from those even for similar treatments in smaller or in-person classes. While students are more likely to be physically present in a room for an in-person class, it is difficult to argue that a large lecture hall provides a more interactive or personalized experience. The increased prevalence of online courses also suggests the need for more experimentation on what works in these environments. Much of the previous literature relies on similar email-based approaches (Li, 2018; Bayer et al., 2019; Pugatch and Schroeder, 2021; Bedard et al., 2021; Carrell and Kurlaender, 2023; Gomez-Vasquez and Serra, 2025), though it is unclear whether an additional email from the professor has more or less value in this context.[2]

The focus on high-achieving students is consonant with previous literature suggesting that these students are more responsive to interventions (Li, 2018; Porter and Serra, 2020). Further, TAMU does not issue plus or minus letter grades, meaning that students' sense of their place in the score distribution is more limited than at many other institutions. This intervention, therefore, provides more information about a student's performance, even among those who earned an A in the course.[3]

Building on the existing literature that explores the influence of information, mentorship, and institutional interventions on students' academic choices, this paper contributes to the understanding of how targeted encouragement can shape educational trajectories within higher education. By leveraging a large-scale experiment within a consistent academic environment, we are able to rigorously assess the causal impact of a light-touch intervention on students' decisions to pursue further studies in economics. The following sections provide a detailed overview of the institutional context, describe the data and methodology employed, and present the empirical results.

2 Institutional Details

Texas A&M University (TAMU) is a land-grant institution with an incoming first-year first-time-in-college cohort size of about 12,500 in 2023; about 200 to 250 of these are economics majors. Students rank two majors at the application stage; admitted students are

[2] The online setting potentially mitigates other influences on major choice. Students are less aware of the gender composition of their peers or their overall quality, with some prior findings suggesting that female students are more likely to be affected by these factors (Fischer, 2017; Ost, 2010).

[3] Owen (2023) finds that students are unclear about their relative performance, with women being less confident. Owen (2021) finds that higher grades generated by a shift in the grade distribution policy in introductory economics led students with the same underlying performance to take more economics courses, but there was no evidence that women were more responsive. However, Avilova and Goldin (2018) find that female students are more sensitive to their grades in introductory economics than male students.

accepted into one of these two choices depending on availability.[4] Nevertheless, there are a significant number of students who change their majors, with about 14 percent of the students in our sample doing so.[5]

The Principles of Economics (Micro) course at TAMU, henceforth "Principles," is a core curriculum class required for a number of majors, including those in the business school and agricultural economics, making it one of the largest classes on campus. Less than 10 percent of the students who take the course are economics majors.[6]

Following two semesters of pilot courses in the 2016-17 academic year, Principles has been delivered asynchronously online to all students in the fall and spring semesters in every semester beginning in the fall of 2017.[7] There is a live event at the beginning of the semester and numerous opportunities to interact with the professor(s) and teaching assistants. While improvements have been made to the course since its inception, the general structure of the class has remained the fairly consistent.

The course was co-taught by two tenured faculty members until Fall 2021. They alternated being listed as the instructor of record, but the course content was identical irrespective of which of them was listed and both professors participated in the start-of-semester live event. Following the retirement of one of these instructors at the end of the 2020-21 academic

[4]Students admitted to the College of Engineering and the Mays Business School select a field of study after their first or second year.

[5]TAMU does have barriers to switching majors, including a credit-hour threshold. Students must fulfill some prerequisites for certain majors, including economics, before having their change-of-major approved. However, these requirements are generally not onerous, particularly for high-performing students. For example, economics requires an overall GPA of 2.75 and grades of C or better in Principles and two core math courses.

[6]Among the 929 students in the sample who began the course as economics majors, 294 switch out, with 169 going to the business school; no other program receives more than 10 students. 226 students who took the class as non-majors switch into economics, with 47 originally enrolling at TAMU as engineering majors, 15 from mathematics or applied mathematics, 13 from political science, 12 from biomedical sciences, and 8 from the business school. Many economics majors are transfer students from other institutions who have already taken this course prior to entry.

[7]About 30 to 40 students take the course in the summer, generally taught in-person by a Ph.D. student, and a single in-person section for honors students is offered in the fall to a maximum of 25 students. These sections are not included this study.

year, the other instructor has taught the class in the fall and spring semesters.[8] Table 1 summarizes the characteristics of the student sample, including the distribution of majors, treatment status, and outcomes of interest.[9]

Most of the students in the course are in their first year at TAMU, though some are classified as second-year students due to advanced placement and dual-credit enrollment in high school. Students transferring from other institutions into the economics major (about 120 in fall 2021) are required to have already completed the equivalent of this course.

2.1 Encouragement Email

Beginning in the fall 2017 semester (the first semester of full implementation of the course), one instructor sent emails to high-performing students in the course shortly after final grades had been posted. Students were not aware of the cutoff for an A grade, though the instructor did inform the entire class of the grade distribution; about 25 to 30 percent of the class earns an A in each semester. Students were not aware of their relative rank in the class beyond their letter grade.

After filtering out students classified as third-year or above, the instructor emailed roughly the top ten percent of the remaining students.[10] That is, these students were in the top one-half to one-third of the A-grade distribution in the course. The email praised the student's performance, specifically referred to them as being among the top performers in the class, noted that they had an aptitude for the material, and encouraged them to consider taking further economics courses and become (or stay) an economics major or minor. Students were also encouraged to follow up with the professor, and the email included links to contact the

[8]The now-sole instructor refilmed the retired instructor's content, in addition to making other updates to the course.

[9]In Fall 2022, the College of Liberal Arts underwent a merger with the College of Sciences and the College of Geosciences to become the College of Arts and Sciences. We use the legacy classifications of majors in this paper.

[10]This mass email blind-copied the students and was not personalized.

Table 1: Summary Statistics

	Mean	Standard Deviation	N
Treatment			
Treated	0.17	0.376	10600
Control	0.83	0.376	-
Outcomes			
Majors in Econ	0.081	0.273	10600
Declares Econ Minor	0.055	0.228	3247
Takes Intermediate Micro	0.217	0.412	10600
Final Major Earnings	42041.23	11264.88	10600
Academic Characteristics			
Transitional Major during Course	0.121	0.326	10600
Business Major during Course	0.507	0.5	10600
Liberal Arts Major during Course	0.15	0.357	10600
Engineering Major during Course	0.073	0.261	10600
Econ Major during Course	0.088	0.283	10600
Cutoff-Standardized Course Score	-0.92	0.98	10600
Numeric Final Grade	81.77	10.82	10600
Major during Course Earnings	38633.46	9376.82	10600
Observable Characteristics			
Age at Enrollment	18.01	0.66	10600
Female	0.409	0.492	10600
URM	0.261	0.439	10600
First Generation	0.162	0.368	10440

Notes: Summary statistics are based on data from 10,600 students enrolled in Principles of Economics at TAMU. Treated indicates students who received an encouragement email; Control includes those who did not. The Cutoff-Standardized Course Score is normalized around the semester-specific cutoff for receiving the email. Outcome variables reflect the proportion of all students who achieved each respective outcome. Final Major Earnings is based on the higher earning major if a student double-majored. URM combines Hispanic, Black, Native American, and Mixed-Race students.

department's academic advisors, who help students with change-of-major requests.[11]

[11] The language of the email has remained nearly identical in each semester. It also included PDF copies of career and major information from the Department of Economics. In later semesters, it also included a link to a video created by the instructor for prospective applicants to TAMU considering economics as a major.

The instructor did not survey or track any of these students, excepting informal conversations by email, Zoom, or in person with students who responded. The intention behind the emails was purely to offer encouragement, with no systematic follow-up or data collection. Over time, anecdotal evidence from these interactions suggested that the emails may have had a meaningful impact on students' academic decisions. No analysis of the outcomes for these students was conducted until this research project.

3 Data & Methods

3.1 Data

The data are all internal to TAMU. We begin with the Principles class rosters and students' scores from fall 2017 to spring 2023.[12] These are merged with rosters from Intermediate Microeconomics and data from the Office of the Registrar on students' majors, minors, and demographic information. We also merge in data from the Hamilton Project on earnings by major in 2024 dollars (The Hamilton Project, 2024).

We match the list of recipients from each semester to the grades in that semester's roster. The informal nature with which the email lists were compiled means that the cutoff is not sharp. We find the cutoff by searching for the point at which four or more students in a row do not receive an email to account for this imprecision. We then re-normalize scores within a semester around this cutoff. We refer to this as a cutoff-standardized course score (CSCS), which is generally about one standard deviation above the mean.[13]

[12]We exclude three semesters of Principles from this analysis. In fall 2017 and fall 2018, the instructor appears to have sent the email significantly further down the score distribution for certain majors, resulting in a much less clear discontinuity; it is estimated at 0.21 in those semesters, as compared to 0.92 in the other semesters. We also exclude spring 2020 to avoid confounding issues from the initial stages of the COVID-19 pandemic, during which instruction was disrupted and grade distributions shifted significantly. We include the rosters from advanced classes in that semesters to examine subsequent course-taking. The conclusions are unchanged when these semesters are included.

[13]This corresponds to a score of about 91 to 93 percent in the class, depending on the semester. The threshold for an A grade varied between 86 and 89.5 percent. The cutoff for receiving an email was roughly 4 percentage points above that level.

A separate email was sent to a small group of students who were below the cutoff but still within the top quartile of performers. These students were either enrolled in General Studies, indicating they were transitioning between majors, or in one of TAMU's Transition Academic Programs, which involves co-enrollment with a local community college with the intention of transferring to TAMU. Of the 285 students who were treated despite being below the cutoff, 283 fell into this category. They also made up 177 of the 178 students who earned a B in the course but received an encouragement email. Students in these programs who earned scores above the cutoff were treated identically to any other major. These observations are all kept in the sample.[14]

For students who took the class multiple times, we take their first attempt in the class. We exclude students who drop or withdraw from the class, since we cannot observe their final numeric grade and they were not eligible to be treated. These restrictions leave us with 15,708 students. We drop 5,108 students classified as third-year and above or as a non-degree-seeking student.[15] After dropping the fall 2017 and fall 2018 semesters, during which many students in certain majors received emails despite being well below the cutoff, and the spring 2020 semester (COVID-19 pandemic), we are left with 10,600 students, of whom 1,802 received an encouragement email.[16] Figure 1 shows the distribution of scores, truncated at 4 standard deviations below the cutoff.

We examine whether a student takes Intermediate Microeconomics in a later semester, majors in economics, or minors in economics.[17] We also use data from the Hamilton Project

[14]The results are qualitatively unchanged when these students are excluded from the sample.

[15]107 of these (2.1 percent) were treated unintentionally, but they are likely unable to change their academic tracks given the credit-hour cap rule.

[16]34 students were above the cutoff but did not receive an email; these were likely missed in error.

[17]Because they are not recorded in the data until completed, students' minors tend to be registered in the data close to their time of graduation. As such, the prevalence of minors falls to nearly zero with the fall 2021 entering cohort. We use only the earlier cohorts, a total of 3,404 students, for those results. We further remove those who majored in economics (since you cannot both major and minor in the same subject) for a total of 3,247. Of the 178 students who minor in economics, 98 are in the business school, 37 are agricultural economics or agricultural business majors, and 18 are applied mathematics majors.

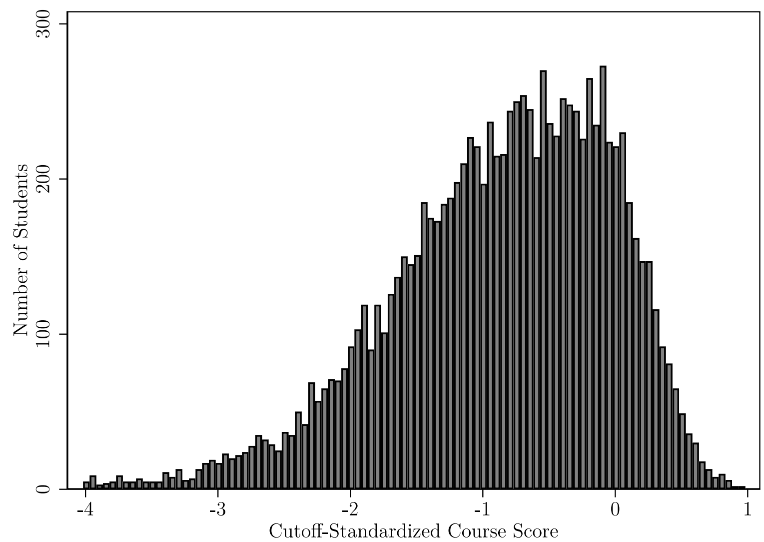

Figure 1: This figure plots the distribution of students' scores across the semester-specific cutoff.

to examine whether students major in a more well-paying major, as well as examining any change-of-major, majoring in an economics-adjacent field, and results by demographic characteristics.

3.2 Empirical Strategy

The imprecision of the selection of students to email, as well as the additional emails sent to students in transitional academic programs below the cutoff leads to fuzziness in the cutoff. But students are unaware both of their relative ranking in the class and this cutoff. This generates a natural experiment that allows use to estimate the causal effects of receiving an encouragement email.

The reduced-form model is expressed as follows:

$$Y_i = \alpha_0 + \alpha_1 \mathbf{1}(\text{Cutoff}) + \alpha_2 \text{CSCS} + \delta_t + \epsilon_i$$

where Y_i is the outcome, $\mathbf{1}(\text{Cutoff})$ is an indicator for being above the cutoff and CSCS is the running variable, in standard deviations relative to the the cutoff. δ_t represents semester fixed effects. Standard errors are clustered at the cohort level to account for correlation among students within the same semester (Eren et al., 2022; Kolesár and Rothe, 2018).[18]

In addition, we report local average treatment effects using the running variable CSCS as an instrument for the treatment variable Gets Email. The IV estimation is conducted using the same bandwidths and kernels as the reduced form analysis. This approach allows us to estimate the local average treatment effect (LATE) for those students whose treatment status was influenced by their score relative to the cutoff. The results from the IV estimation are presented alongside the reduced form results, however, our discussion emphasizes the reduced form estimates.

Non-random sorting around the cutoff is a potential threat that could challenge the design. However, the likelihood of sorting by the students is minimal since students are unaware of the existence of this cutoff and their relative rank in the class. Further, the cutoff does not fall near the letter-grade cutoffs where we might expect some student manipulation. The instructor's decision of whether to stop collecting email addresses is not random, of course, but the distribution of CSCS near the cutoff in Figure 1 shows a smooth progression without any signs of heaping that would constitute evidence of sorting (Barreca et al., 2016; McCrary, 2008).

Figure 2 shows the results of more advanced manipulation testing using local polynomial density estimation (Cattaneo et al., 2022, 2018). There is no apparent manipulation around the cutoff. The aforementioned institutional factors—such as students' unawareness of the email and the cutoff's distance from the "A" letter grade cutoff support the interpretation

[18] We use the rdrobust suite of commands (Calonico et al., 2017), and select the bandwidth that minimizes the mean squared error (MSE) using a uniform kernel. The statistical significance of the results is not affected if the standard errors are not clustered.

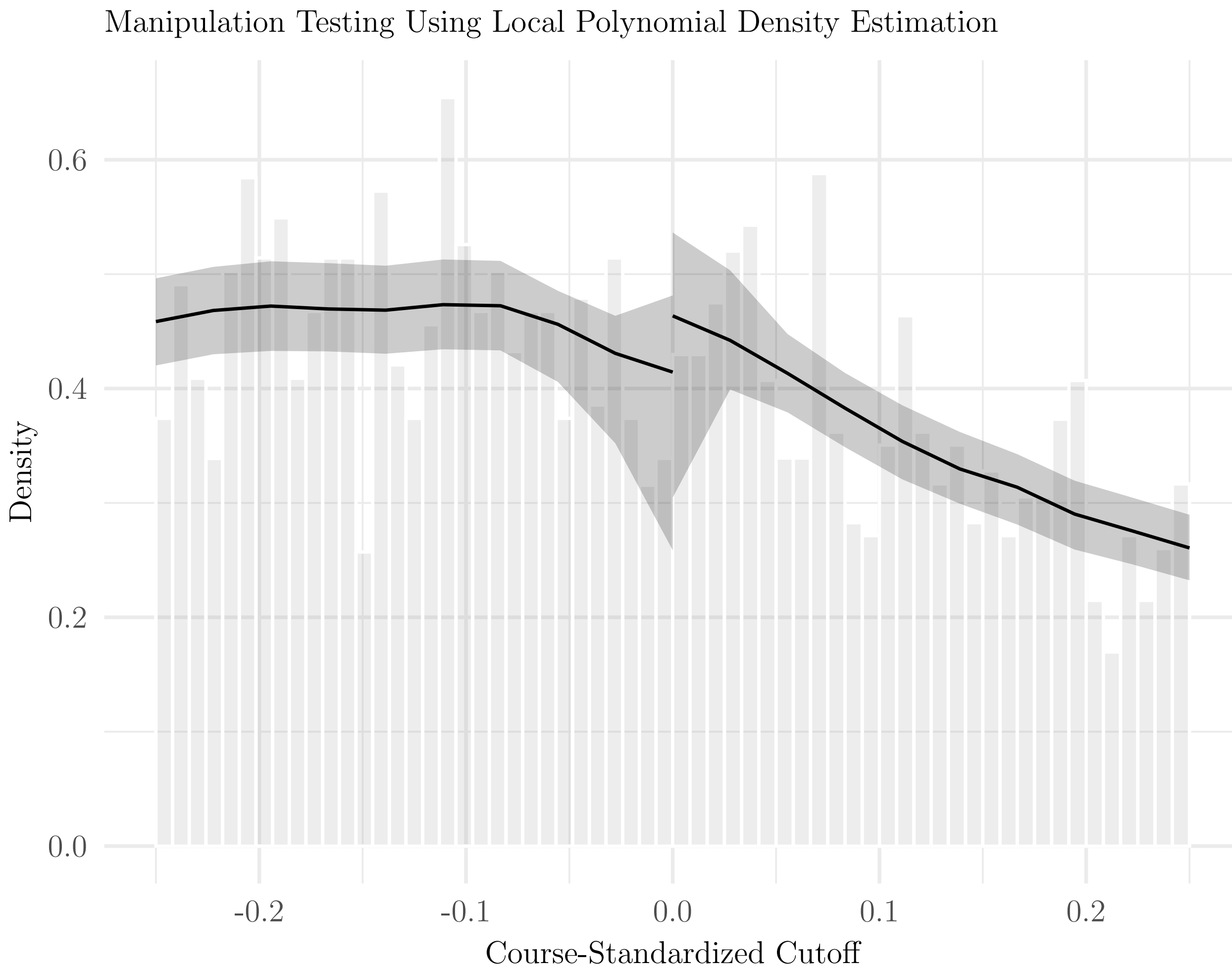

Figure 2: The density plot illustrates the results of manipulation testing using local polynomial density estimation (Cattaneo et al., 2022) using the rddensity (Cattaneo et al., 2023) command. The plot examines the distribution of the running variable around the cutoff using an unrestricted uniform kernel and an MSE-optimal bandwidth. No apparent manipulation is observed within around the cutoff.

that the cutoff is likely not manipulated on the students' end. The balance test in Table 2 provides evidence that the professor did not manipulate the distribution around the cutoff, as no one subgroup of students is more likely to appear on one side of the cutoff than the another.

While our entire sample has more than 10,000 observations, regression discontinuity designs rely entirely on observations close to the cutoff. Figure 3 shows the minimum detectable

Table 2: Regression Discontinuity Balance Test

Observable	**Estimate**	**(SE)**	**N**
White	0.04	(0.04)	3817
URM	-0.02	(0.02)	3817
Female	-0.01	(0.02)	3817
Age	0.01	(0.03)	3817
First Generation	0.03	(0.03)	3753
Numeric Final Grade	0.15	(0.63)	3817
Synchronous Assignment Performance Measure	0.01	(0.14)	2521
Earnings for Major during Course	-547.12	(506.72)	3817
Liberal Arts Major during Course	0.03	(0.03)	3817
Economics Major during Course	0.02	(0.03)	3817
Business Major during Course	-0.02	(0.08)	3817
Engineering Major during Course	-0.01	(0.02)	3817
Transitional Major during Course	0.02	(0.04)	3817

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: This table presents regression discontinuity estimates of the likelihood of each covariate. Reduced form estimates are reported with standard errors clustered at the semester level in parentheses. The third column shows the effective number of observations used in estimation. These counts vary due to missing data from a student failing to report the characteristic or missing exam grades in certain semesters (using in the construction of the synchronous performance measure). The analysis uses a symmetric bandwidth, fixed at half a standard deviation, and a uniform kernel.

effects (MDE) for our outcomes, calculated using the number of observations within the mean-square-error-optimal bandwidths for each outcome.[19] Earnings is excluded from the graph because the outcome unit (dollars) differs significantly from the binary outcomes, but its MDE is $1,373 at 80% power. In absolute terms, we are powered to detect effects of a few percentage points, but the low baseline levels of majoring and minoring mean that these are large relative impacts. Intermediate Micro and Earnings are the only ones for which we have reasonably-sized relatively MDEs, meaning we can detect meaningful differences relative to the baseline rates of these outcomes (25.5% and 3.5% of the sample mean respectively). While we will present the full set of results, we can only make more firm conclusions about these two outcomes. Compared to earlier studies of similar encouragement interventions, we are equally- or better-powered to detect effects for Intermediate Micro and Earnings.

Figure 4 shows the likelihood of treatment around the semester-specific cutoff. The discontinuity is large, with a point estimate of 0.92 (s.e. = 0.033) using an MSE-optimal bandwidth and a uniform kernel, including semester fixed effects and clustering at the semester level. With a large effect on the likelihood of treatment at the cutoff identified, we turn to the results on later academic outcomes.

4 Results

4.1 Full Sample

We begin by examining the likelihood that students take Intermediate Microeconomics; about 21.7 percent of the students who take Principles go on to this course. Figure 5 and the second row of Table 3 show a relatively large and statistically significant discontinuity of 8.8 percentage points (s.e. = 3.3 percentage points), an increase of about 40 percent over the baseline level below the cutoff. Since the treatment cutoff is very nearly sharp,

[19] The MDE represents the smallest treatment effect that can be reliably detected with statistical power, given the sample size and variability of the data.

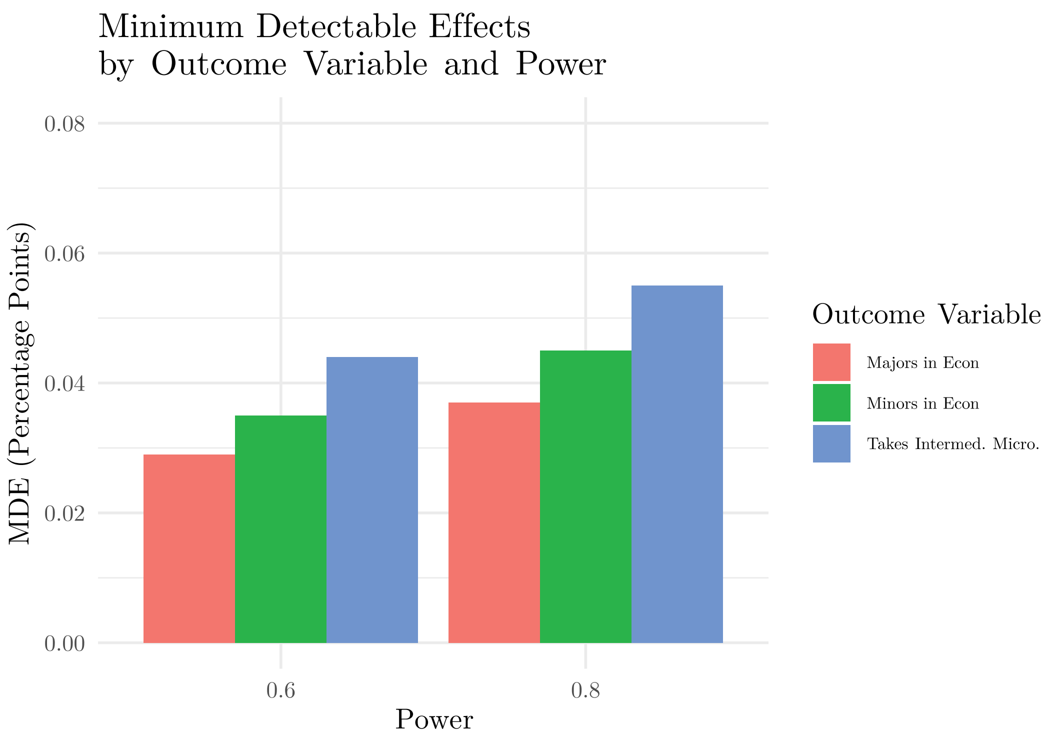

Figure 3: This figure presents minimum detectable effects at various rates of power calculated using the number of observations within the MSE-optimal estimated bandwidth for each outcome. The MDEs (in percentage points) reflect the smallest treatment effect that can be reliably detected at that probability, given the sample size and variability of the data in the bandwidth.

the IV estimate is not much larger, with an estimated local average treatment effect of 9.4 percentage points (s.e. = 3.5 pp).

The figure suggests that these results are driven by the increased takeup just above the cutoff. It is not unreasonable to hypothesize that those students are the most responsive to encouragement email, given that they may be less confident in their performance than students who scored higher. But it is evident that the rate of course-taking drops for those whose scores are slightly higher than this very responsive groups, exhibiting similar take-up rates to those below the cutoff. This finding is more difficult to reconcile with a true effect of the encouragement email – those students are not dissimilar from their classmates who did respond meaningfully. These results are also somewhat sensitive to the bandwidth, as

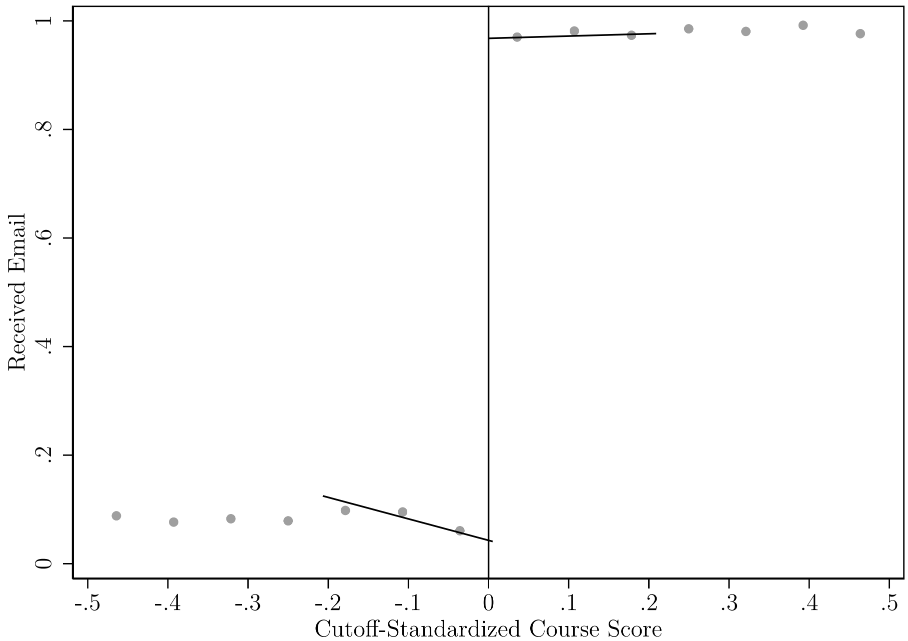

Figure 4: This figure shows results for the likelihood of receiving an encouragement email estimated using a uniform kernel. The running variable the student's standardized course score relative to the cutoff for that semester. The symmetric bandwidth of 0.207 is MSE-optimal and the estimation uses 1819 observations.

we discuss in greater detail below. As such, we view these results are suggestive, though we show below that this course-taking discontinuity seems to be driven by large and meaningful effects for first-generation and minority students.

We next examine whether students are more likely to major in economics (whether switching into it or persisting in the major). 861 of the students in the sample are economics majors when last observed in the data.[20] Figure 6 and the third row of Table 3 show a statistically insignificant effect, albeit a relatively large one in magnitude. It is evident from the figure that the results are driven by lower majoring from those just below the encouragement-email cutoff rather than increased majoring from those above.

[20]Of the 9,671 students who were not economics majors when taking Principles, about 2.3 percent become economics majors. Of the 929 students who took the class as an economics major, 68.4 percent remain in the major.

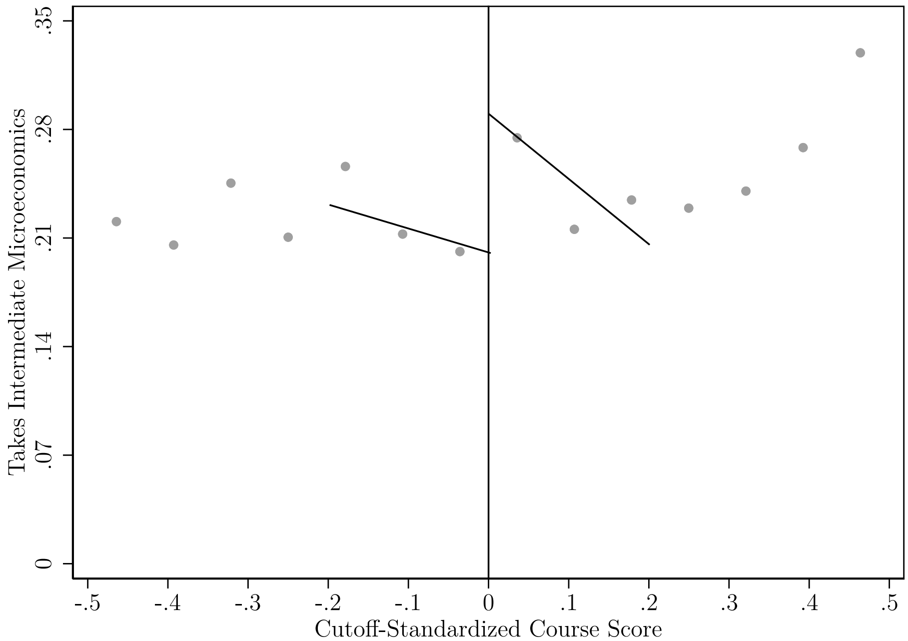

Figure 5: The plot shows the relationship between the cutoff-standardized course score (running variable) and the probability of taking intermediate microeconomics. The vertical line at the cutoff represents the threshold for receiving an encouragement email. Estimates include semester fixed effects. The symmetric bandwidth of 0.198 is MSE-optimal and the estimation uses 1748 observations.

We examine the effect on completing an economics minor, conditional on not being a major. As mentioned above, minors are not recorded in the data until a student has completed the requirements, generally close to graduation; as such, we use 0 observations representing students who were not economics majors for cohorts prior to 2020. About 5.5 percent of students who did not become an economics major become an economics minor. Figure 7 and the fourth row of Table 3 show a small and imprecise estimate of 1.5pp (s.e. = 3.3pp).

We also investigate whether the email treatment affected students' likelihood of switching majors at all, or majoring in economics and economics-adjacent fields (agricultural economics and business). We do not find evidence suggesting that students are more likely to switch majors at all. Further, there is a small and statistically insignificant effect on the overall mix of majors as measured by average earnings; the discontinuity is about -\$179 in Figure 8.

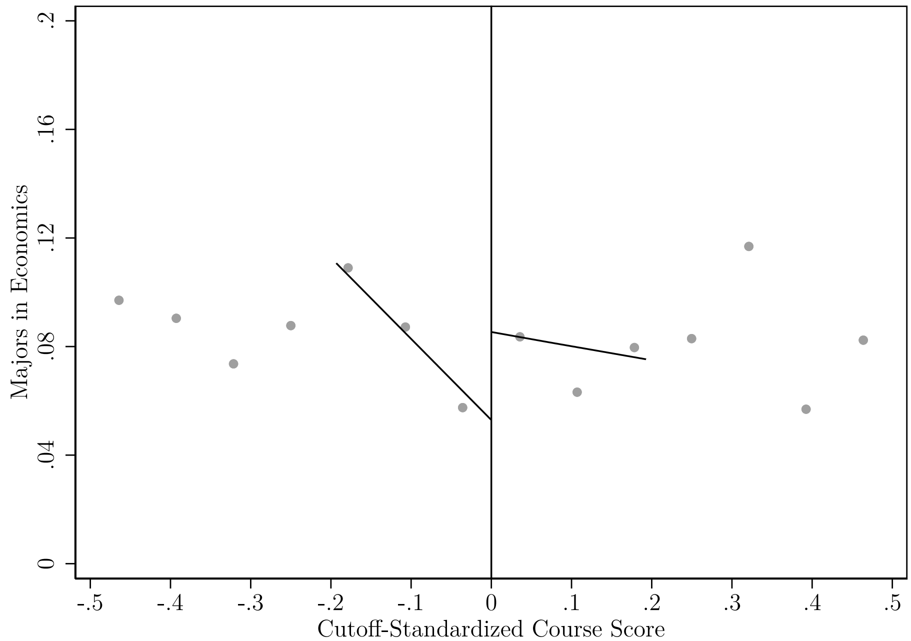

Figure 6: The plot shows the relationship between the cutoff-standardized course score (running variable) and the probability of majoring in economics. The vertical line at the cutoff represents the threshold for receiving an encouragement email. Estimates include semester fixed effects. The symmetric bandwidth of 0.193 is MSE-optimal and the estimation uses 1696 observations.

And while the estimates on majoring in economics or agricultural economics are fairly large (4.1pp, s.e. = 2.6pp), they are noisy; adding business majors to the mix yields a similarly noisy discontinuity of 3.3pp (s.e. = 4.5pp) in Table 3.

Taken together, these results show that the encouragement email may lead to an increase the likelihood of follow-on coursetaking, though one should be cautious in drawing strong conclusions. However, there is little effect on longer-run outcomes like majoring or minoring.

4.2 Sensitivity

Given the noise in the outcome variables, it is worth delving systematically into the sensitivity of the results, particularly for the statistically significant discontinuity found for taking intermediate microeconomics. Figure 9 shows the results using different bandwidths. It is

Table 3: Regression Discontinuity Estimates

Outcome	**Reduced Form Estimate**	**IV Estimate**
Treatment	0.921***	-
(1819 Observations)	(0.033)	-
Takes Intermediate Microeconomics	0.088***	0.094***
(1748 Observations)	(0.033)	(0.035)
Majors in Econ	0.0320	0.035
(1696 Observations)	(0.022)	(0.024)
Declares Econ Minor	0.015	0.016
(819 Observations)	(0.033)	(0.036)
Final Major Earnings	-0.179	-0.196
(2115 Observations)	(0.798)	(0.875)
Majors in Econ or Ag. Econ	0.041	0.045
(1997 Observations)	(0.026)	(0.029)
Majors in Econ or Econ-Adjacent Majors	0.033	0.035
(1643 Observations)	(0.045)	(0.049)
Switches Any Major	0.046	0.05
(1341 Observations)	(0.03)	(0.032)

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: This table presents regression discontinuity estimates of the impact of encouragement emails on academic outcomes. The outcomes examined include the likelihood of taking intermediate microeconomics, switching majors, persisting in an economics major, and declaring a minor in economics. The first column reports reduced form estimates and the second column reports instrumental variable estimates, scaling up the first column by the estimated treatment discontinuity. Standard errors clustered at the semester level are reported in parentheses. Observation counts are included for each outcome. Estimates include semester fixed effects, and the symmetric bandwidth is MSE-optimal, using a uniform kernel. Errors are clustered at the semester level.

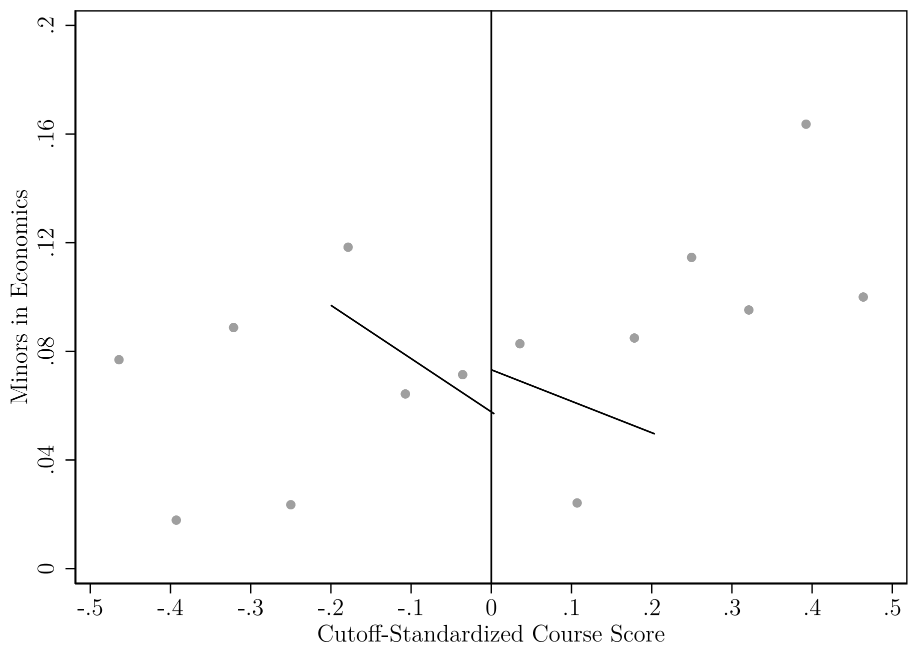

Figure 7: The plot shows the relationship between the cutoff-standardized course score (running variable) and the probability of minoring in economics. The vertical line at the cutoff represents the threshold for receiving an encouragement email. Estimates include semester fixed effects. The symmetric bandwidth of 0.2 is MSE-optimal and the estimation uses 819 observations.

evident that the discontinuity becomes smaller as the bandwidth is expanded. Using wider bandwidths, though, particularly with a uniform kernel, relies on observations fairly far away from the cutoff. Using a triangular kernel, which weights observations closer to the cutoff more heavily, yields a discontinuity of 7.5pp (s.e. = 2.9pp) with a bandwidth of 0.3 and 5.8pp (s.e. = 2.7pp) with a bandwidth of 0.4; even a wide bandwidth of 0.5 yields a large discontinuity that is statistically significant at $p = 0.08$. Using an Epanechnikov kernel, which also weights observations near the cutoff more heavily, yields similar results. We note this to illustrate the degree to which the magnitude and statistical significance of regression discontinuity estimates can still be influenced heavily by researchers' decisions, despite the relative lack of evidence of p-hacking in published papers using this method (Brodeur et al., 2020). The bandwidth plots for the other outcomes – which did not have statistically significant or robust discontinuities in the primary specifications – illustrate the sensitivity of

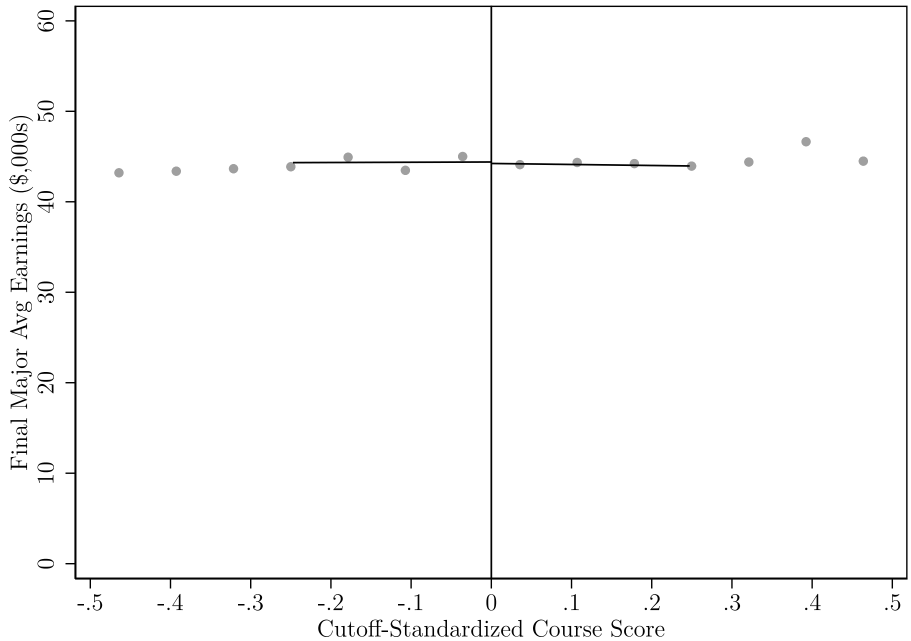

Figure 8: The plot shows the relationship between the cutoff-standardized course score (running variable) and the Hamilton Project earnings of the student's final major. The vertical line at the cutoff represents the threshold for receiving an encouragement email. Estimates include semester fixed effects. The symmetric bandwidth of 0.247 is MSE-optimal and the estimation uses 2115 observations.

those results.

Another approach to examine the robustness of regression discontinuity results is to estimate the specification using placebo cutoffs. Figure 10 shows the results of this exercise. It is instructive to view the results for the treatment variable, where placebo cutoffs clearly deviate substantially from the main estimate. For Takes Intermediate Microeconomics, the discontinuity is nearly at its maximum at the true cutoff, dropping off substantially for placebo levels. While the cutoff is at or nearly at its maximum value at the true level, the placebo cutoff results for Majors and Minors are illustrative of the noisiness of those results.

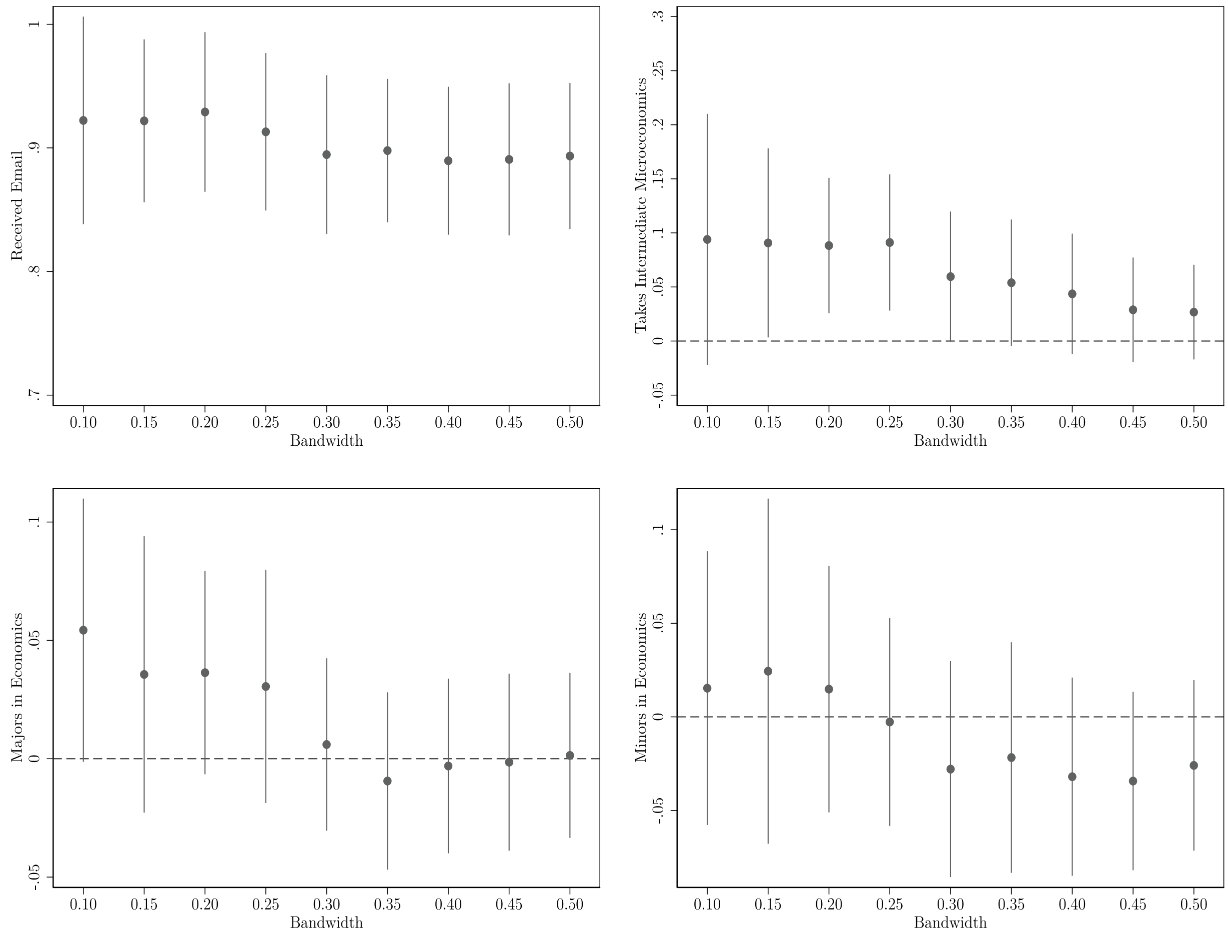

Figure 9: This figure presents regression discontinuity estimates of the impact of encouragement emails on academic outcomes varied by different bandwidth selections. The outcomes examined include the likelihood of taking intermediate microeconomics, majoring in economics, declaring a minor in economics, and the first stage (receiving an email). The RD estimate is reported by the dot and standard errors clustered at the semester level are shown with 95 percent confidence interval bars. Estimates include semester fixed effects and use a uniform kernel.

4.3 Heterogeneity

Certain groups may be more likely to respond to encouragement, particular those that are traditionally underrepresented in economics who may not feel a sense of belonging in the field. Much of the previous research on encouragement interventions has focused on the effects on women and minorities, with findings varying by context (Avilova and Goldin, 2018; Bedard

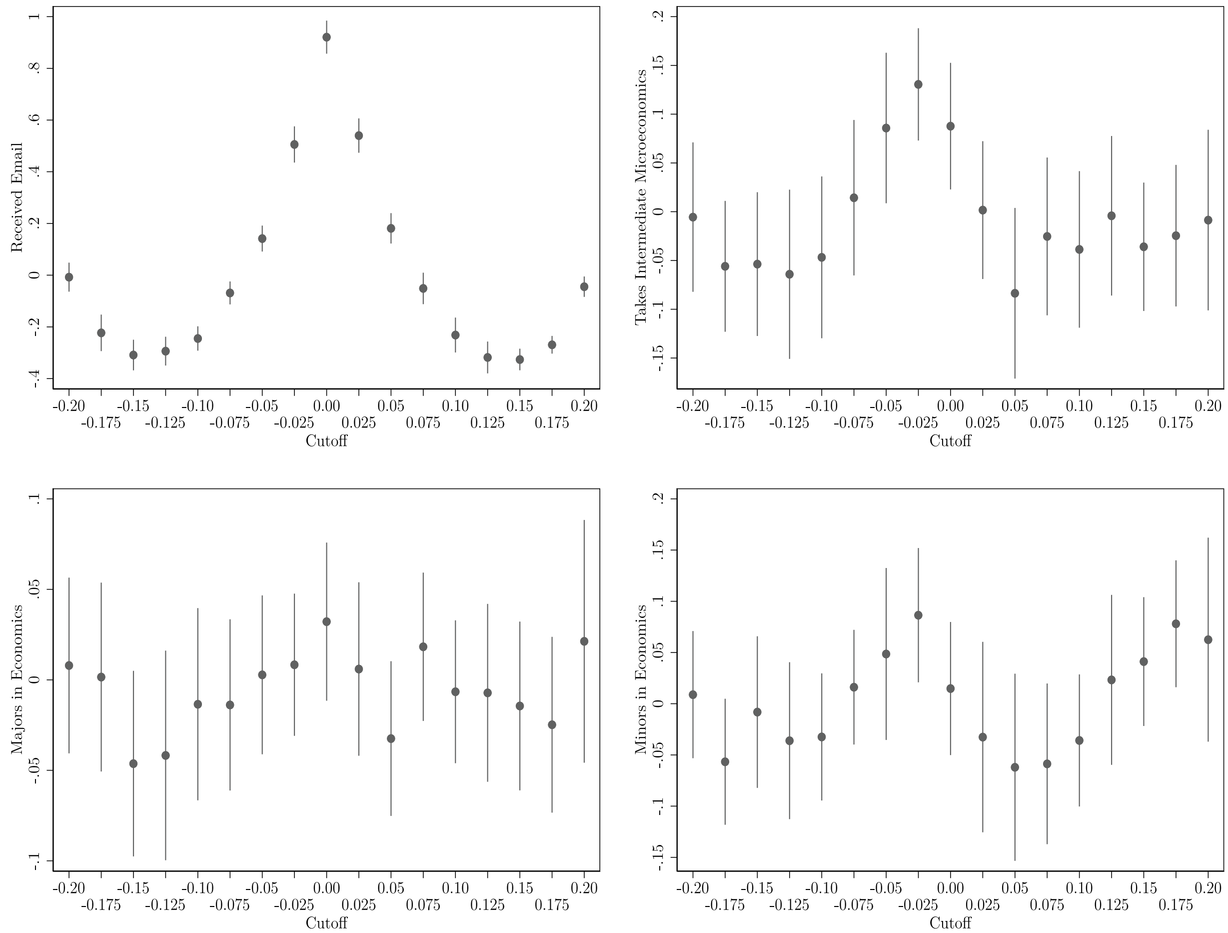

Figure 10: This table presents regression discontinuity estimates of the impact of encouragement emails on academic outcomes varied by different cutoffs (different from zero). The outcomes examined include the likelihood of taking intermediate microeconomics, majoring in economics, declaring a minor in economics, and the first stage (receiving an email). The RD estimate is reported by the dot and standard errors are reported by the confidence interval bars. Estimates include semester fixed effects and use a uniform kernel. Errors are clustered at the semester level.

et al., 2021; Carrell and Kurlaender, 2023; Chambers et al., 2021; Gomez-Vasquez and Serra, 2025; Li, 2018; Oreopoulos et al., 2019; Owen, 2021; Porter and Serra, 2020; Pugatch and Schroeder, 2021, 2024). There has also been extensive research on how the impact of course performance and feedback vary by gender and race (Arcidiacono et al., 2012; Astorne-Figari and Speer, 2019; Bestenbostel, 2023; Fischer, 2017; Li and Xia, 2024; Ost, 2010; Owen, 2023;

Rask and Tiefenthaler, 2008).[21] There has been less focus on low-socioeconomic-status or first-generation students in this literature, though Pugatch and Schroeder (2024) show that first-generation students may be particularly receptive to email nudges about majoring in economics.[22]

TAMU is no exception to the underrepresentation of females, URM, and first-generation students in economics. As a federally designated Hispanic-Serving Institution, TAMU's URM population is predominantly Hispanic, making this a unique setting with a larger Hispanic sample than many other studies.[23] Our data also include a flag for whether the student is from the first generation in their family to attend college. This is strongly correlated with socioeconomic status (U.S. Department of Education, Institute of Education Sciences, 2014), and is perhaps somewhat less correlated with being an underrepresented minority than one would expect. 34.6 percent of the underrepresented minority students in the sample are first generation, as compared to 10.8 percent of other students.

Given the power issues for longer-run outcomes, we focus on Takes Intermediate Microeconomics, and report figures for majoring, minoring, and earnings in Appendix A.

There are no strong patterns by gender. The effect on women's intermediate microeconomics coursetaking is not significantly different than that for men. But the effects for underrepresented and first-generation students are striking. Figure 11 and Table 4 shows large effects on taking intermediate microeconomics for both groups, doubling the mean level

[21] Given that there is no variation in the faculty teaching the course, we are unable to examine the effect of teacher-student gender or race matches, which have been shown in other contexts to have meaningful effects. ((Antecol et al., 2015; Bettinger and Long, 2005; Canes and Rosen, 1995; Carrell et al., 2010; Gershenson et al., 2022; Hoffmann and Oreopoulos, 2009; Holmlund and Sund, 2008; Kugler et al., 2021; Lim and Meer, 2017; Lusher et al., 2018; Muralidharan and Sheth, 2016; Paredes, 2014; Rask and Bailey, 2002). Andrews et al. (2025) document that there are meaningful disparities in access to same-race college instructors.

[22] We also investigate whether students who performed relatively better on the asynchronous aspects of the course (problem sets, post-video quizzes, and forum participation) as compared to the synchronous aspects (exams) respond differently, conditional on earning the same score in the class. We divide the sample into terciles and examine the discontinuity for those in the top and bottom thirds of synchronous performance. No meaningful patterns emerge.

[23] Of the 2,768 students in the sample listed as an underrepresented minority, 79.4 percent are Hispanic.

Table 4: Regression Discontinuity Estimates

Outcome	**Female**	**URM**	**First Gen**
Treatment	0.907***	0.899***	0.897***
	(0.048)	(0.054)	(0.065)
N	669	299	143
Takes Intermediate Micro	0.081	0.265***	0.356**
	(0.066)	(0.101)	(0.159)
N	509	324	123
Declares Econ Minor	0.078	0.103	-0.043
	(0.136)	(0.066)	(0.096)
N	146	145	104
Majors in Econ	0.024	0.069	0.027
	(0.035)	(0.051)	(0.111)
N	471	309	157

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

Notes: This table presents regression discontinuity estimates of the impact of encouragement emails on academic outcomes for selected subgroups. The outcomes examined include the likelihood of taking intermediate microeconomics, majoring in economics, and declaring a minor in economics. Reduced form estimates are provided, with standard errors clustered at the semester level reported in parentheses. Observation counts are included for each outcome. Estimates include semester fixed effects, and the symmetric bandwidth is MSE-optimal, using a uniform kernel.

for those below the cutoff. As in the full sample, the effect dissipates for those further above the cutoff. Of course, the effective sample sizes around the discontinuity are relatively small, though often larger than much of the previous literature when focused on subgroups. In Figure 12, we show bandwidth sensitivity graphs. For underrepresented minority students, the discontinuity remains large and statistically significant, not differing much in magnitude even as observations far from the cutoff are included. For first generation students, the effect attenuates as the bandwidths widen, though remains large in magnitude and statistically significant until it reaches a fairly wide bandwidth.[24]

[24] A total of 780 observations for underrepresented minorities are included when the bandwidth ranges half a standard deviation above and below the cutoff, and 400 observations are included for first generation students.

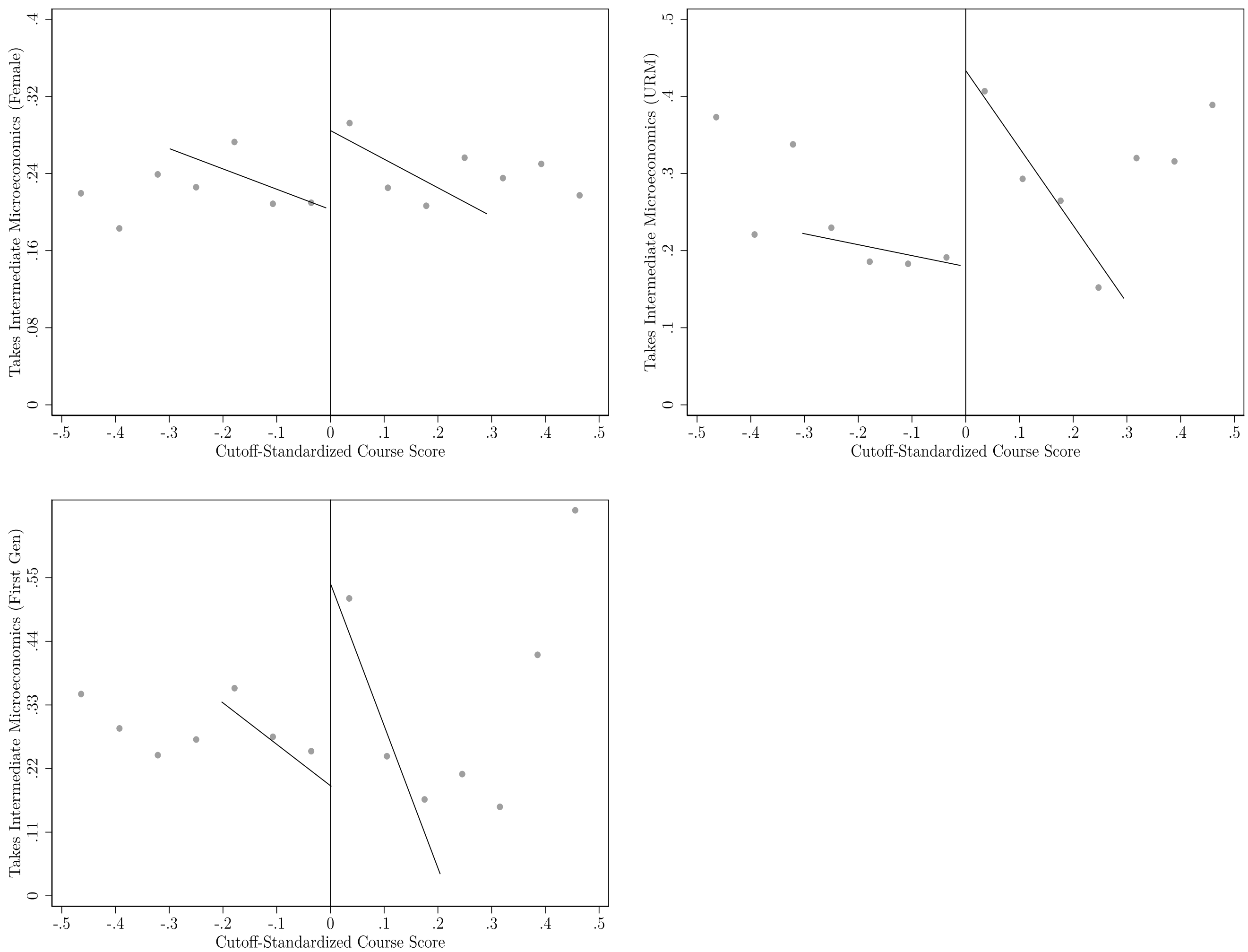

Figure 11: The plot shows the relationship between the cutoff-standardized course score (running variable) and the probability of taking intermediate microeconomics for subgroups including females, URM, and first generation. The vertical line at the cutoff represents the threshold for receiving an encouragement email. Estimates include semester fixed effects, and the symmetric bandwidth is MSE-optimal, using a uniform kernel. Errors are clustered at the semester level.

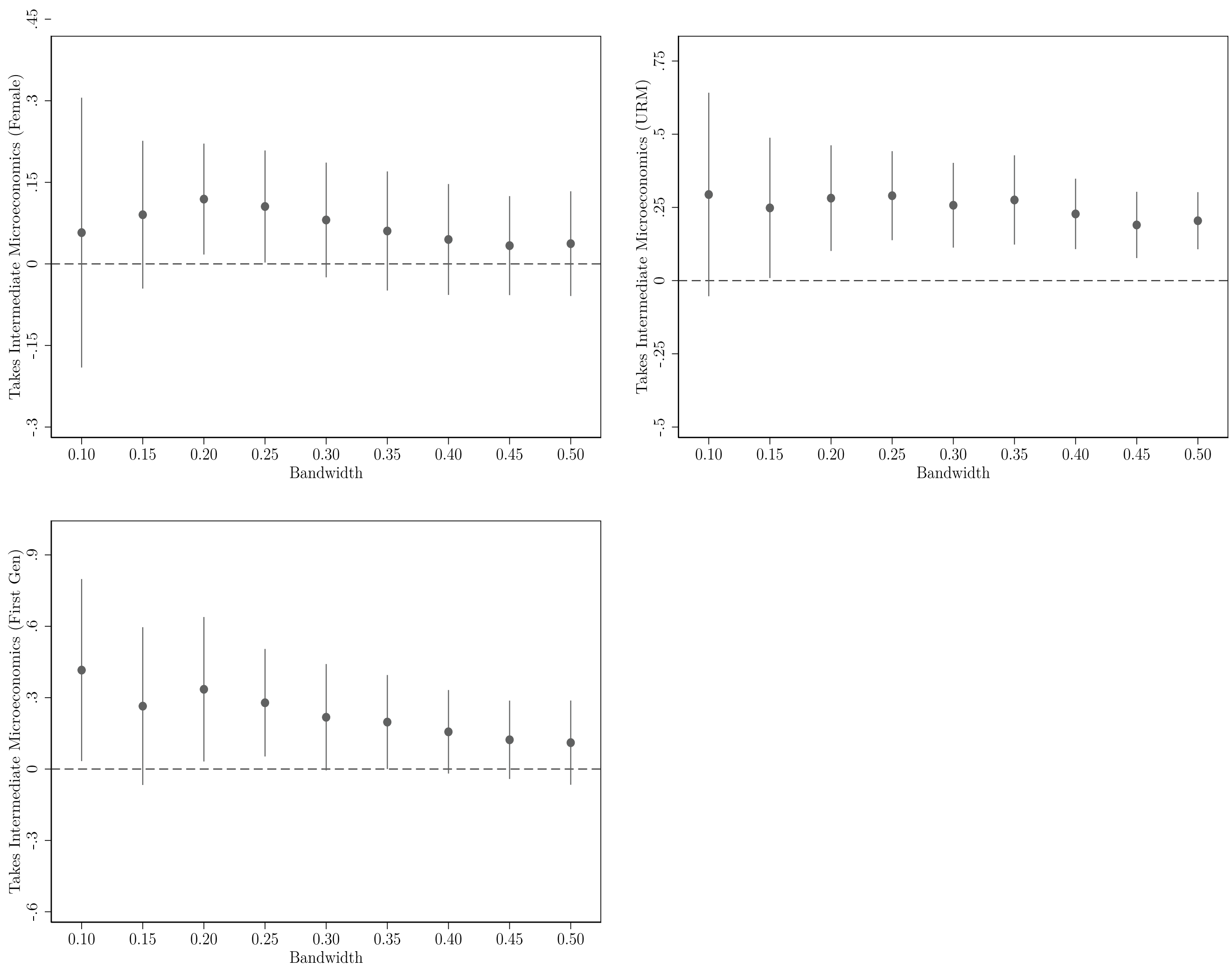

Figure 12: This figure presents regression discontinuity estimates of the impact of encouragement emails on taking Intermediate Micro varied by different bandwidth selections and heterogeneity. The RD estimate is reported by the dot and standard errors clustered at the semester level are shown with 95 percent confidence interval bars. Estimates include semester fixed effects and use a uniform kernel.

As with the full-sample results, longer-run outcomes do not show the same impacts. While the estimated effects on majoring and minoring for underrepresented minorities are large in magnitude, they are noisy and sensitive to bandwidth.

5 Conclusion

We find that the overall impact of an encouragement email to high-achieving students in a Principles of Microeconomics course is modest. Students receiving the email were more likely to take Intermediate Microeconomics, but the effects on longer-run outcomes like switching into the economics major or minoring are limited. Of course, those latter choices require a much larger change in the student's plans. Effects of the intervention on taking Intermediate Microeconomics for underrepresented minorities and first generation students were large. These are the groups that previous research suggests might be most responsive to encouragement, though there was no evidence of persistent effects to majoring or minoring. High-performing students may be less inclined to change their major precisely because they are performing well in their other courses.

Null results face a strong penalty in both publication and perceived reliability (Franco et al., 2014; Chopra et al., 2024). Yet it is crucial for an understanding of the best practices for guiding college students' choices to view the full spectrum of outcomes of such experiments. Light-touch, relatively impersonal interventions such as the one discussed in this paper are likely insufficient to generate meaningful, long-run impacts. Sustained engagement may be the key to inducing more significant changes, and this literature would benefit from rigorous tests of such approaches.

During the preparation of this work, the authors used GPT 4o to make suggestions for improved readability on the first draft of the manuscript. The authors used these suggestions to make edits to the paper themselves.

References

Allgood, S., Walstad, W., and Siegfried, J. (2015). Research on teaching economics to undergraduates. *Journal of Economic Literature*, 53(2):285–325.

Altonji, J., Arcidiacono, P., and Maurel, A. (2016). The analysis of field choice in college and graduate school: Determinants and wage effects. In Hanushek, E., Machin, S., and Woessmann, L., editors, *Handbook of the Economics of Education*, volume 5, chapter 7, pages 305–396. Elsevier.

Altonji, J. and Zimmerman, S. (2018). The costs of and net returns to college major. In Hoxby, C. and Stange, K., editors, *Productivity in Higher Education*. University of Chicago Press, Chicago, Illinois.

Andrews, R., Gottfried, M., Miller, T., and Odle, T. (2025). Who's matched up? access to same-race instructors in higher education. Working Paper 22-681, Annenberg Institute at Brown University.

Andrews, R., Imberman, S., and Lovenheim, M. (2016). Recruiting and supporting low-income, high-achieving students at flagship universities. Working Paper 22260, National Bureau of Economic Research.

Andrews, R., Imberman, S., Lovenheim, M., and Strange, K. (2022). The returns to college major choice: Average and distributional effects, career trajectories, and earnings variability. Working Paper 30331, National Bureau of Economic Research.

Antecol, H., Eren, O., and Ozbeklik, S. (2015). The effect of teacher gender on student achievement in primary school. *Journal of Labor Economics*, 33(1):63–89.

Arcidiacono, P. (2004). Ability sorting and the returns to college major. *Journal of Econometrics*, 121(1):343–375.

Arcidiacono, P., Aucejo, E., and Spenner, K. (2012). What happens after enrollment? an analysis of the time path of racial differences in gpa and major choice. *IZA Journal of Labor Economics*, 1(5).

Astorne-Figari, C. and Speer, J. (2019). Are changes of major major changes? the roles of grades, gender, and preferences in college major switching. *Economics of Education Review*, 70:75–93.

Avilova, T. and Goldin, C. (2018). What can uwe do for economics? *AEA Papers and Proceedings*, 108:186–190.

Barr, A. and Castleman, B. (2021). The bottom line on college advising: Large increases in degree attainment. Working Paper 21-481, Annenberg Institute at Brown University.

Barreca, A., Lindo, J., and Waddell, G. (2016). Heaping-induced bias in regression-discontinuity designs. *Economic Inquiry*, 54(1):268–293.

Bayer, A., Bhanot, S., and Lozano, F. (2019). Does simple information provision lead to more diverse classrooms? evidence from a field experiment on undergraduate economics. *AEA Papers and Proceedings*, 109:110–114.

Bayer, A. and Rouse, C. (2016). Diversity in the economics profession: A new attack on an old problem. *Journal of Economic Perspectives*, 30(4):221–242.

Bedard, K., Dodd, J., and Lundberg, S. (2021). Can positive feedback encourage female and minority undergraduates into economics? *AEA Papers and Proceedings*, 111:128–132.

Bestenbostel, A. (2023). Do grade signals drive the gender gap in stem? evidence from a regression discontinuity. Working Paper.

Bettinger, E. and Long, B. (2005). Do faculty serve as role models? the impact of instructor gender on female students. *American Economic Review*, 95(2):152–157.

Brodeur, A., Cook, N., and Heyes, A. (2020). Methods matter: p-hacking and publication bias in causal analysis in economics. *American Economic Review*, 110(11):3634–3660.

Buckles, K. (2019). Fixing the leaky pipeline: Strategies for making economics work for women at every stage. *Journal of Economic Perspectives*, 33(1):43–60.

Buser, T., Niederle, M., and Oosterbeek, H. (2014). Gender, competitiveness, and career choices. *Quarterly Journal of Economics*, 129(3):1409–1447.

Calonico, S., Cattaneo, M., Farrell, M., and Titiunik, R. (2017). rdrobust: Software for regression-discontinuity designs. *Stata Journal*, 17(2):372–404.

Canaan, S., Deeb, A., and Mouganie, P. (2022). Adviser value added and student outcomes: Evidence from randomly assigned college advisers. *American Economic Journal: Economic Policy*, 14(4):151–191.

Canes, B. and Rosen, H. (1995). Following in her footsteps? faculty gender composition and women's choices of college majors. *Industrial and Labor Relations Review*, 48(3):486–504.

Carrell, S. and Kurlaender, M. (2023). My professor cares: Experimental evidence on the role of faculty engagement. *American Economic Journal: Economic Policy*, 15(4):113–141.

Carrell, S., Page, M., and West, J. (2010). Sex and science: How professor gender perpetuates the gender gap. *Quarterly Journal of Economics*, 125(3):1101–1144.

Castleman, B., Deutschlander, D., and Lohner, G. (2024). Pushing college advising forward: Experimental evidence on intensive advising and college success. Working Paper 20-326, Annenberg Institute at Brown University.

Cattaneo, M., Jansson, M., and Ma, Y. (2018). Manipulation testing based on density discontinuity. *Stata Journal*, 18(1):234–261.

Cattaneo, M., Jansson, M., and Ma, Y. (2022). lpdensity: Local polynomial density estimation and inference. *Journal of Statistical Software*, 101(2):1–25.

Cattaneo, M., Jansson, M., and Ma, Y. (2023). Local regression distribution estimators. *Journal of Econometrics*.

Chambers, A., Dickert-Conlin, S., Elder, C., Haider, S., and Imberman, S. (2021). Info.econ: Increasing diversity among economics majors. *AEA Papers and Proceedings*, 111:133–137.

Chopra, F., Haaland, I., Roth, C., and Stegmann, A. (2024). The null result penalty. *Economic Journal*, 134(657):193–219.

Eren, O., Lovenheim, M., and Mocan, N. (2022). The effect of grade retention on adult crime: Evidence from a test-based promotion policy. *Journal of Labor Economics*, 40:361–395.

Fischer, S. (2017). The downside of good peers: How classroom composition differentially affects men's and women's stem persistence. *Labour Economics*, 46:211–226.

Flory, J., Leibbrandt, A., and List, J. (2015). Do competitive workplaces deter female workers? a large-scale natural field experiment on job entry decisions. *Review of Economic Studies*, 82(1):122–155.

Franco, A., Malhotra, N., and Simonovits, G. (2014). Publication bias in the social sciences: Unlocking the file drawer. *Science*, 345(6203):1502–1505.

Gentry, M., Meer, J., and Serra, D. (2023). Can high school counselors help the economics pipeline? *AEA Papers and Proceedings*, 113:462–466.

Gershenson, S., Hart, C., Hyman, J., Lindsay, C., and Papageorge, N. (2022). The long-run impacts of same-race teachers. *American Economic Journal: Economic Policy*, 14(4):300–342.

Gomez-Vasquez, D. and Serra, D. (2025). My department cares: Supporting students through encouragement emails.

Hastings, J., Neilson, C., and Zimmerman, S. (2013). Are some degrees worth more than others? evidence from college admissions cutoffs in chile. Working Paper 19241, National Bureau of Economic Research.

Hoffmann, F. and Oreopoulos, P. (2009). A professor like me: The influence of instructor gender on college achievement. *Journal of Human Resources*, 44(2):479–494.

Holmlund, H. and Sund, K. (2008). Is the gender gap in school performance affected by the sex of the teacher? *Labour Economics*, 15(1):37–53.

Kirkebøen, L., Leuven, E., and Mogstad, M. (2016). Field of study, earnings, and self-selection. *Quarterly Journal of Economics*, 131(3):1057–1111.

Kolesár, M. and Rothe, C. (2018). Inference in regression discontinuity designs with a discrete running variable. *American Economic Review*, 108(8):2277–2304.

Kugler, A., Tinsley, C., and Ukhaneva, O. (2021). Choice of majors: Are women really different from men? *Economics of Education Review*, 81:1–19.

Li, H. and Xia, X. (2024). Grades as signals of comparative advantage: How letter grades affect major choices. *Journal of Economic Behavior and Organization*, 227:106717.

Li, H.-H. (2018). Do mentoring, information, and nudge reduce the gender gap in economics majors? *Economics of Education Review*, 64:165–183.

Lim, J. and Meer, J. (2017). The impact of teacher–student gender matches: Random assignment evidence from south korea. *Journal of Human Resources*, 52(4):979–997.

Lundberg, S. and Stearns, J. (2019). Women in economics: Stalled progress. *Journal of Economic Perspectives*, 33(1):3–22.

Lusher, L., Campbell, D., and Carrell, S. (2018). Tas like me: Racial interactions between graduate teaching assistants and undergraduates. *Journal of Public Economics*, 159:203–224.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, 142(2):698–714.

Muralidharan, K. and Sheth, K. (2016). Bridging education gender gaps in developing countries: The role of female teachers. *Journal of Human Resources*, 51(2):269–297.

Oreopoulos, P., Patterson, R., Petronijevic, U., and Pope, N. (2019). When studying and nudging don't go as planned: Unsuccessful attempts to help traditional and online college students. Working Paper 25036, National Bureau of Economic Research.

Oreopoulos, P. and Petronijevic, U. (2019). The remarkable unresponsiveness of college students to nudging and what we can learn from it. Working Paper 26059, National Bureau of Economic Research.

Oreopoulos, P. and Petronijevic, U. (2023). The promises and pitfalls of using (mostly) low-touch coaching interventions to improve college student outcomes. *Economic Journal*, 133(656):3034–3070.

Ost, B. (2010). The role of peers and grades in determining major persistence in the sciences. *Economics of Education Review*, 29(6):923–934.

Owen, S. (2021). Ahead of the curve: Grade signals, gender, and college major choice. Working Paper.

Owen, S. (2023). College major choice and beliefs about relative performance: An experimental intervention to understand gender gaps in stem. *Economics of Education Review*, 97:102479.

Paredes, V. (2014). A teacher like me or a student like me? role model versus teacher bias effect. *Economics of Education Review*, 39:38–49.

Patnaik, A., Wiswall, M., and Zafar, B. (2020). College majors 1. In *The Routledge Handbook of the Economics of Education*, pages 415–457. Taylor Francis, Milton Park, Oxfordshire.

Porter, C. and Serra, D. (2020). Gender differences in the choice of major: The importance of female role models. *American Economic Journal: Applied Economics*, 12(3):226–254.

Pugatch, T. and Schroeder, E. (2021). Promoting female interest in economics: Limits to nudges. *AEA Papers and Proceedings*, 111:123–127.

Pugatch, T. and Schroeder, E. (2024). A simple nudge increases socioeconomic diversity in undergraduate economics. *Economic Inquiry*, 62(1):287–307.

Rask, K. and Bailey, E. (2002). Are faculty role models? evidence from major choice in an undergraduate institution. *Journal of Economic Education*, 33(2):99–124.

Rask, K. and Tiefenthaler, J. (2008). The role of grade sensitivity in explaining the gender imbalance in undergraduate economics. *Economics of Education Review*, 27(6):676–687.

Stansbury, A. and Schultz, R. (2023). The economics profession's socioeconomic diversity problem. *Journal of Economic Perspectives*, 37(4):207–230.

The Hamilton Project (2024). Career earnings by college major. Accessed: 2025-01-10.

U.S. Department of Education, Institute of Education Sciences (2014). Web tables: Profile of undergraduate students: 2011-12. Report NCES 2015-167, National Center for Education Statistics. Retrieved April 20, 2020.

Wiswall, M. and Zafar, B. (2015). Determinants of college major choice: Identification using an information experiment. *Review of Economic Studies*, 82(2):791–824.

A Additional Tables and Figures

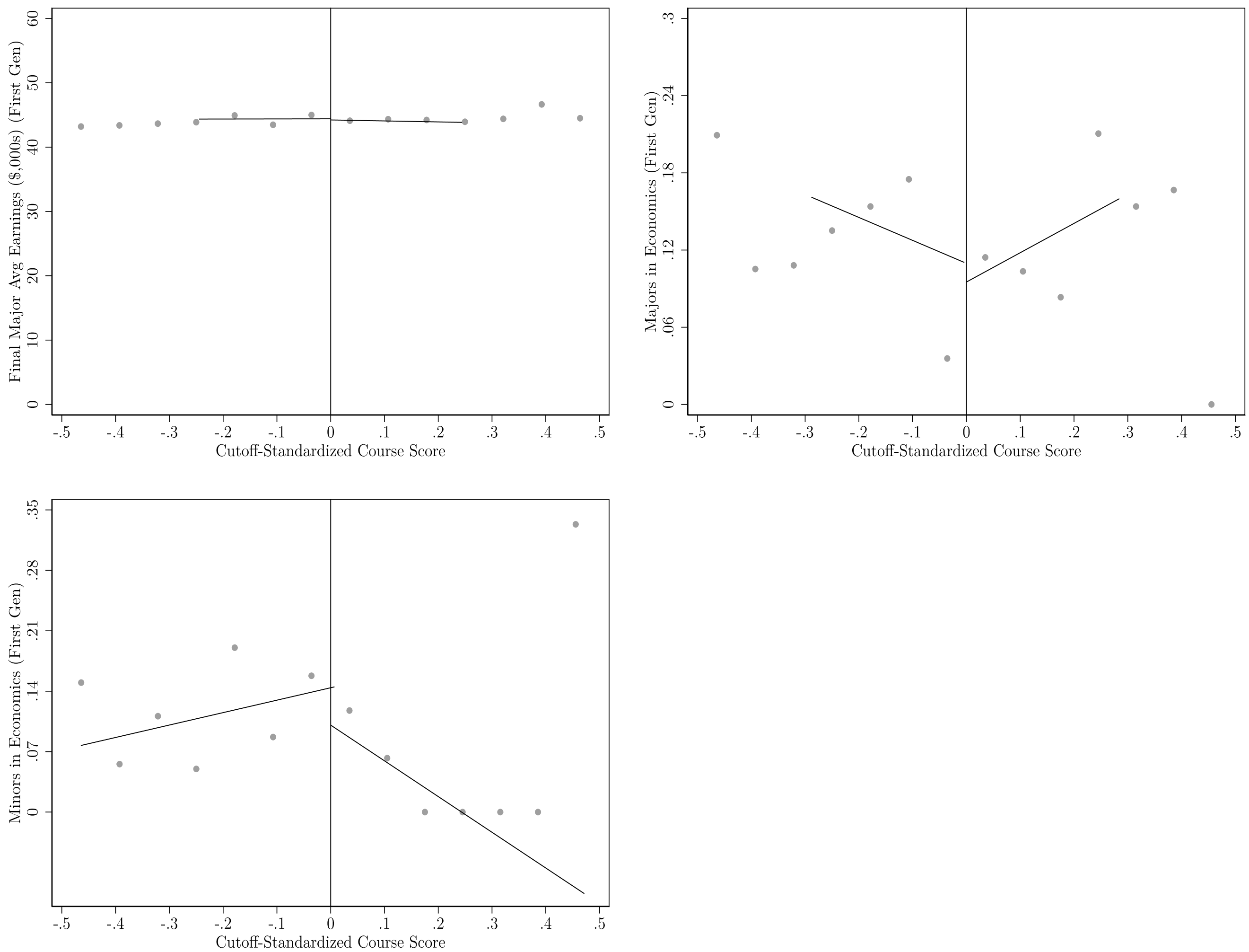

Figure A1: This figure shows the RD graphs for first-generation students for earnings, majoring, and minoring. The vertical line at the cutoff represents the threshold for receiving an encouragement email. Estimates include semester fixed effects. The symmetric bandwidth is MSE-optimal and the estimation uses a uniform kernel.

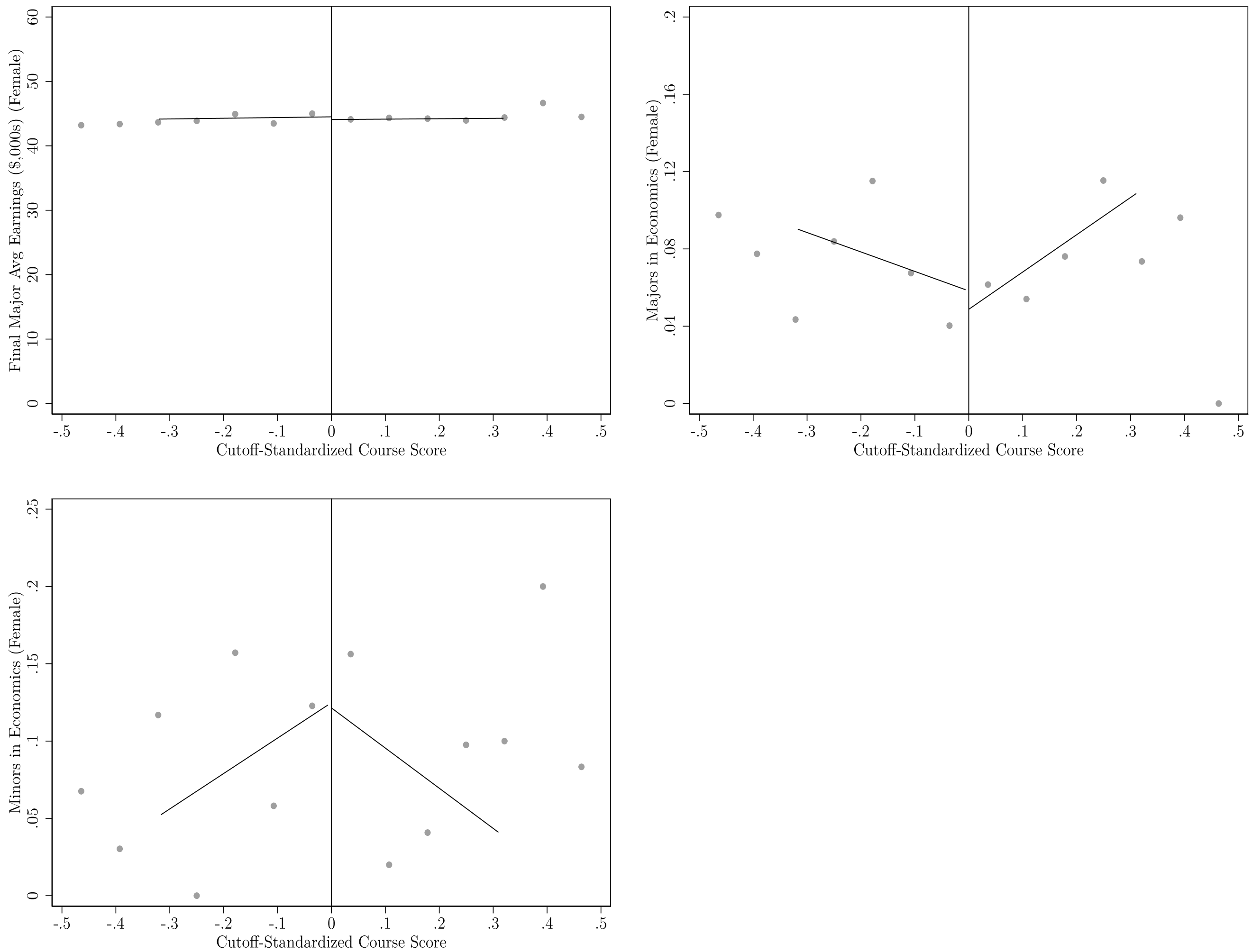

Figure A2: This figure shows the RD graphs for female students for earnings, majoring, and minoring. The vertical line at the cutoff represents the threshold for receiving an encouragement email. Estimates include semester fixed effects. The symmetric bandwidth is MSE-optimal and the estimation uses a uniform kernel.

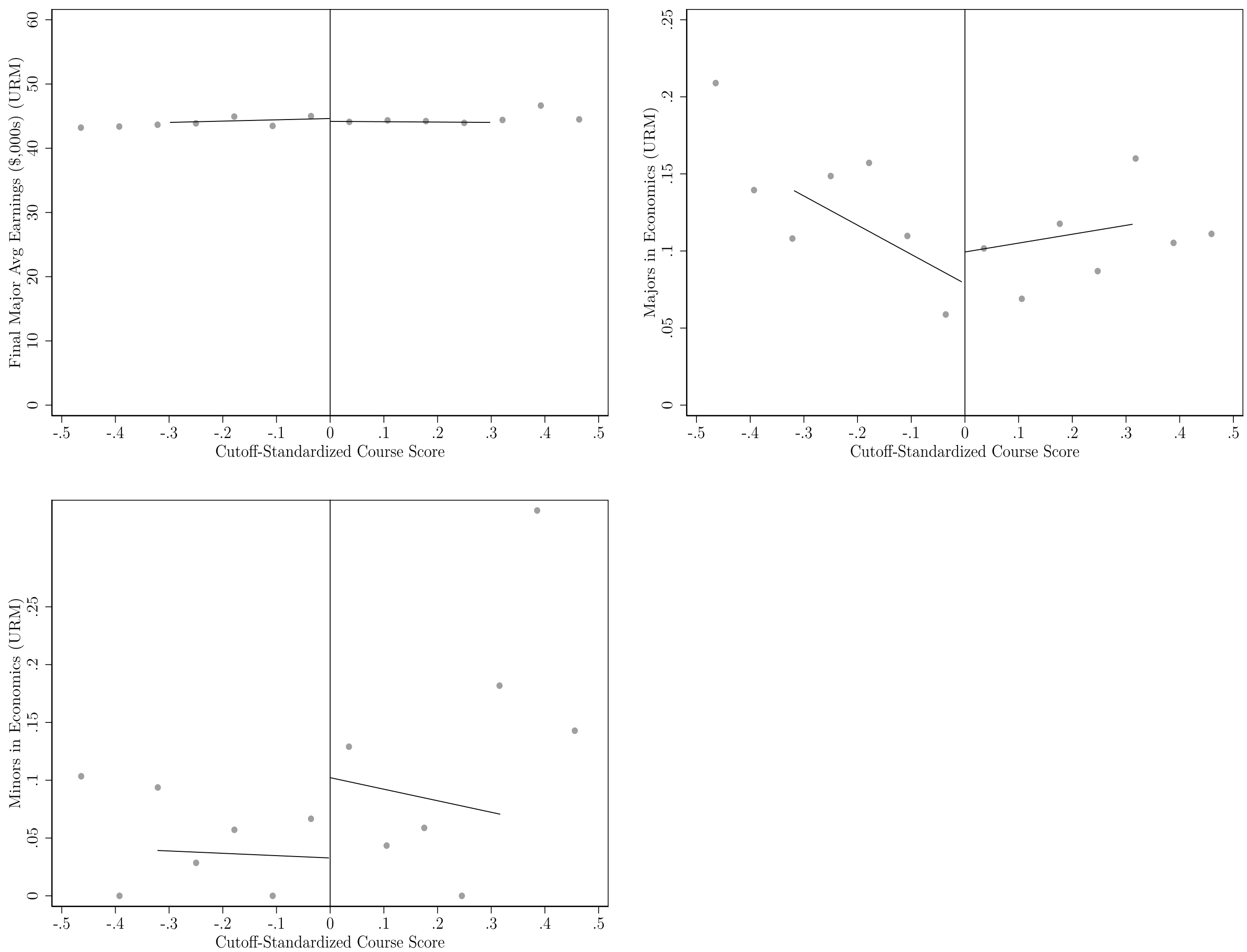

Figure A3: This figure shows the RD graphs for URM students for earnings, majoring, and minoring. The vertical line at the cutoff represents the threshold for receiving an encouragement email. Estimates include semester fixed effects. The symmetric bandwidth is MSE-optimal and the estimation uses a uniform kernel.

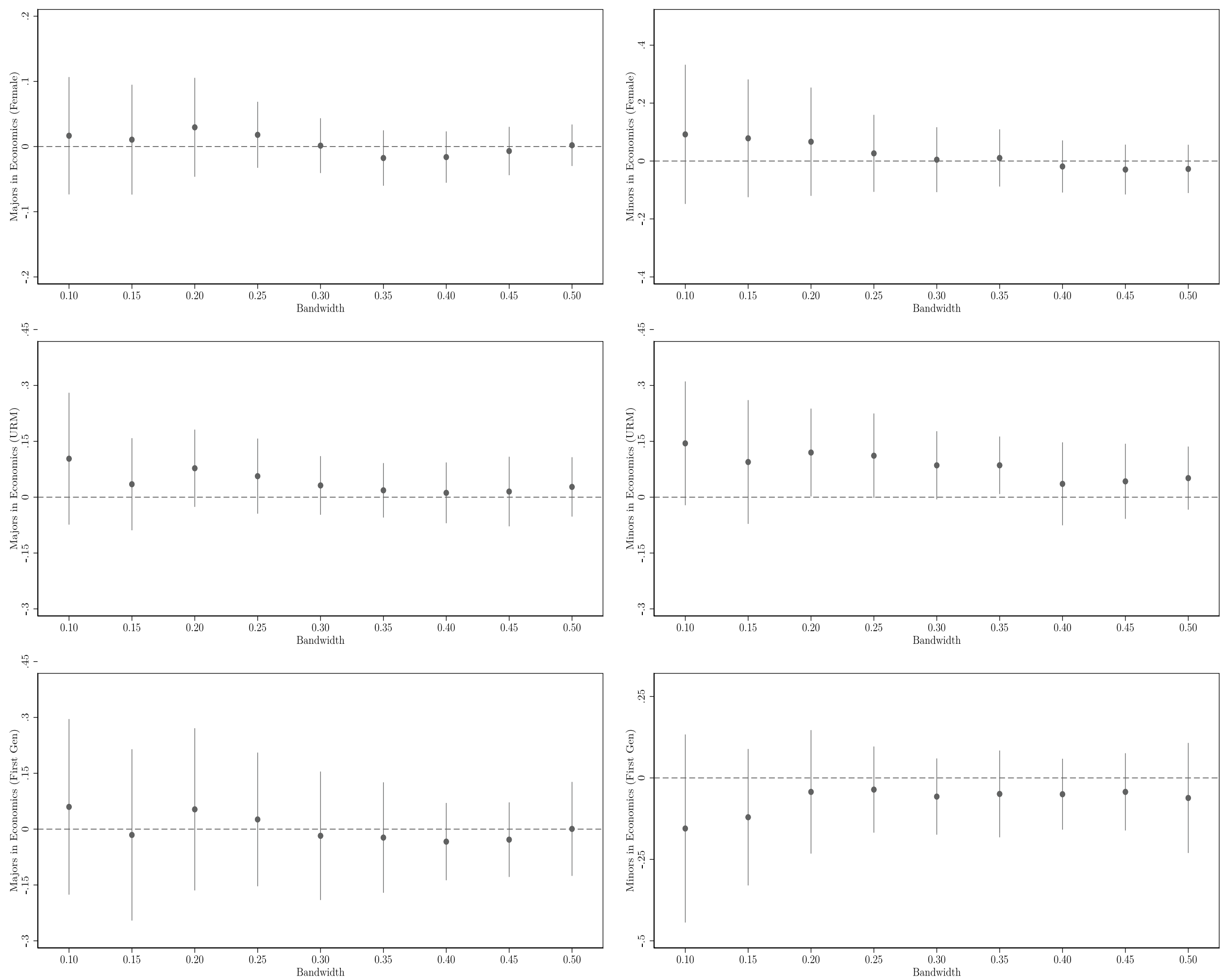

Figure A4: This figure presents regression discontinuity estimates of the impact of encouragement emails on majoring and minoring in economics varied by different bandwidth selections and heterogeneity. The RD estimate is reported by the dot and standard errors clustered at the semester level are shown with 95 percent confidence interval bars. Estimates include semester fixed effects and use a uniform kernel.