# Returns to and Option Values of Majoring in Business and Engineering

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**Abstract**

Leveraging GPA cutoffs for internal transfer, we estimate the ex ante returns to majoring in business and engineering and the ex post returns to attaining college degrees in business and engineering. The ex ante and ex post returns on log earnings are both around 0.12 for business and around 0.30 for engineering. We find significant heterogeneity in the returns, with Asian students and students in less selective institutions having lower returns to business and females having higher returns to both business and engineering. Incorporating effects on degree completions, time to degree, and tuition, we find that the gain in present discounted values is similar to the returns to log earnings for both business and engineering. The option values of graduate degrees consist of close to 23% of the gain in present discounted values from majoring in business, but only 6% of that from majoring in engineering.

## 1 Introduction

Earnings differences across college majors are large, with the gaps in average earnings between the highest and lowest earning majors rivaling the college earnings premium (Altonji, Blom, and Meghir, 2012). However, relatively little is known about the returns to specific college majors, especially in the US context. This information is critical for multiple reasons. On a policy level, spurred by the increasing importance of technology in the economy and beyond, policymakers have been calling for a major increase in the number of STEM graduates in the labor force. Examples of recent policies include the America COMPETES Reauthorization Act of 2010 and the American Innovation and Competitiveness Act of 2017. Without accurate estimates of the returns to STEM degrees, it is difficult to evaluate the efficacy of such policies. On an individual level, most, if not all, US college students need to decide what they would like to major in. Without causal estimates, students often resort to comparing post-college earnings between majors, which can cause severe errors in predicting the returns to their education.

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When considering the returns to majors, two issues are critical for both students and policymakers. First, ex ante returns to choosing a major may differ from the ex post returns to attaining a bachelor's degree in the major when there is uncertainty in educational outcomes (Weisbrod, 1962; Altonji, 1993; Heckman, Lochner, and Todd, 2006). Reduced form evidence suggests that such uncertainty could be large and could vary significantly across majors. Using Texas administrative data, we calculate that among juniors who major in business, 76% attain a bachelor's degree within 8 years of junior year with an average time to degree of 2.6 years. In contrast, among juniors who major in engineering, only 68% attain a bachelor's degree within 8 years of junior year with an average time to degree of 3.0 years. Making decisions based only on ex post returns would therefore overestimate returns when graduation rate is low or when time to degree is lengthy.

Second, the returns to majors include the option values that stem from the possibilities of attaining graduate degrees (Eide and Waehrer, 1998; Black, Sanders, and Taylor, 2003; Stange, 2012). This is driven by the sequential nature of degree attainment, where college degrees are required for graduate admission. Moreover, the importance of the option values would differ across majors. For example, using Texas administrative data, we calculate that 17% of college graduates with business degrees end up attaining graduate degrees (mostly in business), while only 8% of college graduates with engineering degrees eventually attain graduate degrees (mostly in engineering). As a result, the returns to the same major could vary significantly depending on whether an individual is interested in or could afford graduate school.

Using Texas administrative data, we provide causal estimates for the ex ante returns to majoring in business and engineering and the ex post returns to attaining bachelor's degrees in business and engineering. In addition we estimate the causal effects of majoring in business and engineering on the likelihood of attaining different college and graduate degrees. This then allows us to calculate the extent to which option values from graduate degrees matter for the two majors. We focus on business and engineering majors for two reasons. First, business and engineering have high returns according to descriptive evidence (e.g., Altonji, Arcidiacono, and Maurel, 2016) and evidence from other countries using fuzzy regression discontinuity design based on admission cutoffs (Hastings, Neilson, and Zimmerman, 2014; Kirkeboen, Leuven, and Mogstad, 2016). Desk research on search engines and AI chat bots also consistently lists the two majors among the most lucrative college majors. Second, anecdotal evidence suggests that business and engineering are among the most competitive majors to gain admission into.[1] The existence of such excess demand implies that accurately estimating returns for business and engineering is particularly important for students' decision making and for policy purposes. If business and engineering do in fact have high economic returns, then

[1] Our empirical strategy leverages cutoff GPA requirements for internal transfers, and business and engineering are the majors for which we consistently observe such requirements among a large number of institutions. This indirectly shows that business and engineering are the majors with the most excess demand from students.

there is a case for encouraging students to enter these field and for universities to expand access.

The primary challenge for estimating causal returns to majors comes from the endogenous sorting into majors. Students choose what they major in based on their ability and preference across majors, which are partially unobservable. By combing thorough university catalogs of all Texas public four-year institutions, we compile GPA cutoffs for internal transfers into business and engineering majors for eight and two universities, respectively. Leveraging these GPA cutoffs and a fuzzy regression discontinuity (RD) design, we estimate the returns to majoring in business and engineering for students who started college undeclared or in a different major and transferred into their universities' business and engineering majors by the beginning of junior year.[2][3] Essentially, we compare students who just crossed the GPA cutoffs and majored in business and engineering to students who just missed the GPA cutoffs and did not major in business and engineering. Crucially, in the absence of information on which students' applied for internal transfer, we leverage students' course selection to help identify students who are likely interested in applying for internal transfers into the business and engineering majors. Leveraging this RD design as our first stage, we estimate ex ante and ex post returns to business and engineering. We also estimate the effects of majoring in business and engineering on college and graduate degree outcomes. The estimated effects will be the latent average treatment effects (LATE) for students who are on the margin of being admitted into business and engineering majors through internal transfer. This student population is of great interest to policies that aim to expand access to business and engineering majors.

We estimate that the ex ante returns to majoring in business and the ex post returns to college degrees in business are 0.13 (0.02) and 0.12 (0.02) log points. The ex ante returns to majoring in engineering and ex post returns to college degrees in engineering are 0.28 (0.08) and 0.31 (0.10) log points. We find significant heterogeneity in returns for business. Non-Hispanic White students, Hispanic and Black students, and Asian students gain different ex ante returns to majoring in business — 0.20 (0.02) vs. 0.14 (0.03) vs. 0.05 (0.03) — and ex post returns to college degrees in business — 0.19 (0.02) vs. 0.13 (0.03) vs. 0.06 (0.03). We also find that students in more selective institutions gain higher ex ante returns to majoring in business — 0.15 (0.02) vs. 0.09 (0.03) — and ex post returns to college degrees in business — 0.14 (0.02) vs. 0.09 (0.03). Compared to male students, female students gain higher ex ante returns to majoring in business — 0.17 (0.02) vs. 0.13 (0.02) — and ex post returns to college degrees in business — 0.17 (0.02) vs. 0.12 (0.02). Notice, however, that the gender heterogeneity could be explained by sampling errors. As for engineering, we also find that females gain higher ex ante returns to majoring in engineering — 0.50 (0.13) vs. 0.09 (0.10) — and ex post returns to college degrees in engineering — 0.51 (0.13) vs. 0.10 (0.13) —, although

[2]The tranfers account for about 40% of all business graduates and 30% of all engineering graduates.

[3]Throughout the paper, transfer refers to internal transfers into business and engineering majors in the same university, not transfer between universities.

the IV estimates are noisy. The OLS estimates of the ex post return are 0.29 (0.02) for females and 0.25 (0.01) for men suggesting a smaller female advantage. We are under-powered to examine other dimensions of heterogeneity for engineering.

To examine the option values of majoring in business and engineering, we estimate the effects of majoring in business and engineering on college and graduate degree attainment. Unsurprisingly, majoring in business and engineering increase the likelihood of attaining bachelor's degrees in business and engineering, respectively. Examining degree attainment four-years after junior year, we find that majoring in business increases the likelihood of attaining any college degree by 0.05 (0.01), and majoring in engineering increases the likelihood of attaining any college degree by 0.05 (0.01). Examining degree attainment two-years after junior year, which corresponds to the "on-time" graduation timeline, majoring in business increases the likelihood of attaining any college degree by 0.09 (0.03). However, majoring in engineering decreases the likelihood of attaining any college degree by 0.24 (0.03). The effects of majoring in business on college degrees (four years after junior year) display significant gender heterogeneity. Majoring in business decreases the chance of attaining a college degree in engineering by 0.27 (0.03) for males but only by 0.05 (0.01) for females. In contrast, majoring in business decreases the chance of attaining a college degree in social sciences or "other" majors, which includes education and humanities majors, by 0.29 (0.03) for males but by 0.36 (0.03) for females. Notice that engineering is the major category with the highest average earnings, while "other" majors have the lowest average earnings. These results suggest that majoring in business pulls male and female students from very different counterfactual options, which explains the higher returns estimated for females.

The effects of majoring in business and engineering on graduate degrees (eight years after junior year) show substantial difference between the two majors with respect to their effects on the likelihood of attaining graduate degrees. Majoring in business increases the chance of attaining a graduate degree by 0.032 (0.018) and the chance of attaining a graduate degree in business by 0.16 (0.01). In comparison, majoring in engineering decreases the chance of attaining a graduate degree by 0.06 (0.03). These results suggest that the option values of graduate degrees are potentially more important for the returns to majoring in business compared to engineering.

Finally, we incorporate earnings during school, time to degree, and cost of enrollment by calculating the present discounted values (PDV) of majoring in business and engineering. To do so, we compute the weighted average of net income across all possible outcomes from 2 to 39 years after junior year. These outcomes include working in the labor market with various college and graduate degree combinations, and being enrolled in college or graduate school. PDVs are calculated under three scenarios to examine the option values of graduate degrees. The first scenario is the counterfactual scenario, where we use the probabilities

of outcomes from students who did not major in business or engineering. The second scenario is the actual scenario, where we take the probabilities of outcomes from students who majored in business and engineering. The third scenario is what we call the "actual college" scenario, where we take the probabilities of college enrollment and college degree attainment from the actual scenario, but take the probabilities of graduate enrollment and graduate degree attainment from the counterfactual scenario. The third scenario allows us to isolate the option values that come from graduate school. Two results are worth highlighting. First, the PDV gains for majoring in business (13%) and engineering (32%) are largely consistent with the returns to earnings. Second, the option value from graduate school represent a much larger share for the PDV gains from majoring in business (23%) than that from majoring in engineering (6%).

This paper contributes to two bodies of research. First, we contribute to the broad literature examining heterogeneity in higher education (Altonji, Blom, and Meghir, 2012; Altonji, Arcidiacono and Maurel, 2016). More specifically, we contribute to the literature studying returns to different college majors (Hastings, Neilson, and Zimmerman, 2014; Kirkeboen, Leuven, and Mogstad, 2016; Bleemer and Mehta, 2022). Hastings, Neilson, and Zimmerman (2014) and Kirkeboen, Leuven, and Mogstad (2016) leverage score-based admission cutoffs in Chile and Norway to estimate returns to different college majors. Bleemer and Mehta (2022) leverages grade requirements for introductory courses at UC Santa Cruz to estimate the returns to majoring in economics. There are several additional papers studying returns to college majors without quasi-experimental variations. A non-exclusive list includes Britton et al (2022), Andrews, Imberman, Lovenheim, and Stange (2024), and Zhang, Liu, and Hu (2024). We contribute to this literature by presenting quasi-experimental estimates of the returns to two of the most lucrative and popular majors in the US, business and engineering, across multiple institutions. In addition, we are the first to calculate returns to majors in terms of PDVs that combine returns to earnings with time to degree, net tuition, and earnings during enrollment.

Second, we contribute to the literature studying the demand for and returns to college when educational outcomes are uncertain. Previous works in this literature find that the ex ante and ex post returns to starting an educational program can differ when educational decisions are sequential and/or outcomes are uncertain (Weisbrod, 1962; Altonji, 1993). Under this setting, educational decisions carry option values (Heckman, Lochner, and Todd, 2006; Heckman and Urzua, 2008; Stange, 2012). Such option value includes continuation values (e.g., one cannot attain college degrees without starting college) and option values in the Dixit and Pindyck (1994) sense (e.g., there is value in enrolling in college just to preserve the option to attain a degree while learning about one's ability and preference and about labor market payoffs). We contribute to this literature in two ways. First, we extend the examination of ex ante versus ex post returns to college by estimating them for specific college majors. Second, we are the first to isolate the option values

that specifically come from the option to attain graduate degrees.

The remainder of the paper proceeds as follows. Section 2 describes the Texas administrative data used, the coherence measure we use to identify individuals who are likely to apply for internal transfer, and the GPA cutoffs for internal transfer we compiled. Section 3 presents summary statistics. To fix ideas, section 4 sketches a simple dynamic model for college enrollment, major choice, and graduate school enrollment. Section 5 discusses our empirical strategies. Section 6 presents our empirical findings. Finally, section 7 concludes.

# 2 Data, Coherence Measure, and GPA Cutoffs

We use administrative data from Texas for our empirical analysis. The data follows students from high school to college enrollment, advanced degree enrollment (if any), and employment, so long as these activities occur in Texas. The high school data is provided by the Texas Education Agency (TEA), the college data is provided by the Texas Higher Education Coordinating Board (THECB), and the employment and earnings data is provided by the Texas Workforce Commission (TWC).[4]

Earnings observations are from UI records and are quarterly. The earnings data is available since 1990. However, our main sample consists of students who entered college in or after the 2011-2012 academic year, as we explain later. For this reason, most of our analyses use earnings observations from 2011 to 2024. To account for sporadic unemployment episodes, we only keep earnings observations that are (1) part of a sequence of four consecutive quarterly earnings observations; (2) at least three quarters after college degree attainment; (3) not during enrollment in graduate school; (4) either before graduate school or at least three quarters after advanced degree attainment; and (5) below $250,000 and above $3,000 (quarterly earnings). Restricting to positive earnings observations helps mitigate the potential bias from individuals who are employed outside of Texas (Foote and Stange, 2019).

The TEA data contains rich information on students' high school enrollment, course selection, and standardized test scores, which provide valuable information on students' baseline abilities and academic interests. While SAT and ACT test scores are available from college enrollment data, we use the state-wide high school assessment exams in mathematics, reading, and writing as our main standardized test scores. These exams are required for high school graduation and cover a wider population in our sample.[5] Students'

[4]The data is also linked to 2008-2015 National Student Clearinghouse (NSC) data. Out-of-state enrollment and degree attainment of Texas high school graduates are observed between 2008-2015, and out-of-state enrollment of students who previously enrolled in Texas universities are also observed between 2008-2015. In this paper, we do not use information from the NSC, due to the lack of detailed enrollment information for out-of-state enrollment.

[5]The State of Texas Assessments of Academic Readiness (STAAR) is used for years 2012-2016, the Texas Assessment of Knowledge and Skills (TAKS) is used for years 2003-2015, and the Texas Assessment of Academic Skills (TAAS) is used for years 1994-2007. All three versions of the standardized tests have separate modules for mathematics, reading, and writing. TAKS and STAAR also have separate modules for science and social sciences, but we do not use them in our main specification

performances on the standardized exams, are measured using their percentile ranking among their cohort peers. We do not use the SAT and the ACT test scores because they are missing for many students.

The THECB data contains information on all students enrolled in undergraduate and graduate degree programs at public two-year, four-year, and health-related institutions since 1992 and at independent universities since 2003. Enrollment, major of study, semester credit hours, GPA, and degrees received are available for all cohorts of students. College major and graduate field are measured at the 8-digit CIP level. To keep our analyses tractable, we aggregate college majors into the 6 categories — business, science, health, engineering, social sciences, and other. The main majors in the "other" category are humanities majors such as English and History. Similarly, we categorize graduate degrees into 8 categories — business, science, health, engineering, social sciences, law, education, and other. Information on students' parental income and parental education are contained in the students' financial aid files, which are available since 2001.

Throughout, we consider students' major at the beginning of their junior years as their declared major. We restrict our analyses to students who have reached junior year status. Moreover, when studying the returns to business (engineering) majors, we exclude students who entered college as business (engineering) majors. This is because our main empirical strategy relies on GPA cutoffs for the internal transfer process, where students from other majors transfer into business (engineering) majors. The students who declare a major during college are a population of great interest for policies that intend to encourage (or discourage) students into certain majors.

The availability of transcript level data started in the 2011-2012 academic year. Students' course selections is key to our empirical strategy, as it allows us to identify students who are likely interested in applying for internal transfer, even though we do not observe who actually applied for internal transfer. As we discuss in the next section, we use Zhu's (2025) measure of a student's progress towards completing degree-required coursework, which he calls "coherence". As a result, we restrict our main sample to students who started college in or after the 2011-2012 academic year. Since the calculation of students' coherence also requires a significant number of students from their entering cohort to have attained a degree, we further restrict our main sample to students who started college in or before the 2018-2019 academic year.

## 2.1 Coherence Measure for Students' Course Selection and Specific Course Requirements in Engineering

In the absence of data on who applied for a transfer, and because the decision to apply would be influenced by the presence of GPA cutoffs, we use the coherence measure to elicit students' interests and abilities in different majors through their course selections. The coherence measure is designed to capture a student's progress towards completing degree-required coursework and is defined as the share of required courses that

because they are not available in TAAS.

the student has completed (Zhu, 2025). To allow for variations in degree requirements, the coherence measure is institution, major, and cohort (entering class) specific. Formally,

$$\text{coh}_{ijt}^{cs} = \begin{cases} \frac{h_{ijst}^c}{n_{js}^c} & \text{if } h_{ijst}^c < n_{js}^c \\ 1 & \text{if } h_{ijst}^c \geq n_{js}^c \end{cases} \tag{1}$$

where $\text{coh}_{ijst}^c$ denotes the coherence of student $i$ from cohort $s$ of institution $j$ at time $t$ for major $c$. $h_{ijst}^c$ denotes the number of credits in required courses that the student has completed, and $n_{js}^c$ denotes the total number of credits in required courses for major $c$ for students in cohort $s$ of institution $j$. By definition, the coherence measure is a measure between 0 and 1, where having a coherence of 1 means the student has completed all required coursework in major $c$.

The transcript level data makes measuring coherence possible. Following Zhu (2025), we identify the population of students who attain degree $c$ from institution $j$ in cohort $s$, $S_{js}^c$. Second, we identify the courses that more than 90% of $S_{js}^c$ took, and label these courses as the set of required courses, $R_{js}^c$. Third, we identify courses that more than 30% of $S_{js}^c$ took, and label these courses as the set of elective courses, $E_{js}^c$. Fourth, we count the number of elective courses that students in $S_{js}^c$ took and take the 30th percentile value of that distribution, $N_{js}^c$. The tuple $\{R_{js}^c, E_{js}^c, N_{js}^c\}$ then characterizes the degree requirement of degree $c$ from school $j$ in cohort $s$. In particular, students need to complete all courses in the set $R_{js}^c$, and at least $N_{js}^c$ courses in the set $E_{js}^c$. Zhu (2025) compares the distribution of $\{R_{js}^c, E_{js}^c, N_{js}^c\}$ for students who complete a major to official major requirements in course catalogs and finds that this empirical procedure captures students' degree requirement with significant accuracy.

With the tuple characterizing degree requirements, $n_{js}^c = |R_{js}^c| + N_{js}^c$, where $|R_{js}^c|$ is the number of courses in $R_{js}^c$. We calculate $h_{ijst}^c$ as the total number of courses in $R_{js}^c$ and $E_{js}^c$ that a students has completed, making sure not to count more than $N_{js}^c$ courses from the set $E_{js}^c$. To simplify notation, we will drop the "$c$" superscript and "$s$" subscript here on out.

Notice that we restrict our sample to those with more than 0.25 coherence in business by the beginning of junior year when examining the returns to majoring in business and, similarly, restrict our sample to those with more than 0.10 coherence in engineering by the beginning of junior year when examining the returns to majoring in engineering. This is done to ensure our estimates only rely on students who are likely to be interested in majoring in business / engineering.

In the case of engineering, we also identify specific math and science courses that are required for transfers and use them in the RD specification.[6]

[6]For UT Austin, the courses are Math 408D, Physics 303K, and Physics 103M. For Texas A&M, the courses are Math 151,

### 2.2 GPA Cutoffs for Internal Transfers and Other Requirements

The GPA cutoffs for internal transfers into business and engineering majors are collected manually from university catalogs. In all analyses, we restrict to students in institutions and cohorts for which we have GPA cutoffs identified for the major analyzed. The GPA cutoffs are reported in table 1.

We identified GPA cutoffs for transfer into business majors for 8 institutions — UT Austin, Texas A&M, Midwestern State University, Texas State University, UT Arlington, UT Rio Grande Valley, University of Houston, and University of North Texas. The cutoff GPAs range from 2.00 to 3.30 for business majors. As a result, the marginal students identified by the RD design for business, described in detail later, are a mix of students from various levels of academic performances.

In contrast, we found GPA cutoffs for transfering into engineering majors only for the two flagship public universities — UT Austin and Texas A&M. The GPA cutoffs range from 3.00 to 3.50 for engineering majors. The marginal students identified by the RD design for engineering are therefore students that are performing well academically.

## 3 Summary Statistics

In this section, we present summary statistics that assist the discussions of empirical strategies and results to follow. First, table 2 presents the share of students that declare business and engineering majors at different transition periods. The statistics show that among students who graduate with college degrees in business, around 56% enter college as business majors, 40% transfer into business majors during their freshmen and sophomore years, and the remaining 5% transfer into business majors during or after junior year. Among students who graduate with college degrees in engineering, around 70% enter college as engineering majors, 26% transfer into engineering majors during their freshmen and sophomore years, and only 4% transfer into engineering majors during or after junior year. Statistics not conditioning on college degree attainment (bottom panel) show similar patterns.

Students transfer into business and engineering majors from very different majors. Figure 1 present the distributions of students' freshmen year majors for those who transfer into business and engineering major in their freshmen and sophomore years. The figures report the distributions separately for female and male students and exclude students who had undeclared majors in their freshmen year (around 40%). The figures rank majors from top to bottom in ascending order of average post-college earnings. The figures show that freshmen majors are very different for business and engineering students and also different for female and

Math 152, Chemistry 107, and Physics 206.

male students. For both business and engineering transfer students, male students tend to come from higher earning majors.

# 4 Model and Notation (Preliminary and Incomplete)

To clarify what we mean by the ex ante return to choosing a major, the ex post return to the major, and the role played by graduate school, we present a simple four-period model of college major choice and graduate school enrollment decision in the spirit of Altonji (1993). Following Altonji, Arcidiacono, and Maurel (2016), we allow abilities to influence both pecuniary and nonpecuniary costs and benefits rather than separately introduce preferences. All individuals enter the model as currently enrolled college students who have not yet decided their majors. At the beginning of period 1, which corresponds to junior year, individuals choose between two majors, $b$ and $o$, where $b$ stands for business, and $o$ stands for others. Any student can choose $o$, but the choice of $b$ is restricted for students with a GPA below a cutoff $Z_b$. In period 2, which corresponds to senior year, individuals update their beliefs about their abilities and then choose again among the two majors, $b$ or $o$, or dropping out of college, $n$. In period 3, individuals who chose one of the college options in period 2 have the option of enrolling in graduate school and choose among no graduate enrollment, $n$, and majors, $b$ and $o$, again standing for business and others. Denote $d_{ic}^1$ and $d_{ic}^2$ as indicators for whether individual chose college major $c$ in period 1 and 2, and denote $d_{ig}^3$ as an indicator for whether individual chose graduate major $g$ in period 3. In period 4, all individuals work.

Uncertainty in the returns to education stems from the uncertainty in individual's abilities. Denote an individual's major-specific ability as $A_{icg}^{\text{tot}}$, and

$$A_{icg}^{\text{tot}} = A_{ic} + A_{ig} + \zeta_{ic} + \xi_{ig}$$

where $A_{ic}$ and $A_{ig}$ are known in period 1, and $\zeta_{ic}$ and $\xi_{ig}$ are initially unknown and only realized if the individual chooses $c$ in period 1 or 2, and $g$ in period 3, respectively. We assume that $\zeta_{ic}$ is i.i.d. $N(0, \sigma_c^c)$ and $\xi_{ig}$ is i.i.d. $N(0, \sigma_g^g)$.

Denote $\zeta_{ic}^p$ and $\xi_{ig}^p$ as the beliefs of the individual regarding their unknown major-specific ability in period $p$. By construction, $\zeta_{ic}^1 = \xi_{ig}^1 = 0$. Beliefs in period 2 depend on the choices made and are given by

$$\zeta_{ic}^2 = \begin{cases} \zeta_{ic} & \text{if } d_{ic}^1 = 1 \\ 0 & \text{otherwise} \end{cases}$$

Beliefs in period 3 depend on the choices made in the previous two periods and are given by

$$\zeta_{ic}^3 = \begin{cases} \zeta_{ic} & \text{if } d_{ic}^1 = 1 \text{ or } d_{ic}^2 = 1 \\ 0 & \text{otherwise} \end{cases}$$

Notice that $\xi_{ig}^2 = \xi_{ig}^3 = 0$, since no graduate school enrollment is possible before period 3. Beliefs in period 4 depend on the choices made in the previous three periods and are given by

$$\xi_{ig}^4 = \begin{cases} \xi_{ig} & \text{if } d_{ig}^3 = 1 \\ 0 & \text{otherwise} \end{cases}$$

Notice that $\zeta_{ic}^4 = \zeta_{ic}^3$, since students cannot enroll in college in period 3.

Expected flow payoffs for each of the options depend on the individual's beliefs regarding their abilities. We assume that the utility payoff for dropping out of college in period 2 is zero, regardless of major before dropping out. We assume that flow payoffs while in school are linear in abilities. We also specify that switching majors between period 1 and 2 is costly:

$$U_{ic}^1 = \alpha_{0c} + \alpha_{1c} A_{ic}$$

$$U_{ic}^2 = \alpha_{0c} + \alpha_{1c}(A_{ic} + \zeta_{ic}^2) - \alpha_{2c} 1(d_{ic}^1 \neq 1)$$

$$U_{ig}^3 = \beta_{0g} + \beta_{1g} A_{ig} + \gamma_{cg}$$

The term $\gamma_{cg}$ captures the effect of undegraduate major $c$ on access to graduate program $g$ and on the flow utility from the program. The expected flow payoffs for working in period 3 (not going to graduate school) is

$$U_{in}^3 = \sum_{c \in \{b,o,n\}} (\gamma_{0c} + \gamma_{1c}(A_{ic} + \zeta_{ic})) d_{ic}^2$$

Finally, the expected flow payoffs for working in period 4 is

$$U_{in}^4 = \Big( \sum_{c \in \{b,o,n\}} (\gamma_{0c} + \gamma_{1c}(A_{ic} + \zeta_{ic})) d_{ic}^2 \Big) + \Big( \sum_{g \in \{b,o,n\}} (\omega_{0g} + \omega_{1g}(A_{ig} + \xi_{ig})) d_{ig}^3 \Big)$$

Therefore, the first two periods of school offers a utility flow (which could be negative), in addition to

different option values of completing college and graduate school. Under this set up, we define the *ex ante* return to majoring in business as the increase in expected discounted sum of future payoffs for choosing $d^1_{ib} = 1$ in period 1. We define the *ex post* return to majoring in business as the increase in expected discounted sum of future payoffs for choosing $d^2_{ib} = 1$ in period 2.[7] In other words, the *ex post* returns to majoring in business in college includes *ex ante* expected returns to various graduate degree outcomes.

# 5 Econometric Specifications and Methods

## 5.1 Regression Discontinuity Design Using GPA Cutoffs for Internal Transfer

Given the simple model introduced in the previous section, the challenge in identifying the *ex ante* and *ex post* returns to business and engineering in college comes from the fact that the decisions depend on unobserved portions of $A_{ic}$, $A_{ig}$, $\zeta_{ic}$, and $\xi_{ig}$, and from the fact that these elements affect the returns to college majors and graduate degrees.

We describe the empirical strategy for estimating the returns to business. The strategy for engineering is the same except that we use the published list of required courses list in defining who is potentially eligible to transfer. To identify the causal returns to majoring in business, we leverage minimum GPA requirements for internal transfers into business majors. We continue to use the notations in the previous section. Again, note that period 1 in the model maps to a student's junior year in college, while period 2 in the model maps to a student's senior years in college. In other words, $d^1_{ib} = 1$ indicates choosing business as one's major as of the beginning of junior year, and $d^2_{ib} = 1$ indicates attaining a bachelor's degree in business. We restrict our analyses to students who reach junior year status. In addition, we use the subscript $j$ for institution and the subscript $t$ for time.

Denote the cutoff for internal transfer into the business majors at time $t$ for institution $j$ as $Z_{jt}$ and denote student $i$'s cumulative GPA at the beginning of junior year as $\text{gpa}^1_{ijt}$. A simple RD specification for majoring in business is

$$P(d^1_{ib} = 1) = \beta_0 + f(\text{gpa}^1_{ijt}) + \beta_1 \times 1(\text{gpa}^1_{ijt} \geq Z_{jt}) + \beta X_{ijt} + \epsilon_{ijt} \tag{2}$$

where $f(\cdot)$ is a piece-wise quadratic function of students' GPA around the cutoff $Z_{jt}$. The parameter $\beta_1$ identifies the effect of crossing the GPA threshold on the probability of majoring in business for all students.

However, not all students are interested in majoring in business. As a result, the identified effect would

[7] Notice that this is different from the definition of ex post returns in Altonji (1993). Altonji (1993) defines ex post return to starting college as the returns to the first year in college.

be diluted by students who are not interested in transferring to the business majors. Because we do not know who would like to transfer into business, we rely on students' course selections to identify the population of students who are likely to be interested in transferring to the business majors. As mentioned in Section 2, the coherence measure, $\text{coh}_{ijt}$ is the share of degree-required courses that have been completed. In addition, the coherence measure is major and institution-specific. Let $\underline{\text{coh}}_{jt}$ denote the institution-specific median coherence level for business degrees among students who transferred from a non-business major to a business major. When estimating the effect of crossing the GPA thresholds on the probability of majoring in business, we focus on students who have coherence levels higher than $\underline{\text{coh}}_{jt}$. We modify equation (1) to

$$\begin{aligned} P(d^1_{ib} = 1) = {} & \beta_0 + g(\text{coh}^1_{ijt}) + \beta X_{ijt} \\ & + 1(\text{coh}^1_{ijt} < \underline{\text{coh}}_{jt}) \times [f_1(\text{gpa}^1_{ijt}) + \lambda_t \times 1(\text{gpa}^1_{ijt} \geq Z_{jt})] \\ & + 1(\text{coh}^1_{ijt} \geq \underline{\text{coh}}_{jt}) \times [f_2(\text{gpa}^1_{ijt}) + \gamma_t \times 1(\text{gpa}^1_{ijt} \geq Z_{jt})] + \epsilon_{ijt} \end{aligned} \tag{3}$$

The term $1(\text{coh}^1_{ijt} < \underline{\text{coh}}_{jt}) \times [f_1(\text{gpa}^1_{ijt}) + \lambda_t \times 1(\text{gpa}^1_{ijt} \geq Z_{jt})]$ absorbs the effect of crossing the GPA threshold for individuals with less than $\underline{\text{coh}}_{jt}$ coherence. As a result, $\gamma_t$ is the effect of crossing the threshold for our target population — students with coherence in business that are higher than the median level for successful transfers into business majors.

For engineering, we identify students interested in transferring into engineering majors by focusing on students who have completed all required coursework mentioned in Section 2.1. We use this strategy instead of using the coherence measure for two reasons. First, we were able to identify the specific coursework required for transferring into engineering majors for both UT Austin and Texas A&M. In contrast, most colleges did not list specific coursework requirements for transfer into business majors. Second, the catalogs of both UT Austin and Texas A&M have language restricting non-engineering majors from taking engineering courses. As a result, potential transfers may have difficulty accumulating engineering coherence before transferring. Equation (3) is modified accordingly for engineering:

$$\begin{aligned} P(d^1_{ib} = 1) = {} & \beta_0 + g(\text{coh}^1_{ijt}) + \beta X_{ijt} \\ & + 1(C_{ijt} \neq 1) \times [f_1(\text{gpa}^1_{ijt}) + \lambda_t \times 1(\text{gpa}^1_{ijt} \geq Z_{jt})] \\ & + 1(C_{ijt} = 1) \times [f_2(\text{gpa}^1_{ijt}) + \gamma_t \times 1(\text{gpa}^1_{ijt} \geq Z_{jt})] + \epsilon_{ijt} \end{aligned} \tag{4}$$

where $C_{ijt}$ is a binary variable indicating whether all required courses for transferring into engineering majors are completed. The terms $f_1(\cdot)$ and $f_1(\cdot)$ are piece-wise quadratic function of students' GPA around the cutoff $Z_{jt}$.

There is a further complication when bringing the specification in equation (3) and (4) to the data. In particular, there are multiple opportunities for students to transfer from non-business majors to business majors. Students can transfer as early as after their first semester in freshmen year, and as late as after their second semester in sophomore year.[8] As a result, using students' GPA and coherence level immediately before junior year will paint an inaccurate picture of their chances of transferring to business.

To incorporate all potential transition points into the business major, we need to introduce additional notation. Denote $d_{ib}^{01}$, $d_{ib}^{02}$, $d_{ib}^{03}$, $d_{ib}^{04}$ , $d_{ib}^{05}$ as the indicators for a student entering his first, second, third, fourth, and fifth semester as a business major. Similarly, denote $\text{gpa}_{ijt}^{0s}$ and $\text{coh}_{ijt}^{0s}$ as a student's GPA and coherence level entering semester $s$. While students at any of the transition points are assumed to face the same cutoff GPA, the minimum coherence levels we consider are $s$-specific. In particular, $\underline{\text{coh}}_{jt}^{s}$ is defined as the median coherence level among students for whom $d_{ib}^{0s} = 0$ and $d_{ib}^{0(s+1)} = 1$. We adjust equation (3) to model the student's conditional probability of transferring into business for each transition period:

$$
\begin{aligned}
\phi_{is} &= P(d_{ib}^{0(s+1)} = 1 | d_{ib}^{0s} = 0) \\
&= \beta_{0s} + g_s(\text{coh}_{ijt}^{0(s+1)}) + \beta_s X_{ijt} \\
&+ 1(\text{coh}_{ijt}^{0(s+1)} < \underline{\text{coh}}_{jt}^{s+1}) \times [f_{1s}(\text{gpa}_{ijt}^{0(s+1)}) + \lambda_{ts} \times 1(\text{gpa}_{ijt}^{0(s+1)} \geq Z_{jt})] \\
&+ 1(\text{coh}_{ijt}^{0(s+1)} \geq \underline{\text{coh}}_{jt}^{s+1}) \times [f_{2s}(\text{gpa}_{ijt}^{0(s+1)}) + \gamma_{ts} \times 1(\text{gpa}_{ijt}^{0(s+1)} \geq Z_{jt})] + \epsilon_{ijts}
\end{aligned} \tag{5}
$$

Given $\phi_{is}$ for $s \in \{1, 2, 3, 4\}$, we can model the probability of entering junior year as a business major, $P(d_{ib}^1 = 1)$, with a survival model, where "survival" is not declaring a business major. Specifically, we have

$$
\begin{aligned}
\Phi_i &= P(d_{ib}^1 = 1) \\
&= 1 - P(d_{ib}^1 = 0) \\
&= 1 - \Pi_{s=1}^4 (1 - \phi_{is})
\end{aligned} \tag{6}
$$

The main assumption for modeling the transition into business majors with a survival model is that

[8] Transfers that occur after junior year are already captured by the model with $d_{ic}^2$.

business major is an absorbing state.

**Assumption 1 (No Switch Out)**: Conditional on reaching junior status, students who previously transferred into business majors do not transfer into another major before junior year. Namely, for all $s \in \{1, 2, 3, 4\}$:

$$P(d_{ib}^{1} = 0 | d_{ib}^{0(s+1)} = 1) = 0$$

This assumption is close to what we observe empirically — among those who transfer into business (engineering) majors after the first semester and reach junior status, 88% (80%) remain a business (engineering) major by the beginning of junior year. If we look at those who transfer after the second or third semester, the statistics are around 95% for both business and engineering.[9]

We calculate $\hat{\Phi}_i = 1 - \Pi_{s=1}^{4}(1 - \hat{\phi}_{is})$, where $\hat{\phi}_{is}$ is the predicted value following equation (5). We also create a second variable, $\bar{\Phi}_i = 1 - \Pi_{s=1}^{4}(1 - \bar{\phi}_{is})$, where $\bar{\phi}_{is}$ is the predicted value following equation (5) but excluding the RD variation in GPA for those with $\text{coh}_{ijt}^{0(s+1)} \geq \underline{\text{coh}}_{jt}^{s+1}$ :

$$\begin{aligned}
\bar{\phi}_{is} = {} & \beta_{0s} + g_s(\text{coh}_{ijt}^{0(s+1)}) + \beta_s X_{ijt} \\
& + 1(\text{coh}_{ijt}^{0(s+1)} < \underline{\text{coh}}_{jt}^{s+1}) \times [f_{1s}(\text{gpa}_{ijt}^{0(s+1)}) + \lambda_{ts} \times 1(\text{gpa}_{ijt}^{0(s+1)} \geq Z_{jt})] \\
& + 1(\text{coh}_{ijt}^{0(s+1)} \geq \underline{\text{coh}}_{jt}^{s+1}) \times f_{2s}(\text{gpa}_{ijt}^{0(s+1)}) + \epsilon_{ijts}
\end{aligned}$$

In our main empirical specification, which we call the survival-RD, we include $\bar{\Phi}_i$ as a control variable in the first and second stage of our IV procedure and use $\hat{\Phi}_i$ as the excluded instrument. As a result, for identification we are relying on variation in the predicted probability of (not) majoring in business, $\hat{\Phi}_i$, that comes from the RD variation in GPA for those with high coherence.

We also implement an alternative empirical specification that does not rely on Assumption 1 and accounts for optimal bandwidth for the RD procedure. We modify equation (5) to

[9] If the assumption is false, then in principle one could improve efficiency by constructing separate instruments for tranferring into business after the first semester, after the second semester, etc. but we prefer the more parsimonious approach. Note if the effect of majoring in business in the first semester of junior year depends on the semester of transfer, then our IV procedure identifies a weighted average of different LATE parameters. For discussion of LATE in the context of multiple instruments, see Mogstad, Torgovistsky, and Walters (2021). We lack the statistical power to estimate separate treatment parameters.

$$
\begin{aligned}
\tilde{\phi_{is}} &= P(d_{ib}^{0(s+1)} = 1 | d_{ib}^{0s} = 0) \\
&= \beta_0 + g_s(\text{coh}_{ijt}^{0(s+1)}) + \beta X_{ijt} \\
&+ 1(\text{coh}_{ijt}^{0(s+1)} < \underline{\text{coh}}_{jt}^{s+1}) \times [f_{1s}(\text{gpa}_{ijt}^{0(s+1)}) + \lambda_{ts} \times 1(\text{gpa}_{ijt}^{0(s+1)} \geq Z_{jt})] \\
&+ 1(\text{coh}_{ijt}^{0(s+1)} \geq \underline{\text{coh}}_{jt}^{s+1}) \times [f_{2s}(\text{gpa}_{ijt}^{0(s+1)}) + \gamma_{ts} \times 1(\text{gpa}_{ijt}^{0(s+1)} \geq Z_{jt})] \\
&+ 1(\text{coh}_{ijt}^{0(s+1)} \geq \underline{\text{coh}}_{jt}^{s+1}) \times 1(-b^s \leq \text{gpa}_{ijt}^{0(s+1)} \leq b^s) \times [f_{3s}(\text{gpa}_{ijt}^{0(s+1)}) + \omega_{ts} \times 1(\text{gpa}_{ijt}^{0(s+1)} \geq Z_{jt})] + \epsilon_{ijts}
\end{aligned} \tag{7}
$$

where $b^s$ is the optimal bandwidth of the RD procedure in period $s$, computed following Calonico, Cattaneo, and Titiunik (2014a and 2015b). We use $1(\text{coh}_{ijt}^{0(s+1)} \geq \underline{\text{coh}}_{jt}^{s+1}) \times 1(-b^s \leq \text{gpa}_{ijt}^{0(s+1)} \leq b^s) \times 1(\text{gpa}_{ijt}^{0(s+1)} \geq Z_{jt})$ for each $s$ as the excluded instruments and include the remaining terms in $\tilde{\phi_s}$ as controls.[10] That is, we use the effects of crossing the GPA cutoffs for students who pass the coherence thresholds and have GPAs within the bandwidth for identification. We call this specification the linear-RD and use it as a robustness check to the survival-RD model. We call it the linear-RD model because, $\tilde{\phi_1}$, $\tilde{\phi_2}$, $\tilde{\phi_3}$, and $\tilde{\phi_4}$ enter the model linearly, instead of being aggregated through the survival model. The main disadvantage of the linear-RD model is its larger standard errors, due to the inclusion of piece-wise linear terms for all transition periods.

## 5.2 Estimating Ex Ante and Ex Post Returns to Majors

As mentioned in Section 4, we define ex ante returns to business majors as the causal effect of declaring as business major (by junior year) on an individual's earnings. In comparison, we define ex post returns to business majors as the causal effect of earning a business bachelor's degree on an individual's earnings. The earnings models for ex ante and ex post returns are:

$$
y_{it} = a_0 + a_1 d_{ib}^1 + a_2 \bar{\Phi} + aX_{it} + \epsilon_{it} \tag{8}
$$

$$
y_{it} = b_0 + b_1 d_{ib}^2 + b_2 \bar{\Phi} + bX_{it} + \epsilon_{it} \tag{9}
$$

[10] The terms are $g_s(\text{coh}_{ijt}^{0(s+1)})$, $X_{ijt}$, $1(\text{coh}_{ijt}^{0(s+1)} < \underline{\text{coh}}_{jt}^{s+1}) \times f_{1s}(\text{gpa}_{ijt}^{0(s+1)})$ , $1(\text{coh}_{ijt}^{0(s+1)} < \underline{\text{coh}}_{jt}^{s+1}) \times 1(\text{gpa}_{ijt}^{0(s+1)} \geq Z_{jt})$, $1(\text{coh}_{ijt}^{0(s+1)} \geq \underline{\text{coh}}_{jt}^{s+1}) \times f_{2s}(\text{gpa}_{ijt}^{0(s+1)})$, $1(\text{coh}_{ijt}^{0(s+1)} \geq \underline{\text{coh}}_{jt}^{s+1}) \times 1(\text{gpa}_{ijt}^{0(s+1)} \geq Z_{jt})$, and $1(\text{coh}_{ijt}^{0(s+1)} \geq \underline{\text{coh}}_{jt}^{s+1}) \times 1(-b^s \leq \text{gpa}_{ijt}^{0(s+1)} \leq b^s) \times f_{3s}(\text{gpa}_{ijt}^{0(s+1)})$.

where $d^1_{ib}$ and $d^2_{ib}$ are instrumented with $\hat{\Phi}$. $X_{it}$ includes a gender specific cubic age profile as well as students' coherence level at the beginning of junior year for all of the 18 majors at the 2 digit level. For our preferred specification, survival-RD, we use $\hat{\Phi}_i$ to instrument for declaring a business major and attaining a business bachelor's degree. We include $\bar{\Phi}_i$ as a control so that we are only using variation $\hat{\Phi}_i$ driven by the gpa discontinuity terms for high coherence students, $1(\text{coh}^{0(s+1)}_{ijt} \geq \underline{\text{coh}}^{s+1}_{jt}) \times [\gamma_{ts} \times 1(\text{gpa}^{0(s+1)}_{ijt} \geq Z_{jt})]$, to identify the effects of majoring in business.

Assuming that crossing the GPA cutoffs is exogenous to unobservable abilities and preferences, $a_1$ identifies the causal effect of majoring in business (at the beginning of junior year) on earnings relative to a weighted average of the causal effects of 5 alternative majors. The weight for a given alternative is the effect of crossing the business GPA transfer threshold on the probabilities of choosing that alternative. Because we restrict our analyses to students who reach junior status and did not enter college as business majors, the counterfactual group identified are students who are similar to those who declared major in business but ended up declaring other majors. In section 6, we report comparisons of the compliers to the overall population over several observable characteristics.

With the additional assumption that crossing the GPA cutoffs only affects earnings through degree attainment, $b_1$ identifies the causal effect of attaining bachelor's degrees in business majors on earnings relative to a weighted average of the causal effects of the counterfactual degree outcomes. The six counterfactual degree outcomes include ending up with a bachelor's degree in one of the 5 non-business majors and not graduating from college despite reaching junior year status. The weights are the effects of crossing the business GPA transfer threshold on the probabilities of the alternatives. Our estimates of ex poste returns are *not* estimates of the ex post return to obtaining a bachelors in business or in engineering relative to not going to college.

### 5.3 Estimating Degree Outcomes and Time to Degrees

The motivation for distinguishing between ex ante and ex post returns comes from the uncertainty in degree outcomes. In this paper, we study three important sources of degree outcome uncertainty. First, $d^2_{ib}$ might not equal one even if $d^1_{ib} = 1$. This reflects the possibility that students might drop out of college and or change majors after reaching junior year status.[11] Second, students may take varying number of years to complete their undergraduate degrees. For example, an engineering degree typically requires more credit

[11] Late college dropout after reaching junior year status is surprisingly prevalent in the US. Zhu (2025) uses the same Texas data set to calculate that dropout rate is 8% for juniors and 11% for seniors, although these figures would include students who transfer to an out of state institution and complete their degree.

hours than liberal arts degrees, perhaps requiring more effort and lengthier enrollment. Third, different majors could lead to different pathways through graduate school. It is possible, for example, that part of the value of majoring in business as an undergraduate comes from the increased likelihood of attaining an MBA in the future.

To examine these three factors, we break down periods 2 and 3 of the model in Section 4 into years. Denote $d_{ic}^{2y}$ as an indicator for whether individual $i$ attained a bachelor's degree in major $c$, $y$ years after reaching junior year status. Similarly, denote $d_{ig}^{3y}$ as an indicator for whether individual $i$ attained a graduate degree in major $g$, $y$ years after reaching junior year status. We estimate undergraduate degree outcomes for $y \in \{2, 3, \cdots, 8\}$ using

$$d_{ic}^{2y} = c_0^{cy} + c_1^{cy} d_{ib}^1 + c_2^{cy} \bar{\Phi} + c^{cy} X_{it} + \epsilon_{it}\,, \tag{10}$$

where $d_{ib}^1$ is instrumented with $\hat{\Phi}$. The paremater $c_1^{by}$ is the causal effect of declaring as a business major (by the beginning of junior year) on the probability of attaining a BA in business. Similarly, $c_1^c$ for $c \neq b$ is the causal effect of declaring business major on the probability of attaining a bachelor's degree in another field. These parameters indicate what the likely counterfactual majors are for students who are on the margin. For example, if $c_1^{\text{engineering}}$ is significantly negative, this indicates that compared to the treated group, who declared business major, the counterfactual students are more likely to end up majoring in engineering.

Finally, we estimate graduate degree outcomes for $y \in \{4, 5, \cdots, 8\}$ using

$$d_{ig}^{3y} = g_0^{gy} + g_1^{gy} d_{ib}^2 + g_2^{gy} \bar{\Phi} + g^{gy} X_{it} + \epsilon_{it} \tag{11}$$

where, again, $d_{ib}^2$ is instrumented with $\hat{\Phi}$.

# 6 Results

In this section, we present our main empirical results. We begin in section 6.1 by presenting RD results on how crossing the GPA cutoffs affect the likelihoods of declaring majors in business and engineering. Section 6.1 also presents results on balance tests for the RD design and summary statistics on the compliers. Section 6.2 reports results on the ex ante returns to majoring in business and engineering and the ex post returns to attaining bachelor's degrees in business and engineering. Section 6.3 presents results on the effects of majoring in business and engineering on degree outcomes and time to degrees. Section 6.4 presents results from alternative specifications and reports imputed ex ante returns that help validate our findings. Finally,

section 6.5 combines the returns estimates, the effects on time to degrees, and the cost of enrollment to calculate present discounted values (PDV) of majoring in business and engineering.

## 6.1 Effects of Crossing the GPA Cutoffs on Declaring Majors.

Figures 2-3 present the probabilities of transferring into business majors in each of the transition periods, conditional on not being a business major before the transition period. The horizontal axes represent students' distance to the GPA cutoff.[12] Figure 2 reports results for all students in institutions and cohorts for which we have identified GPA cutoffs for internal transfer into business majors. Notice that the panels of figure 2 are essentially the reduced form figures for fuzzy RD following equation (2). Meanwhile, figure 3 reports results for students with coherence levels greater or equal to the median coherence among students who successfully transferred into business majors in the transition period of interest. From figure 2, we observe that the probability of internally transferring into business majors is very small ($<5\%$), and we only observe a small discontinuous effect for crossing the GPA cutoffs. From figure 3, we can observe that the probability of transferring into business majors is substantially higher for students with high enough coherence. The effects of crossing the GPA cutoffs are now salient and show a discontinuous positive effect on transferring into business majors. The comparison between figures 2 and 3 shows the necessity of leveraging the coherence measure to identify the relevant student population for the RD design.

Figures 4 and 5 present the results for the probabilities of transferring into engineering majors, conditional on not being an engineering major before the transition period. Figure 4 reports results for all students in institutions and cohorts for which we have GPA cutoffs for internal transfer into engineering majors, and figure 5 reports results for the subset of students who have completed all required coursework for transferring into engineering majors. Similar to the case for business, the overall probabilities of transferring into engineering majors and the effects of crossing the GPA cutoffs are not detectable in the overall sample. Once we focus on the population of students who have completed all required courses for transferring into engineering majors, we observe a salient positive effect of crossing the GPA cutoff on the probabilities of transferring into engineering majors. We do not find significant effects for crossing GPA cutoffs in semester 1 and semester 4 (not reported). For all analyses on engineering majors we only leverage variations that come from crossing the GPA cutoffs in semester 2 and semester 3.

[12] The bins are selected with the variance evenly spaced method using spacing estimators.

### 6.1.1 Balance Tests and Complier Characteristics

The RD design relies on the assumption that crossing the GPA cutoffs is random. It is therefore necessary to test if crossing the GPA cutoffs is correlated with any observable characteristics that may also affect our dependent variables. We use the RD specification in equation (4) and replace the dependent variable with (a) student's percentile ranking in Texas' standardized high school reading exam; (b) percentile ranking in Texas' standardized high school math exam; (c) economic status; (d) gender; and (e) first declared major. In the balance tests for students' first declared major, we use dummy variables for whether the student's first major was engineering and social sciences for business cutoffs and use dummy variables for whether the student's first major was business and sciences for engineering cutoffs.

The results are reported in table 3. The top panel shows the effects of crossing the GPA cutoffs for business. Among the 24 balance tests performed, only one (crossing cutoff in semester 4 on economic status) appear statistically significant. The bottom panel shows the effects of crossing the GPA cutoffs for engineering. Among the 12 balance tests performed, only one (crossing cutoff in semester 3 on first major being business) appear statistically significant.[13]

As mentioned in the introduction, the effects of majoring in business and engineering estimated using the variations from crossing the GPA cutoffs are the LATE for the compliers — students who gets nudged into business/engineering by crossing the GPA cutoffs for internal transfers. For policies that aim to expand access to business and engineering majors, these students are arguably the most relevant population. Nevertheless, it is useful to understand whether and how these students may be different from the overall population. We follow Angrist and Pischke (2008) and compare the characteristics of the compliers to the overall sample included in our main specifications.[14] For a Bernoulli-distributed characteristic $x_i$, the relative likelihood that compliers have $x_i = 1$ is given by the ratio of the first stage among those with $x_i = 1$ to the overall first stage.

The results are presented in table 4. The compliers for business have higher high school standardized math and reading scores, are less likely to be female, and slightly less likely to be economically disadvantaged. The compliers for engineering also have higher standardized high school test scores, are much less likely to be female, and slightly less likely to be economically disadvantaged. In addition, the engineering compliers are substantially less likely to be non-hispanic whites.

[13]Notice that the direction of the estimate for the effect of crossing cutoff in semester 2 on first major being business is in the opposite direction, suggesting that the statistically significant effect in semester 3 is unlikely to be of concern.

[14]For example, for returns to business major, the overall sample includes individuals who reach junior status, did not start college as business majors, and have at least 0.25 business coherence by the beginning of junior year.

## 6.2 Estimates for Ex Ante and Ex Post Returns to Business and Engineering

Table 5 reports the ex ante and ex post returns to business and engineering on log earnings. The instrumental variable (IV) estimate shows a 0.13 (0.03) ex ante returns for majoring in business. The estimated ex post returns for attaining a business bachelor's degree is 0.12 (0.03). The OLS estimates for the ex ante and ex post returns are slightly smaller at 0.09 (0.004) and 0.11 (0.003) respectively. The fact that the IV estimates are larger than OLS may be due to higher returns for the marginal students identified with the IV specification.

Columns (3) and (4) of table 5 report ex ante and ex post returns for engineering. The IV estimates show a 0.28 (0.08) ex ante returns for majoring in engineering, and a 0.31 (0.10) ex post returns for attaining an engineering bachelor's degree. Similar to the case for business, the OLS estimates are similar but slightly smaller for both ex ante returns — 0.24 (0.01) — and ex post returns — 0.26 (0.01).

Table 6 reports results for ex ante and ex post return to business by gender, socioeconomic status, ethnicity, and selectivity of institution. Note that we define an institution to be selective if the freshmen admission rate for Texas applicants in the 2024-2025 academic year is lower than 70%. For the institutions we consider for business majors, the selective institutions are University of Texas at Austin, Texas A&M University, University of North Texas, University of Houston, and University of Texas at Arlington. The non-selective institutions are Midwestern State University, University of Texas at Rio Grande Valley, and Texas State University. Table 6a shows higher ex ante and ex post returns for females. The ex ante returns for females — 0.17 (0.02) — is 30% higher than that for males — 0.13 (0.02). The ex post returns for females — 0.17 (0.02) — is also substantially higher than that for males — 0.12 (0.02). The same pattern is present in the OLS estimates. Notice, however, that the differences between females and males are not statistically significant at the 10% level for the IV estimates.[15] Table 6b shows that economically disadvantaged students have lower ex ante and ex post returns to business. The ex ante return to majoring in business for economically disadvantaged students is around 60% of that for other students — 0.10 (0.04) vs. 0.16 (0.02). This is also true for ex post return to attaining a bachelor's degree in business — 0.09 (0.05) vs 0.15 (0.02). the differences in the IV estimates are not statistically significant, but the same pattern is present in the OLS estimates, which are precise.

Tables 6d and 6e show significant heterogeneity in return across ethnicity. Non-Hispanic white have the highest ex ante and ex post returns — 0.20 (0.02) and 0.19 (0.02). Hispanic and black students have lower

[15] We investigated whether the gender difference in returns arises because females and males major different sub-fields within business. Examining the distribution of four-digit CIP codes within business, we find that the most popular four-digit CIP code is 5202 (business administration, management, and operation) and the share of students in each four-digit CIP codes are similar for the most part. The only exception is that more male students major in finance while more female students major in accounting, sales, and marketing. These differences, however, would favor higher returns for male students, since finance is the highest earning sub-field in business.

ex ante and ex post returns — 0.14 (0.03) and 0.13 (0.03). Asian students have the lowest returns — 0.05 (0.03) and 0.06 (0.03). Finally, table 6c shows that students in selective institutions have significantly higher ex ante and ex post returns to business. The ex ante returns to majoring in business is 67% higher — 0.15 (0.02) vs. 0.09 (0.03) — and the ex post returns to attaining business undergraduate degree is 64% higher — 0.14 (0.02) vs. 0.09 (0.03). The differences are statistically significant.

Table 7 reports heterogeneity results for ex ante and ex post return to engineering. Due to the smaller sample size for engineering majors, we are under-powered to look at heterogeneity in the returns to engineering for dimensions other than gender. Females have substantially higher ex ante returns — 0.50 (0.13) vs. 0.10 (0.10) — and ex post returns — 0.51 (0.10) vs. 0.10 (0.13). The differences are significant at the 1 percent level. However, the OLS estimates of the ex post return are .292 (0.015) for females and 0.252 (0.010) for males, suggesting a smaller female advantage.

### 6.3 Estimates for Effects on Degree Outcomes and Time to Degrees

In this subsection, we discuss the effects of majoring in business and engineering on college degree attainment, graduate degree attainment, and time to degrees.

Table 8 reports the IV estimates of the effects of majoring in business on college degree outcomes four years after reaching junior status. In other words, these results reflect degree outcomes in the standard six-year graduation time frame. Several patterns can be observed. First, the results in the first row show that, majoring in business increases the likelihood of attaining a bachelor's degree in business by 0.998 (0.009). This estimate for the marginal student is well above the OLS estimate of 0.848. Second, the results in the last row labeled "All" show that majoring in business leads to an increase of 0.052 (0.014) in the likelihood of attaining any bachelor's degree four years after reaching junior status, which is substantial. Third, results in the other rows show that social sciences, engineering, and other majors are the most prevalent counterfactual majors for business students. The OLS estimates follow the same pattern. Fourth, the counterfactual majors differ substantially by gender. Majoring in business decreases the likelihood of attaining an engineering bachelor's degree by 0.27 (0.03) for males but only 0.05 (0.01) for females. In contrast, majoring in business decreases the likelihood of attaining a bachelor's degree in social sciences and "other" majors, which includes humanities and education, by 0.65 for females but only 0.54 for males. Since engineering graduates have substantially higher average earnings than graduates of social science and "other" majors, the stark differences in counterfactual majors help explain the higher return to majoring in business for female students. In section 6.5, we provide a more systematic accounting exercise following this logic

Table 9 reports the effects of majoring in business on graduate degree outcomes eight years after reaching

junior status. Overall, majoring in business increases the likelihood of attaining a graduate degree in the future by 0.032 (0.018). This is mostly driven by the increase of 0.16 (0.01) in the likelihood of attaining a graduate degree in business, including an MBA . The results suggests that the option value of attaining a graduate degree, and an MBA in particular, is likely a significant part of the return to majoring in business. In section 6.5, we will provide a more rigorous calculation of the option value.

#### 6.3.1 Engineering

We now turn to results on the effects of majoring in engineering on the probabilities of degree outcomes. Table 10 reports the effects of majoring in engineering on college degree outcomes four years after reaching junior status. First, majoring in engineering significantly increases the likelihood of attaining an engineering bachelor's degree. Second, the most prevalent counterfactual majors for engineering students are science and "other". Third, similar to the case for business, gender heterogeneity in degree outcomes can help explain the higher ex ante and ex post returns to engineering. In particular, females are much more likely than males to have the lowest-earning "other" majors as their counterfactual major — -0.44 (0.04) vs. -0.12 (0.15) — , although the effect on "All degrees" is negative for females and positive for males.Table 11 presents the effects of majoring in engineering on graduate degree outcomes eight years after junior year. Unlike majoring in business, majoring in engineering decreases the likelihood of attaining any graduate degree by 0.06 (0.03). The decreases in likelihoods are particularly salient for business — -0.04 (0.02) — science — -0.03 (0.01) — and health — -0.06 (0.01). The results show that graduate degree attainment is likely not as important to the return to majoring in engineering.

#### 6.3.2 Effects on Time to Degree

Finally, we examine the effects of majoring in business and engineering on the time to degrees. Anecdotal evidence suggests that engineering is a challenging degree to attain. The degree requirements are dense in STEM courses and typically demand more credit hours. For example, students are required to attain 128 semester credit hours to attain a bachelor's degree in mechanical engineering in TAMU, while the general university-wide requirement for bachelor's degree is 120 semester credit hours.[16] Our results on time to degrees reflect the difficulty of engineering. Tables 12 and 13 report the effects of majoring in business and engineering on college degree outcomes two years after reaching junior status. In other words, these results reflect degree outcomes for "on-time" graduation. The results in the fourth row of table 13, compared to

[16]The 2025-26 edition of the University Catalogs for UT Austin states that 132 credit hours are required for a BS in Biomechanical Engineering, and 126 are required for Mechanical Engineering. 120 credit hours are required for a bachelors in Finance, Management, Economics, and all of the liberal arts majors that we checked.

those in the fourth row of Table 10, suggest that a large share of students who transfer into engineering majors do not complete the degrees in four years. Majoring in business increases the likelihood of earning a business undergraduate degree by 0.48 (0.01) two years after reaching junior status. In comparison, majoring in engineering only increases the likelihood of earning an engineering degree by 0.19 (0.03) two years after reaching junior status. The last row of table 13 implies that majoring in engineering decreases the likelihood of "on-time" graduation with any degree by 0.24 (0.03). In comparison, the last row of table 12 implies that majoring in business increases the likelihood of "on-time" graduation by 0.09 (0.03).

### 6.4 Robustness Checks and Accounting for Differences in Estimates

Before turning to the results on option values, we report results that help unpack the previous results on earnings and degree attainment. The results tackle three main questions. First, are the results using the survival-RD model robust to alternative specifications? Second, can we reconcile the differences in estimates of the effects on earnings between OLS and survival-RD with the differences in estimates of the effects on degree attainment between OLS and survival-RD? Third, and similarly, can we reconcile the differences in estimates of the effects on earnings for different populations with the differences in estimates of the effects on degree attainment for the different populations?

First, we consider two alternative empirical strategies. The first is the survival-RD model when restricting the sample to students whose GPA are within 0.3 of the cutoff GPA for each semester prior to junior year. 0.3 is the optimal bandwidth calculated for both business and engineering following Calonico, Cattaneo, and Titiunik (2014a and 2015b). The second is the linear-RD model we mentioned at the end of section 5.1. The linear-RD model does not impose the survival model structure and includes the RD variations for all periods linearly. Table 14 presents the results from these two alternative empirical strategies, along with those from the OLS and survival-RD models, for comparison. The results for business show that our main estimate for ex ante returns (0.13) is very similar to the estimate restricting to students whose GPAs are within 0.3 of the cutoffs (0.14) and the estimate using the linear-RD model (0.14). The main estimate for ex post returns to business degree (0.12) is slightly smaller than the estimate restricting to students whose GPAs are within 0.3 of the cutoffs (0.15) and the estimate using the linear-RD model (0.19), although the differences are not statistically significant. As expected, the survival-RD model has the advantage of having more precision compared to the linear-RD model. The results for engineering show that our main estimate for ex ante returns (0.28) is between the estimate restricting to students whose GPAs are within 0.3 of the cutoffs (0.24) and those using the linear-RD model (0.33). The main estimate for ex post returns to engineering degree (0.31) is higher than the estimates using the two alternative strategies (0.23 and 0.25). The differences are

not large compared to the standard errors.

Second, we try to predict the ex ante returns to business and engineering by combining the survival-RD estimates of the effects on undergraduate degree outcomes and OLS estimates of the earnings premium of each undergraduate degrees. The first component, the effects of majoring in business and engineering on undergraduate degree outcomes are the coefficient estimates reported in tables 8 and 10. Following the notation from equation (9), let $\hat{c}_1^{c4}$ be the effect of majoring in business/engineering on the likelihood of attaining bachelor's degree in major $c$ four years after junior year. The second component, the earnings premium of each undergraduate degrees, is estimated using an OLS regression:

$$y_{it} = b_0 + \sum_{c=1}^{6} b_{1c} d_{ic}^2 + bX_{it} + \epsilon_{it} \tag{12}$$

where $d_{ic}^2$ is an indicator for whether individual $i$ has a bachelor's degree in major $c \in \{1, ..., 6\}$. The omitted category is $c = 0$, no college degree. $X_{it}$ includes controls for gender, ethnicity, gender-specific cubic age profile, semester credit hours accumulated, a quadratic for GPA, and institution fixed effects. In addition, we follow Andrews, Imberman, Lovenheim, and Stange (2024) and include fixed effects for students' high school $\times$ cohort combination.[17] $\hat{b}_{1c}$ is the estimated earnings premium for college degree $c$ (relative to no degree). We predict the ex ante returns to majoring in business and to engineering using the linear combinations $\sum_{i=1}^{6} \hat{b}_{1c}\hat{c}_1^{c4}$. We implement the prediction with $\hat{c}_1^{c4}$ estimates from both the OLS and survival-RD models and also compute the predictions separately for the different populations we consider.[18]

The predicted ex ante returns for business and engineering are reported in tables 15 and 16, along with the actual estimated OLS and survival-RD estimates for comparison. Table 15 reports results for the ex ante returns to majoring in business. The results in columns 1 and 2 show that the ex ante returns estimates from both the OLS and survival-RD models (0.09 and 0.13) are approximated reasonably well by the predicted ex ante returns (0.11 and 0.16). The results in columns 3-9 show that the ex ante returns estimates from the survival-RD models for different populations (e.g., females, males, economically disadvantaged) are also approximated well by the predicted ex ante returns for each population. Table 16 report results for the ex ante returns to majoring in engineering. The results in columns 1 shows that the ex ante returns estimates from the OLS model (0.24) is well approximated with the predicted ex ante returns (0.29). The ex ante returns estimates from the survival-RD models for the full sample, female, and male students (0.28, 0.50, and 0.09) are not as well approximated (0.39, 0.40, and 0.38). However, the overall discrepancy and the discrepancy for females is not large compared to the standard errors of the ex ante returns estimates.

[17] The internal GPA transfer cutoffs are only available for engineering and business and thus are not sufficient to identify the earnings premiums for all of the degrees. OLS with detailed controls is the best available option for this exercise.

[18] Note that equation (12) is re-estimated for each sub-population for the procedure.

Overall the results from the two exercises show that the estimates from the survival-RD model are robust to alternative specifications and that the estimates of the effects on earnings are broadly consistent with the estimates of the effects on degree attainment. In particular, the ex ante returns to majoring in business and to a lesser extent, engineering can, for the most part, be predicted with the effects of majoring in business and engineering on undergraduate degree attainment. It is important to note, however, that this does not imply that graduate degree attainment is not an important part of the returns to majoring in business and engineering. This is because the earnings premiums of college degrees implicitly incorporates the option values of graduate degree. In the next subsection, we will turn to examine the present discount values of majoring in business and engineering and the option values of graduate degrees.

## 6.5 Present Discounted Values of Majoring in Business and Engineering and the Option Value of Graduate School

Two questions remain: first, what is the value of majoring in business and engineering when taking into account tuition and time to degree? Second, what share of this value comes from the (option) value of graduate school? We answer these questions by calculating the actual and counterfactual present discounted values (PDV) of majoring in business and engineering.

### 6.5.1 Procedure for Calculating PDVs

We take the following procedure to calculate the PDVs. Consider the case for business. First, we extend equations (10) and (11) and run regressions where the dependent variables are replaced with combinations of college degree, graduate degree, college enrollment, and graduate enrollment. Specifically, for each $y \in \{2, 3, \cdots, 8\}$ and each potential outcome $o \in O$, we estimate:

$$d_{io}^{y} = \delta_0^{oy} + \delta_1^{oy} d_{ib}^{1} + \delta_2^{oy} \bar{\Phi} + \delta^{oy} X_{it} + \epsilon_{it} \tag{13}$$

where, again, $d_{ib}^{1}$ is instrumented with $\hat{\Phi}$. Note that we have six categories for $c$ and eight categories for $g$. To avoid small cells, we make the assumption that students can attain graduate degrees only after 3 or more years after junior year. In addition, we include college enrollment and graduate enrollment as possible outcomes. This results in 16 possible outcomes in $O$ two years after junior year: (1) enrolled in college — one outcome; (2) no college degree — one outcome; (3) college degree in field $c$ — six outcomes; and (4) graduate enrollment in field $g$ — eight outcomes. For three or more years after junior year, there are 64

possible outcomes in $O$: (1) enrolled in college — one outcome; (2) no college degree — one outcome; (3) college degree in field $c$ — six outcomes; (4) graduate enrollment in field $g$ — eight outcomes; (5) and college degree in field $c \times$ graduate degree in field $g$ — 48 outcomes.

Second, we predict the actual and counterfactual probabilities of each outcome at each time period from 2 to 8 years after junior year. The predicted actual probabilities are calculated as $P_{oy}^{Actual} = \hat{\delta}_0^{oy} + \hat{\delta}_1^{oy} + \hat{\delta}_2^{oy}\bar{\bar{\Phi}} + \hat{\delta}^{oy}\bar{X}_{it}$, where $\bar{\bar{\Phi}}$ denotes the sample average of $\bar{\Phi}$ and $\bar{X}_{it}$ denotes the sample average of the vector of control variables. Similarly, the counterfactual probabilities are calculated as $P_{oy}^{Counter} = \hat{\delta}_0^{oy} + \hat{\delta}_2^{oy}\bar{\bar{\Phi}} + \hat{\delta}^{oy}\bar{X}_{it}$.[19]

Third, we calculate another set of probabilities, $P_{oy}^{ActualCollege}$, assuming that majoring in business only changes the likelihoods of college enrollment and attaining college degrees but does not change the likelihoods of graduate enrollment or attaining graduate degrees. Specifically, we let (1) $P_{oy}^{ActualCollege} = P_{oy}^{Counter}$ for the eight outcomes representing graduate enrollment; (2) $P_{oy}^{ActualCollege} = P_{oy}^{Actual}$ for the one outcome representing enrolled in college; (3) $\sum_{o \in O_c} P_{oy}^{ActualCollege} = \sum_{o \in O_c} P_{oy}^{Actual}$ for all $c$, where $O_c$ denote the set of outcomes where student attains college degree in field $c$; and (4) $P_{cgy}^{ActualCollege} / \sum_{o \in O_c} P_{oy}^{ActualCollege} = P_{cgy}^{Counter} / \sum_{o \in O_c} P_{oy}^{Counter}$, so that the probability of attaining a graduate degree in $g$ conditional on attaining college degree in $c$ is the same as the counterfactual. We extend the probabilities calculated in steps two and three to years $y \in \{9, 10, \cdots, 39\}$ by making the assumption that they are the same as when $y = 8$.

Fourth, we calculate the expected earnings under each outcome $o$ in years $y \in \{2, 3, \cdots, 39\}$. Since we have 64 possible outcomes (16 for two years after junior year) and only two sets of cutoff GPAs, we need to rely on OLS for this step. For the OLS estimation, we do not restrict to data after 2012, as we do in our main specifications. Instead, we use earnings observations from as early as 1991. We include detailed controls, including gender, ethnicity, gender-specific cubic age profile, semester credit hours accumulated, a quadratic for GPA, and institution fixed effects. In addition, we follow Andrews, Imberman, Lovenheim, and Stange (2024) and include fixed effects for students' high school $\times$ cohort combination. Our PDV estimates will be biased if earnings are different for business majors and counterfactual students, conditional on final outcomes and our detailed controls. The finding reported in section 6.4 — that we can predict the ex ante returns with reasonable accuracy using IV estimates of the effects on degree attainment and OLS estimates of the earnings premiums of degrees — suggest the issue is likely not severe.

Fifth, we take the average cost of attendance for college and graduate enrollment in field $g$ from administrative financial aid data. We then add average earnings during enrollment in college and graduate enrollment in field $g$ calculated with the administrative data. We use OLS regression to estimate the average earnings per year enrolled in college conditional on $C_{i2}^c$ for the first 2 years and $C_{i4}^c$ for years 3 and 4 for

[19] Operationally, since $X_{it}$ includes discrete variables such as gender, ethnicity, and school, we repeat the procedure for each gender $\times$ ethnicity $\times$ institution cell and calculate the weighted average of $P_{oy}^{Actual}$ and $P_{oy}^{Counter}$

persons who obtain a degree by 4 years after the start of junior year. We also condition on the other control variables in our earnings model.

Finally, we assume a discount rate of 5%, and combine the predicted probabilities and the expected earnings (net of costs when enrolled) to calculate the PDVs under the three scenarios: Actual, Counterfactual, and ActualCollege. Comparing Actual and Counterfactual PDVs allows us to examine the value of majoring in business (engineering) when taking into account tuition and time to degree. Comparing ActualCollege and Counterfactual PDVs allows us to examine the value of majoring in business (engineering) net of the value from graduate degrees.

### 6.5.2 PDV Results

Table 17 presents PDVs for Actual, Counterfactual, and ActualCollege scenarios for both business and engineering. We also separately calculate the PDVs by gender.

The top panel presents results for business majors. The overall PDV gain for business major is 12.7%. Notably, 23% of the gain in PDV comes from changes in the probabilities for attaining graduate degrees — the gain in PDV would only be 9.8% if we assume no change in graduate school enrollment and graduate degree attainment. Heterogeneity results align with what we see in the returns estimates — females have significantly higher PDV gains.

The bottom panel presents results for engineering majors. The overall PDV gain for engineering major is 32.0%. Different from the case for business major, the option value of graduate degrees appear insignificant for the PDV gains. The overall PDV gain is 30.3% when we assume no effect of majoring in engineering on graduate enrollment and graduate degree attainment.

## 7 Conclusion

In this paper, we leverage GPA cutoffs for internal transfers into business and engineering majors and use RD designs to estimate the ex ante returns to majoring in business and engineering and the ex post returns to attaining college degrees in business and engineering. The ex ante and ex post returns to business are both around 0.12, while those for engineering are 0.28 and 0.31. We find that females have higher returns to both business and engineering, although the gender difference for business could be explained by sampling errors. Estimates of the effects on degree outcomes suggest that the gender heterogeneity may be driven in part by the fact that females have lower earning counterfactual majors. We find that, for business, non-

Hispanic white students have higher returns than black/Hispanic students, while Asian students have the lowest returns. Students in selective institutions gain significantly higher returns to business than those in less selective institutions..

Our calculations of PDVs incorporate returns to earnings, time to degrees, and cost of enrollment. We find that while 26% of the PDV gain from majoring in business comes from the option values of graduate schools, the share is only around 6% for engineering.

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# Tables and Figures

Table 1: GPA Cutoffs for Internal Transfer into Business and Engineering Majors

| Institution | Years | GPA Cutoff: Business | GPA Cutoff: Engineering |
|---|---|---|---|
| Midwestern State University | 2011-2018 | 2.20 | N/A |
| Texas A&M University | 2011-2018 | 3.25 | 3.50 |
| Texas State University | 2011-2016 | 3.00 | N/A |
| | 2017-2018 | 3.25 | N/A |
| University of Texas at Arlington | 2011-2018 | 2.25 | N/A |
| University of Texas at Austin | 2011 | 3.30 | 2.50 |
| | 2012-2015 | 3.00 | 3.00 |
| | 2016-2018 | 3.25 | 3.00 |
| University of Texas Rio Grande Valley | 2011-2012 | 2.00 | N/A |
| (Formerly UT Pan America) | 2013-2017 | 2.50 | N/A |
| | 2018 | 2.60 | N/A |
| University of Houston | 2011-2012 | 3.00 | N/A |
| | 2013-2016 | 2.50 | N/A |
| | 2017-2018 | 3.00 | N/A |
| University of North Texas | 2011-2018 | 2.70 | N/A |

Notes: This table presents the cutoff GPA for internal transfer into business and engineering majors in Texas public four-year universities. The GPA cutoffs were collected from university catalogs between 2011-2018.

Table 2: Share of Students Transferring into Final Major in Different Semesters

(a) Final Major = Major of BA Degree

| | After Semester | | | | | |
|---|---|---|---|---|---|---|
| Majors | 0 (start) | 1 | 2 | 3 | 4 | 5+ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| All | 69% | 5% | 9% | 6% | 6% | 5% |
| Business | 56% | 7% | 14% | 9% | 10% | 4% |
| Engineering | 70% | 4% | 11% | 7% | 5% | 4% |

(b) Final Major = Major at Junior Year

| | After Semester | | | | |
|---|---|---|---|---|---|
| Majors | 0 (start) | 1 | 2 | 3 | 4 |
| | (1) | (2) | (3) | (4) | (5) |
| All | 72% | 6% | 10% | 6% | 6% |
| Business | 62% | 6% | 13% | 8% | 11% |
| Engineering | 81% | 3% | 8% | 5% | 3% |

Note: This table reports the share of students that declare the their final major at different transition periods. Column (1) reports the share of students who started college in their final major. Column (2)-(6) for sub-table a and (2)-(5) for sub-table b report the share of students who transitioned to their final major after the semester in the second row. Sub-table a takes students' final major as their BA degree major, while sub-table b takes students' final major as their junior year major.

Table 3: Balance Test for Regression Discontinuity

| | Business | | | | | |
|---|---|---|---|---|---|---|
| | HS Math | HS Reading | Not Econ Disadv | Male | First Major Engineering | First Major Social Sciences |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Semester 1-2 | -0.57 | -0.88 | 0.02 | 0.00 | 0.01 | -0.01 |
| | (0.78) | (0.62) | (0.02) | (0.00) | (0.01) | (0.01) |
| Semester 2-3 | -1.12 | -0.17 | 0.00 | 0.00 | 0.01 | 0.01 |
| | (1.02) | (0.82) | (0.03) | (0.00) | (0.01) | (0.01) |
| Semester 3-4 | 0.93 | 0.67 | 0.02 | 0.00 | 0.02 | 0.01 |
| | (1.08) | (0.96) | (0.03) | (0.00) | (0.02) | (0.01) |
| Semester 4-5 | 0.94 | 0.74 | 0.09*** | 0.00 | 0.02 | 0.02 |
| | (1.22) | (1.05) | (0.03) | (0.00) | (0.02) | (0.02) |
| | Engineering | | | | | |
| | Math TEA | Reading TEA | Not Econ Disadv | Male | First Major Business | First Major Sciences |
| | (7) | (8) | (9) | (10) | (11) | (12) |
| Semester 2-3 | 8.37 | -8.45 | -0.55 | 0.00 | 0.14 | 0.20 |
| | (11.89) | (10.52) | (0.41) | (0.00) | (0.17) | (0.34) |
| Semester 3-4 | 0.28 | 3.75 | 0.27 | 0.00 | -0.28*** | -0.07 |
| | (5.35) | (4.62) | (0.19) | (0.00) | (0.08) | (0.15) |

Note: This table presents results from balance tests for the RD using GPA cutoffs for internal transfer. In each panel, the first row lists the dependent variables for the tests — high school standardized math test score, high school standardized reading test score, binary indicator for whether student is not economically disadvantaged, dummy for whether student is male, binary indicator for whether the student's first major was engineering, social sciences, business, or sciences. Results in the top panel are for business cutoffs, and use the RD specification in equation 3. Results in the bottom panel are for engineering cutoffs, and use the RD specification in equation 4. The first column lists the transition period the cutoff crossing is examined. For example, the row "Semester 1-2" looks at the effect of crossing the GPA cutoff in the first semester. Standard errors are clustered at the individual level.

Table 4: Complier Characteristics Relative to Full Sample

| | Business | | | | |
|---|---|---|---|---|---|
| | HS Math $>$ 80 pct | HS Reading $>$ 80 pct | Female | Econ Disadv | Non-Hisp White |
| | (1) | (2) | (3) | (4) | (5) |
| Business | 1.07 | 1.05 | 0.91 | 0.97 | 0.99 |
| Engineering | 1.08 | 1.01 | 0.42 | 0.96 | 0.63 |

Note: This table shows the relative likelihood of various characteristics in the complier groups compared to the overall population. The column headings list the Bernoulli-distributed characteristics we examine: a dummy variable for whether an individual scored above the 80th percentile in their high school standardized math test, a dummy variable for whether an individual scored above the 80th percentile in their high school standardized reading test, a binary indicator for being female, an indicator for whether a student is economically disadvantaged, and an indicator for whether a student is non-hispanic white. The row labeled "Business" shows results for the compliers of the business GPA cutoffs. These are the students who would transfer into business majors if they passed the GPA cutoffs but would not transfer if they did not pass the GPA cutoffs. The row labeled "Engineering" shows results for the compliers of the engineering GPA cutoffs. For a Bernoulli-distributed characteristic $x_i$, the relative likelihood that compliers have $x_i = 1$ is given by the ratio of the first stage among those with $x_i = 1$ to the overall first stage. A ratio larger than 1 indicates that the tested characteristic is more common in compliers, whereas a ratio smaller than 1 indicates that the tested characteristic is less common in compliers, compared to the overall sample.

Table 5: Ex Ante and Ex Post Returns to Business and Engineering

| | Log Earnings | | | |
|---|---|---|---|---|
| | Business | | Engineering | |
| | OLS | IV | OLS | IV |
| | (1) | (2) | (3) | (4) |
| Ex Ante Returns | 0.093 | 0.125 | 0.235 | 0.277 |
| (to declaring major) | (0.004) | (0.026) | (0.009) | (0.077) |
| Ex Post Returns | 0.109 | 0.123 | 0.261 | 0.314 |
| (to BA degree) | (0.003) | (0.025) | (0.008) | (0.104) |
| N | 590528 | 590528 | 317651 | 317651 |

Notes: This table reports the ex ante returns to declaring major in business and engineering by the beginning of the junior year and the ex post returns to receiving a bachelor's degree in business and engineering. Columns (1) and (3) report OLS results, and columns (2) and (4) report IV results with the survival-RD model following equations (7) and (8). Each cell represents one separate regression. All regressions include basic controls for gender, ethnicity, gender-specific cubic age profile, semester credit hours accumulated, coherence for each of the 18 2-digit CIP codes at the beginning of junior year, quadratic for GPA, and institution fixed effects. Standard errors are computed with block bootstrap procedure over 200 bootstrap samples. The construction of the instrument, $\hat{\Phi}$, and control, $\bar{\Phi}$ are included in the bootstrap procedure.

Table 6: Heterogeneous Ex Ante and Ex Post Returns to Business

Table 6a: Gender

| | Log Earnings | | | | | |
|---|---|---|---|---|---|---|
| | OLS | | | IV | | |
| | Female | Male | Diff | Female | Male | Diff |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ex Ante Returns | 0.110 | 0.096 | 0.014$^{\dagger}$ | 0.169 | 0.127 | 0.042 |
| (to declaring major) | (0.005) | (0.006) | (0.008) | (0.024) | (0.024) | (0.034) |
| Ex Post Returns | 0.132 | 0.107 | 0.025$^{\dagger\dagger\dagger}$ | 0.165 | 0.124 | 0.041 |
| (to BA degree) | (0.005) | (0.006) | (0.008) | (0.023) | (0.024) | (0.033) |
| N | 214337 | 142874 | - | 214337 | 142874 | - |

Table 6b: Economic Disadvantage Status

| | Log Earnings | | | | | |
|---|---|---|---|---|---|---|
| | OLS | | | IV | | |
| | Disadv | Not Disadv | Diff | Disadv | Not Disadv | Diff |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ex Ante Returns | 0.060 | 0.104 | -0.044$^{\dagger\dagger\dagger}$ | 0.095 | 0.160 | -0.065 |
| (to declaring major) | (0.009) | (0.005) | (0.010) | (0.044) | (0.020) | (0.048) |
| Ex Post Returns | 0.079 | 0.121 | -0.042$^{\dagger\dagger\dagger}$ | 0.094 | 0.154 | -0.060 |
| (to BA degree) | (0.009) | (0.005) | (0.010) | (0.045) | (0.020) | (0.049) |
| N | 78672 | 215967 | - | 78672 | 215967 | - |

Table 6c: Selective vs. Non-Selective

| | Log Earnings | | | | | |
|---|---|---|---|---|---|---|
| | OLS | | | IV | | |
| | Selective | Non-Selective | Diff | Selective | Non-Selective | Diff |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ex Ante Returns | 0.095 | 0.079 | 0.016$^{\dagger}$ | 0.146 | 0.087 | 0.059$^{\dagger}$ |
| (to declaring major) | (0.005) | (0.007) | (0.009) | (0.021) | (0.026) | (0.033) |
| Ex Post Returns | 0.111 | 0.098 | 0.013 | 0.141 | 0.086 | 0.055$^{\dagger}$ |
| (to BA degree) | (0.005) | (0.007) | (0.009) | (0.021) | (0.026) | (0.033) |
| N | 200527 | 156684 | - | 200527 | 156684 | - |

Table 6d: Ethnicity Non-Hispanic White and Hispanic/Black

| | Log Earnings | | | | | |
|---|---|---|---|---|---|---|
| | OLS | | | IV | | |
| | Non-Hispanic White | Hispanic/Black | Diff | Non-Hispanic White | Hispanic/Black | Diff |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ex Ante Returns (to declaring major) | 0.121 (0.006) | 0.075 (0.006) | 0.046$^{\dagger\dagger\dagger}$ (0.008) | 0.196 (0.022) | 0.139 (0.034) | 0.057 (0.040) |
| Ex Post Returns (to BA degree) | 0.144 (0.006) | 0.093 (0.006) | 0.051$^{\dagger\dagger\dagger}$ (0.008) | 0.193 (0.022) | 0.128 (0.034) | 0.065 (0.040) |
| N | 147480 | 159506 | - | 147480 | 159506 | - |

Table 6e: Ethnicity Non-Hispanic White and Asian

| | Log Earnings | | | | | |
|---|---|---|---|---|---|---|
| | OLS | | | IV | | |
| | Non-Hispanic White | Asian | Diff | Non-Hispanic White | Asian | Diff |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ex Ante Returns (to declaring major) | 0.121 (0.006) | 0.050 (0.011) | 0.071$^{\dagger\dagger\dagger}$ (0.013) | 0.196 (0.022) | 0.054 (0.025) | 0.142$^{\dagger\dagger\dagger}$ (0.033) |
| Ex Post Returns (to BA degree) | 0.144 (0.006) | 0.054 (0.011) | 0.090$^{\dagger\dagger\dagger}$ (0.013) | 0.193 (0.022) | 0.056 (0.026) | 0.137$^{\dagger\dagger\dagger}$ (0.034) |
| N | 147480 | 34485 | - | 147480 | 34485 | - |

Notes: This table reports the ex ante returns to declaring major in business by the beginning of the junior year and the ex post returns to receiving a bachelor's degree in business for different subsamples. Table 4a compares females and males, table 4b compares economically disadvantaged students and those who are not, table 4c compares students in selective versus non-selective institutions, table 4d compares non-hispanic white students and hispanic/black students, and table 4e compares non-hispanic white students and Asian students. For each table, columns (1) and (2) report the OLS estimates and columns (4) and (5) report the IV estimates from the survival-RD model following equations (7) and (8). Column (3) reports the differences between columns (1) and (2), while column (6) reports the differences between columns (4) and (5). In columns (3) and (6), we use $^{\dagger}$,$^{\dagger\dagger}$, and $^{\dagger\dagger\dagger}$ to denote differences that are statistically significant at the 10%, 5%, and 1% levels. All regressions include basic controls for gender, ethnicity, gender-specific cubic age profile, semester credit hours accumulated, coherence for each of the 18 2-digit CIP codes at the beginning of junior year, quadratic for GPA, and institution fixed effects. Standard errors are computed with block bootstrap procedure over 200 bootstrap samples. The construction of the instrument, $\hat{\Phi}$, and control, $\bar{\Phi}$ are included in the bootstrap procedure.

Table 7: Heterogeneous Ex Ante and Ex Post Returns to Engineering by Gender

| | Log Earnings | | | | | |
|---|---|---|---|---|---|---|
| | OLS | | | IV | | |
| | Female | Male | Diff | Female | Male | Diff |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ex Ante Returns | 0.252 | 0.229 | 0.023 | 0.501 | 0.091 | 0.410$^{\dagger\dagger}$ |
| (to declaring major) | (0.016) | (0.011) | (0.019) | (0.129) | (0.102) | (0.164) |
| Ex Post Returns | 0.290 | 0.252 | 0.038$^{\dagger\dagger}$ | 0.509 | 0.100 | 0.409$^{\dagger\dagger}$ |
| (to BA degree) | (0.015) | (0.010) | (0.018) | (0.099) | (0.131) | (0.164) |
| N | 214337 | 142874 | - | 214337 | 142874 | - |

Notes: This table reports the ex ante returns to declaring major in business by the beginning of the junior year and the ex post returns to receiving a bachelor's degree in business for females and males separately. Columns (1) and (2) report the OLS estimates and columns (4) and (5) report the IV estimates from the survival-RD model following equations (7) and (8). Column (3) reports the differences between columns (1) and (2), while column (6) reports the differences between columns (4) and (5). In columns (3) and (6), we use $^{\dagger}$,$^{\dagger\dagger}$, and $^{\dagger\dagger\dagger}$ to denote differences that are statistically significant at the 10%, 5%, and 1% levels. All regressions include basic controls for gender, ethnicity, gender-specific cubic age profile, semester credit hours accumulated, coherence for each of the 18 2-digit CIP codes at the beginning of junior year, quadratic for GPA, and institution fixed effects. Standard errors are computed with block bootstrap procedure over 200 bootstrap samples. The construction of the instrument, $\hat{\Phi}$, and control, $\bar{\Phi}$ are included in the bootstrap procedure.

Table 8: Effects of Business Major on Undergraduate Degrees — 4 Years Post Junior

| Bachelor's Degree in... | OLS | IV | | | | |
|---|---|---|---|---|---|---|
| | Full Sample | Full Sample | Female | Male | Econ Disadv | Not Econ Disadv |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Business | 0.848 | 0.998 | 0.994 | 1.000 | 0.973 | 1.004 |
| | (0.005) | (0.009) | (0.011) | (0.023) | (0.022) | (0.011) |
| Science | -0.101 | -0.058 | -0.047 | -0.105 | -0.072 | -0.011 |
| | (0.003) | (0.014) | (0.017) | (0.025) | (0.051) | (0.015) |
| Health | -0.057 | -0.136 | -0.179 | -0.050 | -0.217 | -0.112 |
| | (0.002) | (0.012) | (0.019) | (0.013) | (0.031) | (0.011) |
| Engineering | -0.178 | -0.152 | -0.054 | -0.269 | -0.189 | -0.168 |
| | (0.004) | (0.014) | (0.012) | (0.033) | (0.042) | (0.016) |
| Social Sciences | -0.197 | -0.279 | -0.291 | -0.254 | -0.293 | -0.280 |
| | (0.004) | (0.022) | (0.029) | (0.039) | (0.086) | (0.025) |
| Other | -0.291 | -0.321 | -0.355 | -0.290 | -0.245 | -0.382 |
| | (0.005) | (0.021) | (0.030) | (0.029) | (0.061) | (0.021) |
| All | 0.025 | 0.052 | 0.069 | 0.031 | -0.043 | 0.050 |
| | (0.004) | (0.014) | (0.017) | (0.028) | (0.065) | (0.013) |
| N | 60001 | 60001 | 35265 | 24736 | 11471 | 33047 |

Note: This table reports the effects of majoring in business (by the beginning of the junior year) on the probability of attaining bachelor's degrees in different majors 4 years after the beginning of the junior year. Column (1) reports OLS results and columns (2) — (6) report IV estimates following equation (9). Each cell represents one separate regression. All regressions include basic controls for gender, ethnicity, gender-specific cubic age profile, semester credit hours accumulated, coherence for each of the 18 2-digit CIP codes at the beginning of junior year, quadratic for GPA, and institution fixed effects. Standard errors are computed with block bootstrap procedure over 200 bootstrap samples. The construction of the instrument, $\hat{\Phi}$, and control, $\bar{\Phi}$ are included in the bootstrap procedure.

Table 9: Effects of Business Major on Graduate Degrees — 8 Years Post Junior

| Adv. Degree in... | OLS | IV | | | | |
|---|---|---|---|---|---|---|
| | Full Sample | Full Sample | Female | Male | Econ Disadv | Not Econ Disadv |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Business | 0.075 | 0.160 | 0.156 | 0.159 | 0.148 | 0.145 |
| | (0.004) | (0.010) | (0.013) | (0.020) | (0.024) | (0.013) |
| Science | -0.007 | 0.004 | -0.004 | 0.013 | 0.004 | -0.002 |
| | (0.001) | (0.005) | (0.005) | (0.009) | (0.018) | (0.005) |
| Health | -0.017 | -0.065 | -0.069 | -0.043 | -0.101 | -0.051 |
| | (0.001) | (0.010) | (0.015) | (0.013) | (0.041) | (0.012) |
| Engineering | -0.009 | -0.020 | -0.006 | -0.042 | -0.015 | -0.022 |
| | (0.001) | (0.004) | (0.004) | (0.010) | (0.013) | (0.004) |
| Social Sciences | -0.016 | -0.020 | -0.030 | -0.007 | -0.020 | -0.016 |
| | (0.001) | (0.007) | (0.010) | (0.008) | (0.023) | (0.008) |
| Law | -0.002 | -0.008 | -0.015 | 0.003 | 0.003 | -0.006 |
| | (0.001) | (0.004) | (0.005) | (0.008) | (0.013) | (0.005) |
| Education | -0.009 | -0.011 | -0.018 | -0.003 | -0.023 | -0.016 |
| | (0.001) | (0.006) | (0.008) | (0.006) | (0.017) | (0.006) |
| Other | -0.006 | -0.009 | -0.014 | -0.004 | -0.002 | -0.012 |
| | (0.001) | (0.005) | (0.007) | (0.007) | (0.015) | (0.005) |
| All | 0.009 | 0.032 | 0.002 | 0.077 | -0.005 | 0.020 |
| | (0.005) | (0.018) | (0.025) | (0.025) | (0.053) | (0.018) |
| N | 60001 | 60001 | 35265 | 24736 | 11471 | 33047 |

Note: This table reports the effects of majoring in business (by the beginning of the junior year) on the probability of attaining advanced degrees in different majors 8 years after the beginning of the junior year. Column (1) reports OLS results and columns (2) — (6) report IV estimates following equation (10). Each cell represents one separate regression. All regressions include basic controls for gender, ethnicity, gender-specific cubic age profile, semester credit hours accumulated, coherence for each of the 18 2-digit CIP codes at the beginning of junior year, quadratic for GPA, and institution fixed effects. Standard errors are computed with block bootstrap procedure over 200 bootstrap samples. The construction of the instrument, $\hat{\Phi}$, and control, $\bar{\Phi}$ are included in the bootstrap procedure.

Table 10: Effects of Engineering Major on Undergraduate Degrees — 4 Years Post Junior

| Bachelor's Degree in... | OLS | IV | | |
|---|---|---|---|---|
| | Full Sample | Full Sample | Female | Male |
| | (1) | (2) | (3) | (4) |
| Business | -0.139 | -0.028 | -0.035 | -0.022 |
| | (0.007) | (0.032) | (0.020) | (0.181) |
| Science | -0.507 | -0.587 | -0.764 | -0.602 |
| | (0.011) | (0.083) | (0.053) | (0.193) |
| Health | -0.003 | -0.020 | 0.073 | -0.020 |
| | (0.003) | (0.038) | (0.025) | (0.084) |
| Engineering | 0.836 | 0.981 | 1.137 | 0.906 |
| | (0.011) | (0.026) | (0.033) | (0.109) |
| Social Sciences | -0.077 | -0.062 | -0.018 | -0.042 |
| | (0.006) | (0.020) | (0.023) | (0.078) |
| Other | -0.125 | -0.236 | -0.438 | -0.115 |
| | (0.008) | (0.038) | (0.036) | (0.150) |
| All | -0.015 | 0.047 | -0.045 | 0.105 |
| | (0.009) | (0.010) | (0.011) | (0.083) |
| N | 33030 | 33030 | 20056 | 12974 |

Note: This table reports the effects of majoring in engineering (by the beginning of the junior year) on the probability of attaining bachelor's degrees in different majors 4 years after the beginning of the junior year. Column (1) reports OLS results and columns (2) — (6) report IV estimates following equation (9). Each cell represents one separate regression. All regressions include basic controls for gender, ethnicity, gender-specific cubic age profile, semester credit hours accumulated, coherence for each of the 18 2-digit CIP codes at the beginning of junior year, quadratic for GPA, and institution fixed effects. Standard errors are computed with block bootstrap procedure over 200 bootstrap samples. The construction of the instrument, $\hat{\Phi}$, and control, $\bar{\Phi}$ are included in the bootstrap procedure.

Table 11: Effects of Engineering Major on Graduate Degrees — 8 Years Post Junior

| Adv. Degree in... | OLS | IV | | |
|---|---|---|---|---|
| | Full Sample | Full Sample | Female | Male |
| | (1) | (2) | (3) | (4) |
| Business | -0.035 | -0.035 | -0.034 | -0.027 |
| | (0.004) | (0.015) | (0.014) | (0.151) |
| Science | -0.028 | -0.029 | -0.009 | -0.027 |
| | (0.004) | (0.011) | (0.010) | (0.038) |
| Health | -0.065 | -0.057 | -0.059 | -0.037 |
| | (0.005) | (0.014) | (0.022) | (0.052) |
| Engineering | 0.032 | 0.064 | 0.048 | 0.060 |
| | (0.007) | (0.018) | (0.007) | (0.050) |
| Social Sciences | -0.007 | -0.007 | -0.001 | -0.008 |
| | (0.001) | (0.006) | (0.006) | (0.024) |
| Law | -0.008 | -0.002 | -0.028 | 0.009 |
| | (0.002) | (0.010) | (0.005) | (0.083) |
| Education | -0.009 | 0.003 | -0.001 | -0.007 |
| | (0.001) | (0.004) | (0.006) | (0.025) |
| Other | 0.000 | 0.004 | 0.006 | -0.003 |
| | (0.002) | (0.003) | (0.005) | (0.025) |
| All | -0.120 | -0.060 | -0.079 | -0.040 |
| | (0.010) | (0.025) | (0.029) | (0.134) |
| N | 33030 | 33030 | 20056 | 12974 |

Note: This table reports the effects of majoring in engineering (by the beginning of the junior year) on the probability of attaining advanced degrees in different majors 8 years after the beginning of the junior year. Column (1) reports OLS results and columns (2) — (6) report IV estimates following equation (9). Each cell represents one separate regression. All regressions include basic controls for gender, ethnicity, gender-specific cubic age profile, semester credit hours accumulated, coherence for each of the 18 2-digit CIP codes at the beginning of junior year, quadratic for GPA, and institution fixed effects. Standard errors are computed with block bootstrap procedure over 200 bootstrap samples. The construction of the instrument, $\hat{\Phi}$, and control, $\bar{\Phi}$ are included in the bootstrap procedure.

Table 12: Effects of Business Major on Undergraduate Degrees — 2 Years Post Junior

| Bachelor's Degree in... | OLS | IV | | | | |
|---|---|---|---|---|---|---|
| | Full Sample | Full Sample | Female | Male | Econ Disadv | Not Econ Disadv |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Business | 0.391 | 0.482 | 0.509 | 0.441 | 0.440 | 0.493 |
| | (0.007) | (0.013) | (0.017) | (0.025) | (0.036) | (0.015) |
| Science | -0.041 | -0.021 | -0.011 | -0.052 | -0.006 | -0.007 |
| | (0.002) | (0.011) | (0.014) | (0.019) | (0.049) | (0.011) |
| Health | -0.026 | -0.050 | -0.068 | -0.016 | -0.064 | -0.045 |
| | (0.001) | (0.008) | (0.014) | (0.008) | (0.026) | (0.010) |
| Engineering | -0.046 | -0.044 | -0.002 | -0.093 | -0.063 | -0.048 |
| | (0.002) | (0.008) | (0.006) | (0.018) | (0.027) | (0.008) |
| Social Sciences | -0.117 | -0.155 | -0.163 | -0.146 | -0.191 | -0.153 |
| | (0.003) | (0.016) | (0.021) | (0.025) | (0.071) | (0.018) |
| Other | -0.145 | -0.125 | -0.160 | -0.089 | -0.059 | -0.148 |
| | (0.003) | (0.019) | (0.026) | (0.026) | (0.050) | (0.019) |
| All | 0.016 | 0.087 | 0.107 | 0.045 | 0.068 | 0.091 |
| | (0.008) | (0.025) | (0.032) | (0.041) | (0.070) | (0.026) |
| N | 60001 | 60001 | 35265 | 24736 | 11471 | 33047 |

Note: This table reports the effects of majoring in engineering (by the beginning of the junior year) on the probability of attaining bachelor's degrees in different majors 2 years after the beginning of the junior year. Column (1) reports OLS results and columns (2) — (6) report IV estimates following equation (8). Each cell represents one separate regression. All regressions include basic controls for gender, ethnicity, gender-specific cubic age profile, semester credit hours accumulated, coherence for each of the 18 2-digit CIP codes at the beginning of junior year, quadratic for GPA, and institution fixed effects. Standard errors are computed with block bootstrap procedure over 200 bootstrap samples. The construction of the instrument, $\hat{\Phi}$, and control, $\bar{\Phi}$ are included in the bootstrap procedure.

Table 13: Effects of Engineering Major on Undergraduate Degrees — 2 Years Post Junior

| Bachelor's Degree in... | OLS | IV | | |
|---|---|---|---|---|
| | Full Sample | Full Sample | Female | Male |
| | (1) | (2) | (3) | (4) |
| Business | -0.049 | 0.028 | -0.030 | 0.022 |
| | (0.004) | (0.026) | (0.017) | (0.078) |
| Science | -0.206 | -0.267 | -0.263 | -0.307 |
| | (0.007) | (0.021) | (0.025) | (0.071) |
| Health | 0.001 | -0.002 | 0.039 | -0.005 |
| | (0.001) | (0.016) | (0.011) | (0.029) |
| Engineering | 0.154 | 0.185 | 0.145 | 0.164 |
| | (0.011) | (0.027) | (0.035) | (0.052) |
| Social Sciences | -0.038 | -0.046 | 0.028 | -0.066 |
| | (0.004) | (0.019) | (0.017) | (0.073) |
| Other | -0.062 | -0.141 | -0.213 | -0.058 |
| | (0.005) | (0.027) | (0.025) | (0.086) |
| All | -0.201 | -0.242 | -0.294 | -0.251 |
| | (0.013) | (0.034) | (0.044) | (0.114) |
| N | 33030 | 33030 | 20056 | 12974 |

Note: This table reports the effects of majoring in engineering (by the beginning of the junior year) on the probability of attaining bachelor's degrees in different majors 2 years after the beginning of the junior year. Column (1) reports OLS results and columns (2) — (6) report IV estimates following equation (8). Each cell represents one separate regression. All regressions include basic controls for gender, ethnicity, gender-specific cubic age profile, semester credit hours accumulated, coherence for each of the 18 2-digit CIP codes at the beginning of junior year, quadratic for GPA, and institution fixed effects. Standard errors are computed with block bootstrap procedure over 200 bootstrap samples. The construction of the instrument, $\hat{\Phi}$, and control, $\bar{\Phi}$ are included in the bootstrap procedure.

Table 14: Alternative Estimates for Ex Ante and Ex Post Returns to Business and Engineering

| | Log Earnings | | | |
|---|---|---|---|---|
| | Business | | | |
| | OLS | IV | | |
| | | Survival | Survival-0.3BW | Linear |
| | (1) | (2) | (3) | (4) |
| Ex Ante Returns | 0.093 | 0.125 | 0.144 | 0.142 |
| (to declaring major) | (0.004) | (0.026) | (0.026) | (0.091) |
| Ex Post Returns | 0.109 | 0.123 | 0.145 | 0.187 |
| (to BA degree) | (0.003) | (0.025) | (0.026) | (0.099) |
| N | 590528 | 590528 | 98078 | 590528 |
| | Log Earnings | | | |
| | Engineering | | | |
| | OLS | IV | | |
| | | Survival | Survival-0.3BW | Linear |
| | (5) | (6) | (7) | (8) |
| Ex Ante Returns | 0.235 | 0.277 | 0.235 | 0.328 |
| (to declaring major) | (0.009) | (0.077) | (0.093) | (0.198) |
| Ex Post Returns | 0.261 | 0.314 | 0.230 | 0.247 |
| (to BA degree) | (0.008) | (0.104) | (0.089) | (0.166) |
| N | 317651 | 317651 | 71869 | 317651 |

Notes: This table reports the ex ante returns to declaring major in business and engineering by the beginning of the junior year and the ex post returns to receiving a bachelor's degree in business and engineering using multiple empirical specifications. Columns (1), (2), (5), and (6) report the OLS and IV estimates in Table 3. Columns (3) and (7) report IV results with the survival-RD model following equations (7) and (8), while restricting the sample to individuals whose GPA before junior year were within 0.3 of the cutoff GPA for each semester that we use to construct the instrument. For business, these include the second, third, and fourth semesters. For engineering, these include the second and third semesters. Columns (4) and (8) report IV results with the linear-RD model with optimal bandwidth as described at the end of section 5.1. Each cell represents one separate regression. All regressions include basic controls for gender, ethnicity, gender-specific cubic age profile, semester credit hours accumulated, coherence for each of the 18 2-digit CIP codes at the beginning of junior year, quadratic for GPA, and institution fixed effects. Standard errors are clustered at the individual level, except for columns (2) and (6), where the standard errors are computed with block bootstrap procedure over 200 bootstrap samples. The construction of the instrument, $\hat{\Phi}$, and control, $\bar{\Phi}$ are included in the bootstrap procedure.

Table 15: Estimated Ex Ante Returns and Predicted Ex Ante Returns - Business

| | Log Earnings | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Business | | | | | | | | |
| | OLS | IV | | | | | | | |
| | Full Sample | Full Sample | Female | Male | Econ Disadv | No Econ Disadv | Non-Hisp White | Hispanic/Black | Asian |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Ex Ante Returns (Estimated) | 0.093 | 0.125 | 0.169 | 0.127 | 0.095 | 0.160 | 0.196 | 0.139 | 0.054 |
| | (0.004) | (0.026) | (0.024) | (0.024) | (0.044) | (0.020) | (0.022) | (0.034) | |
| Ex Ante Returns (Predicted) | 0.110 | 0.157 | 0.164 | 0.110 | 0.093 | 0.156 | 0.149 | 0.152 | 0.081 |
| N | 590528 | 590528 | 214337 | 142874 | 78672 | 215967 | 147480 | 159506 | 34485 |

Notes: This table reports the ex ante returns to declaring major in business. The first row reports estimates from the OLS and survival-RD models. The second row reports ex ante returns calculated using the procedure described in section 6.4. In particular, let $\hat{b}_{1c}$ be the estimated earnings premium for college degree $c$ estimated with OLS. Following the notation from equation (9), let $\hat{c}_1^{c4}$ be the effect of majoring in business on the likelihood of attaining bachelor's degree in major $c$ four years after junior year. We compute the linear combinations $\sum_{i=1}^{6} \hat{b}_{1c}\hat{c}_1^{c4}$. All regressions include basic controls for gender, ethnicity, gender-specific cubic age profile, semester credit hours accumulated, coherence for each of the 18 2-digit CIP codes at the beginning of junior year, a quadratic for GPA, and institution fixed effects. The calculation is done for the full sample, as well as for sub-samples by gender, economic status and ethnicity.

Table 16: Estimated Ex Ante Returns and Predicted Ex Ante Returns - Engineering

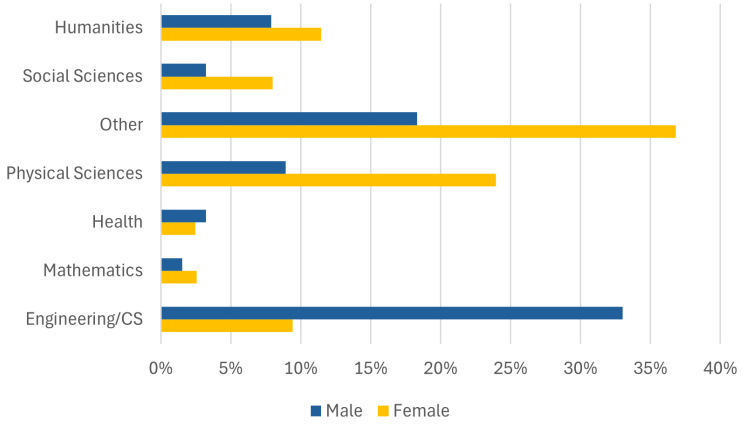
| | Log Earnings | | | |
|---|---|---|---|---|
| | Engineering | | | |
| | OLS | IV | | |
| | Full Sample | Full Sample | Female | Male |
| | (1) | (2) | (3) | (4) |
| Ex Ante Returns (Estimated) | 0.235 | 0.277 | 0.501 | 0.091 |
| Ex Ante Returns (Computed) | 0.290 | 0.385 | 0.397 | 0.381 |
| N | 317651 | 317651 | 192094 | 125557 |

Notes: This table reports the ex ante returns to declaring major in engineering. The first row reports estimates from the OLS and survival-RD models. The second row reports ex ante returns calculated using the procedure described in section 6.4. In particular, let $\hat{b}_{1c}$ be the estimated earnings premium for college degree $c$ estimated with OLS. Following the notation from equation (9), let $\hat{c}_1^{c4}$ be the effect of majoring in engineering on the likelihood of attaining bachelor's degree in major $c$ four years after junior year. We compute the linear combinations $\sum_{i=1}^{6} \hat{b}_{1c}\hat{c}_1^{c4}$. All regressions include basic controls for gender, ethnicity, gender-specific cubic age profile, semester credit hours accumulated, coherence for each of the 18 2-digit CIP codes at the beginning of junior year, a quadratic for GPA, and institution fixed effects. The calculation is done for the full sample, as well as for sub-samples by gender, economic status and ethnicity.

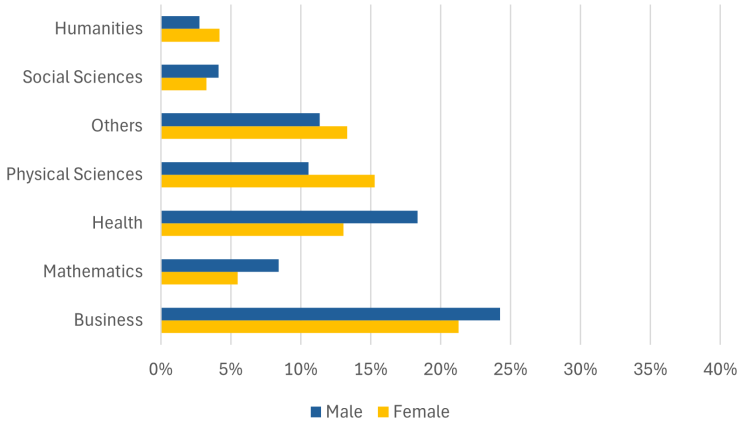
Table 17: Effects of Business and Engineering Major on Present Discounted Values

| Subsample | Counterfactual (1) | ActualCollege (2) | Actual (3) |
|---|---|---|---|
| | Business | | |
| Overall | 1047782 | 1150765 (9.8%) | 1180882 (12.7%) |
| Female | 902893 | 1006599 (11.5%) | 1045803 (15.8%) |
| Male | 1234442 | 1308606 (6.0%) | 1345768 (9.0%) |
| | Engineering | | |
| Overall | 1173318 | 1528307 (30.3%) | 1548806 (32.0%) |
| Female | 1038402 | 1281877 (23.4%) | 1317040 (26.8) |
| Male | 1313660 | 1712210 (30.3%) | 1733056 (31.9%) |

Notes: This table reports the PDVs calculated for various scenarios and subsamples. As discussed in section 6.4.1, the Counterfactual scenario (column 1) is computed assuming that the probability of various educational outcomes at different periods follow those for the counterfactual population that did not major in business (engineering). The Actual scenario (column 3) is computed assuming that the probability of various educational outcomes at different periods follow those for the population that majored in business (engineering). The ActualCollege scenario (column 2) is computed assuming that the probability of college enrollment and bachelor's degree outcomes follow those in the Actual case, but the probability of graduate enrollment and advanced degree outcomes follow those in the Counterfactual case. The percentage gain compared to the Counterfactual scenario is reported in parentheses in columns (2) and (3).



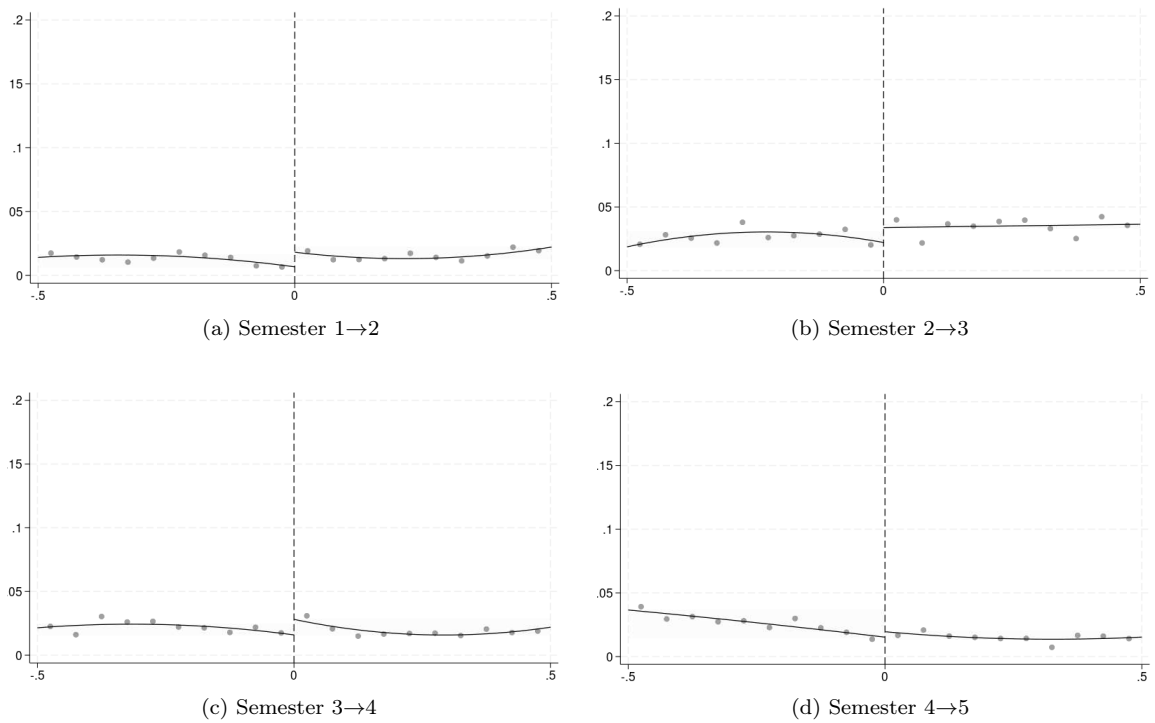

(a) Business




(b) Engineering

Figure 1: Share of Freshmen Majors Among Students who Transfer into Business / Engineering Majors, by Gender

Notes: This figure shows the share of students' freshmen major among those who transferred into business / engineering majors by the start of their junior year. The figure shows the shares separately for males and females. The majors are ranked from top to bottom in ascending order of average post-college earnings. This figure excludes students who have undeclared as their major in their freshmen year. They make up 44% of the sample for males and 43% for females.




(a) Semester 1→2

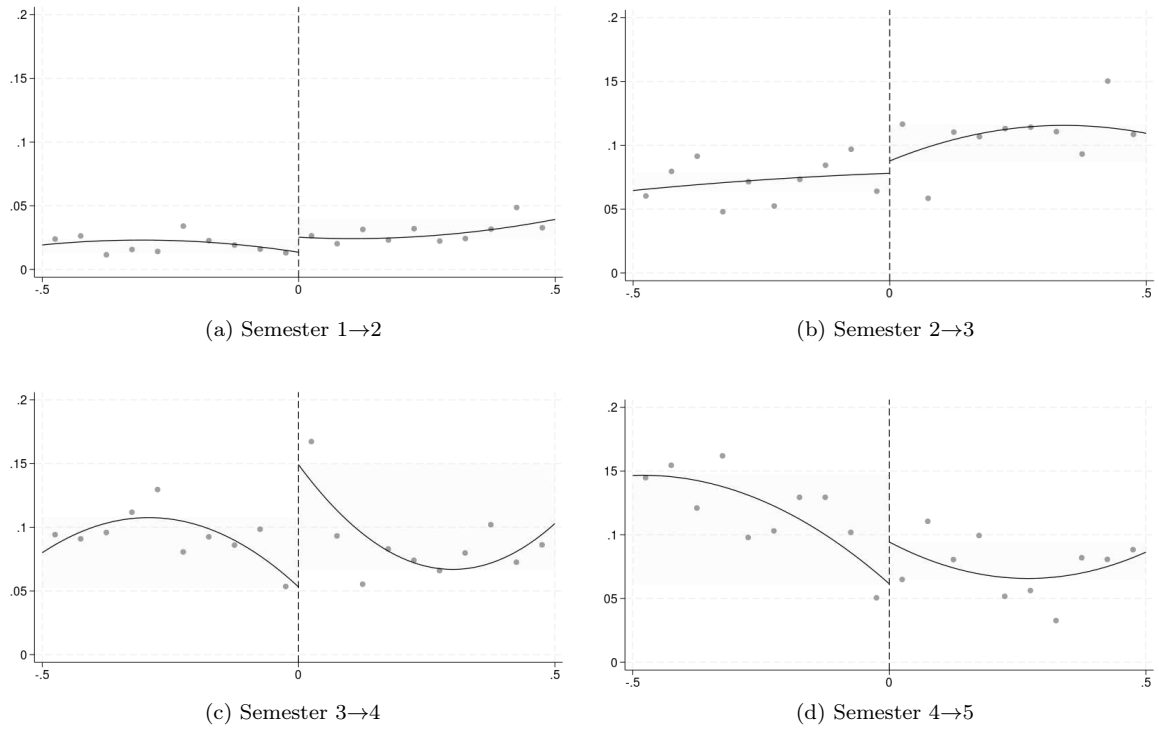
(b) Semester 2→3

(c) Semester 3→4

(d) Semester 4→5

Figure 2: Regression Discontinuity: Business; All Coherence Levels

Notes: This figure shows the raw probability of transferring into business majors among students who previously were not in business majors. The four panels represent the four different transition periods considered — first semester to second semester, second semester to third semester, third semester to fourth semester, and fourth semester to fifth semester. The horizontal axis represents the difference between students' GPA and the cutoff GPA for internal transfer into business majors.




(a) Semester 1→2

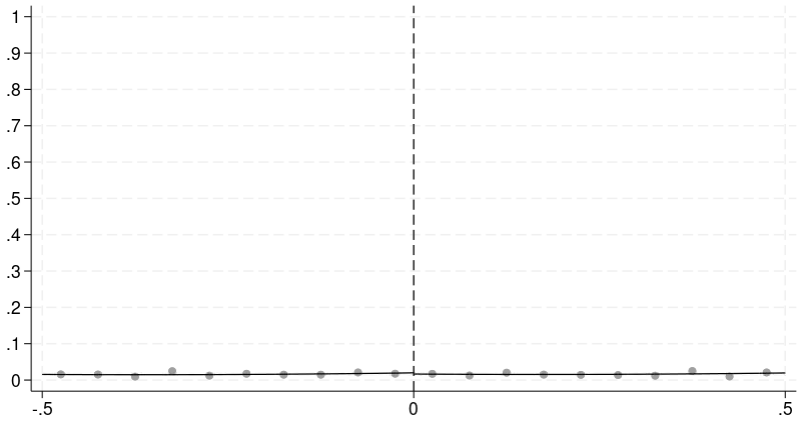
(b) Semester 2→3

(c) Semester 3→4

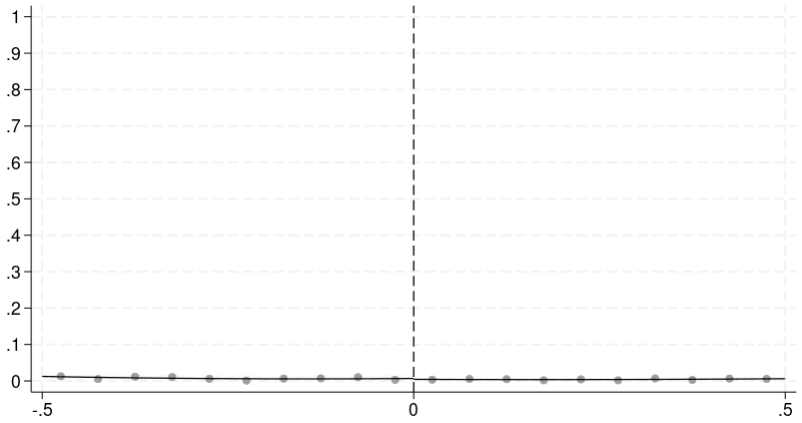
(d) Semester 4→5

Figure 3: Regression Discontinuity: Business; coh $\geq$ median

Notes: This figure shows the raw probability of transferring into business majors among students who previously were not in business majors. The four panels represent the four different transition periods considered — first semester to second semester, second semester to third semester, third semester to fourth semester, and fourth semester to fifth semester. The figures restrict to students who have coherence levels equal to or larger than the median coherence level among students who transfer into business majors in the corresponding transition periods. The horizontal axis represents the difference between students' GPA and the cutoff GPA for internal transfer into business majors.



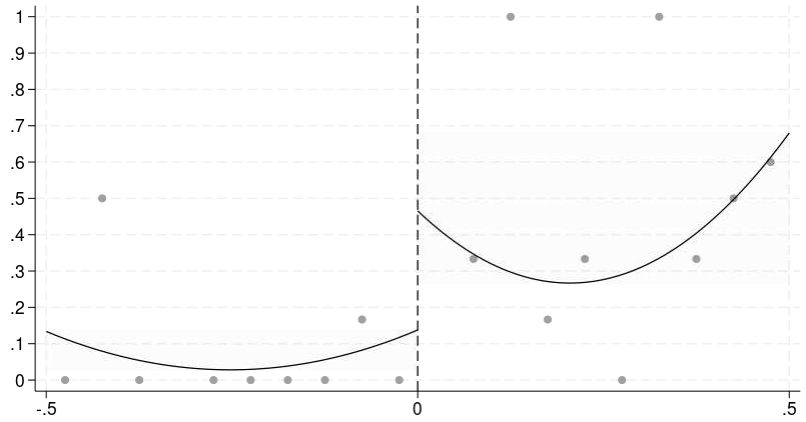

(a) Semester 2→3



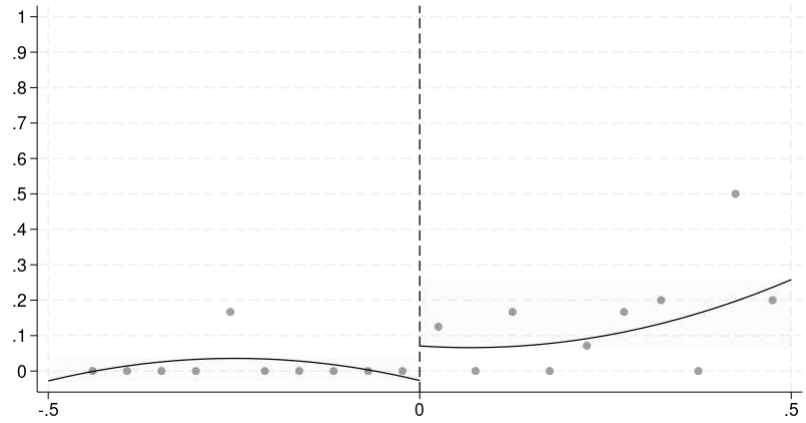

(b) Semester 3→4

Figure 4: Regression Discontinuity: Engineering; All Coherence Levels

Notes: This figure shows the raw probability of transferring into engineering majors among students who previously were not in engineering majors. The two panels represent the two different transition periods considered — second semester to third semester and third semester to fourth semester. The transition periods from the first semester to the second semester and from the fourth semester to fifth semester are not considered because we do not find any significant effects of GPA cutoffs for those transition periods (not reported). The horizontal axis represents the difference between students' GPA and the cutoff GPA for internal transfer into engineering majors.




(a) Semester 2→3




(b) Semester 3→4

Figure 5: Regression Discontinuity: Engineering; Required courses completed: $C_{ijt} = 1$

Notes: This figure shows the raw probability of transferring into engineering majors among students who previously were not in engineering majors. The two panels represent the two different transition periods considered — second semester to third semester and third semester to fourth semester. The transition periods from the first semester to the second semester and from the fourth semester to fifth semester are not considered because we do not find any significant effects of GPA cutoffs for those transition periods (not reported). The figures restrict to students who have coherence levels equal to or larger than the median coherence level among students who transfer into engineering majors in the corresponding transition periods (see Table 3 for the corresponding coherence levels). The horizontal axis represents the difference between students' GPA and the cutoff GPA for internal transfer into engineering majors. The blue lines show the linear fits for the probability of transfer on GPA distance for GPA distance under 0.