# Where College Majors Lead: Returns to and Option Values of Majoring in Business and Engineering

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Leveraging GPA cutoffs for internal transfer, we estimate the returns to majoring in business and engineering among students who reach junior year status. The return relative to a mix of alternative degree outcomes, including not graduating, is 0.125 for business and 0.277 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 value is similar to the returns to log earnings for both business and engineering. In addition, we show that college majors shape students' downstream educational and labor-market options, and those options contribute differently to the value of majoring in business and engineering. The option value of graduate degree accounts for about 23% of the gain in present discounted values from majoring in business, but only 6% of the gain from majoring in engineering. Meanwhile, we find that the option value of access to higher-paying industries accounts for a larger share of the gain from engineering than from business.

## 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

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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 return to STEM degrees, it is difficult to evaluate the efficacy of such policies. On an individual level US college students must decide what they major in. Without causal estimates, students often resort to comparing post-college earnings between majors, which can be misleading.

When considering the return to choosing a major, it is also important to take into account the uncertainty in educational outcomes. In particular, the return to choosing a major may differ from the value of 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 the value of the corresponding bachelor's degree would overestimate the return when the graduation rate is low or when time to degree is lengthy.

Another important source of uncertainty in the return to a major stems from the option value of attaining a graduate degree (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 return 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 returns to majoring 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 allows us to calculate the extent to which option values from graduate degrees matter for the two majors. Business and engineering majors are of special interest 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 there is a case for encouraging students to enter these fields and for universities to expand access.

The primary challenge for estimating the 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 through university catalogs of all Texas public four-year institutions, we compile GPA cutoffs for internal transfers for eight universities in the case of business and two in the case of engineering majors. 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. 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 the return to majoring in business and in engineering. We also estimate the effects of majoring in business and engineering on college and graduate degree outcomes. The estimated effects will be the local average treatment effects (LATE) for students who are on the margin of being admitted into business and engineering majors through internal transfer. They are relative to the counterfactual majors of those near the GPA cutoffs. This student population is of great interest for policies that aim to expand access to business and engineering majors.

We estimate that the return to majoring in business is 0.13 (0.03) log points and the return to majoring in engineering is 0.28 (0.08) log points. We find significant heterogeneity in the return for business. Non-Hispanic White students, Hispanic and Black students, and Asian students experience different returns to majoring in business — 0.20 (0.02) vs. 0.14 (0.03) vs. 0.05 (0.03). We also find that students in more selective institutions gain a higher return to majoring in business — 0.15 (0.02) vs. 0.09 (0.03). Compared to male students, female students have a higher return to majoring in business — 0.17 (0.02) vs. 0.13 (0.02), although the difference is not statistically significant. As for engineering, we also find that females gain

[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.

[2] Transfers account for about 40% of all business graduates and 30% of all engineering graduates. Throughout the paper, transfers refers to internal transfers into business and engineering majors in the same university, not transfers between universities.

[3]

higher returns to majoring in engineering — 0.50 (0.13) vs. 0.09 (0.10). 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 among those who reach junior year status. Unsurprisingly, majoring in business and engineering increase the probability 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 probability of attaining any college degree by 0.052 (0.014), and majoring in engineering increases the probability of attaining any college degree by 0.047 (0.010). Examining degree attainment two-years after junior year, which corresponds to the "on-time" graduation timeline, majoring in business increases the probability 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 0.54 for males but by 0.65 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 return 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. Relative to the counterfactual majors for those near the GPA cutoff, 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).

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. To compute the weighted average, we take the probabilities of different outcomes from the RD models and compute the net income for each outcome with OLS estimates from a earnings model with rich controls.

Subject to potential biases in the OLS estimates, 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 use 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 return to earnings. Second, the option value from graduate school represents a much larger share for the PDV gains from majoring in business (23%) than that from majoring in engineering (6%).

Majors may also change the labor market opportunities available to students, including occupations and industries they can access. We do not observe occupation, but conduct similar analyses to examine how access to higher-paying industries contributes to the PDV of college majors. In other words, we examine how business and engineering majors lead students to higher-paying industries versus higher earnings within an industry. We find that the option value of access to higher-paying industries is more important for the PDV gain from majoring in engineering (12%) compared to majoring in business (3.5%).

This paper contributes to two bodies of research. First, we contribute to the literature studying returns to different college majors surveyed in Altonji, Blom, and Meghir (2012), Altonji, Arcidiacono and Maurel, 2016) and Lovenheim and Smith (2023). 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 return to majoring in economics. There are many additional papers studying returns to college majors without quasi-experimental variation. 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 effects on earnings with time to degree, net tuition, and earnings during enrollment.

Second, we contribute to the literature studying the demand for and return to college when educational outcomes are uncertain. Previous works in this literature find that, when educational decisions are sequential and/or outcomes are uncertain, the ex ante return to starting an educational program can differ from the ex post return to attaining the corresponding degrees (Weisbrod, 1962; Altonji, 1993). Under this setting, educational decisions carry option values (Altonji, 1993; 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 by calculating the option values of college majors that come from the option to attain graduate degrees, building on prior work by Eide and Waehrer (1998), Black Sanders, and Taylor (2003) and Stange (2012)

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 quarterly UI records. 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, 2022). However, we do not consider effects of majors on employment probabilities.

The TEA data contains rich information on students' high school enrollment, course selection, and

[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 degrees.

standardized test scores, which provide valuable information on students' baseline abilities and academic interests. 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' performances on the standardized exams are measured using their percentile ranking among their cohort peers.

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 return to being a business (engineering) major, we exclude students who entered college as a business (engineering) major. 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 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 are key to our empirical strategy, as they allow 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. Because calculating a student's coherence requires a sufficient number of peers from their entering cohort to have completed a degree, we restrict our main sample to students who began college no later than the 2018–2019 academic year.

[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 because they are not available in TAAS. SAT and ACT scores are available from college enrollment data for some students but we do not use them because they are often missing.

## 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 a measure developed by Zhu (2025) to elicit students' interests and abilities in different majors through their course selections. The measure, called "coherence" is designed to capture a student's progress towards completing degree-required coursework. It is defined as the share of required courses that the student has completed. To allow for variations in degree requirements, the coherence measure is institution, major, and cohort (entering class) specific.[6] 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 ranges from 0 to 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 requirements well.

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 student 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.

[6] Our estimate of the return to majoring in business is similar when we compute coherence by institution and major.

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 return 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 return 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. Table A2 provides summary statistics about the distribution of coherence by semester of enrollment.

In the case of engineering, the specific math and science courses required for transfer play a key role in the RD specification.[7]

### 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 performance.

In contrast, we found GPA cutoffs for transferring 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, 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 their third (junior)

[7] For UT Austin, the courses are Math 408D, Physics 303K, and Physics 103M. For Texas A&M, the courses are Math 151, Math 152, Chemistry 107, and Physics 206.

year. Among students who graduate with college degrees in engineering, 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.

Figure 1a and 1b present the distributions of students' freshmen year majors for those who transfer into business and engineering in their freshmen and sophomore years. The figures report the distributions separately for female (gold) and male (blue) 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 male students. For both business and engineering transfer students, male students tend to come from higher earning majors.

Appendix table A1 reports summary statistics for high school test scores, demographic backgrounds, and degree attainment of students in the business and engineering analysis samples. The business sample consists of students who reach junior status, did not matriculate as business majors, and enrolled in one of the institutions for which we have business GPA cutoffs. The engineering sample consists of students who reach junior status, did not matriculate as engineering majors, and enrolled in one of the institutions for which we have engineering GPA cutoffs. Students' high school math and reading test scores percentiles are both around 80-85 percentile. About 40% of students in the samples attain a BA on time (two years after reaching junior status) and more than 90% attain BA within 4 years of reaching junior status. 10-20% of students attain advanced degrees within 8 years of reaching junior status.

# 4 Model and Notation

We present a dynamic model of college major choice and graduate school enrollment that formalizes our definition of returns and option values. This model also helps clarify what the parameter that the sequential RD design in section 5 identifies. Section 4.1 presents the dynamic programming problem underlying the sequential choice of major, BA degree outcome, and graduate degree attainment, and labor market earnings. The model implies education choice probabilities. Section 4.2 presents the return to majoring in business relative to alternatives when business is not an option. Section 4.3 defines the part of the return to majoring in business that is due to its effect on graduate school options.

### 4.1 Information Structure

We use the following notation. The index $m \in \mathcal{M}$ denotes a college major. The categorical variable $M_i$ is person $i's$ choice of major, and the indicator $M_{mi}$ is 1 if $i$ $M_i = m$. The bachelor's degree outcomes are indexed by $c \in \mathcal{C}$ and $c = 0$ corresponds to no degree. The categorical variable $C_{it}$ is the bachelor's degree that $i$ holds in $t$ (with 0 corresponding to no degree), and the indicator $C_{cit}$ is 1 if $C_{it} = c$. Similarly, graduate degree outcomes are indexed by $g \in \mathcal{G}$, with $g = 0$ for no degree. $G_{it}$ is the degree held by $i$ in $t$, and $G_{git}$ is an indicator variable for $G_{it} = g$. Examples are a master's in engineering, a master's in education, and an MBA. We often suppress the $i$ and $t$ subscripts. We set net tuition to 0 in the model to reduce notational burden, although we account for it in the empirical work.

All individuals enter the model as currently enrolled college students who have not yet decided their majors. In period 1, which corresponds to junior year, individuals choose $M_i$. For concreteness and for simplicity, we focus on the decision to declare a major in business and let $m = b$ denote business. Later we use $e$ to denote engineering. The model easily extends to the scenario where the $\mathcal{M}$ includes 6 categories of majors, but since we only have one instrument (crossing GPA cutoff for business), we continue with the binary decision when considering major choice. In period 2, which corresponds to senior year, individuals update their beliefs about their abilities and then choose their undergraduate degree outcome $c \in \mathcal{C}$, where in our application $\mathcal{C} = \{0, \text{business}, \text{science}, \text{health}, \text{engineering}, \text{social sciences}, \text{others}\}$ and 0 denotes dropping out of college without degree. In period 3, individuals who chose one of the college degrees in period 2 have the option of enrolling in graduate school and choose $g \in \mathcal{G}$ where $\mathcal{G} = \{0, \text{business}, \text{science}, \text{health}, \text{engineering}, \text{law}, \text{social sciences}, \text{education}, \text{others}\}$. Those who do not get a college degree cannot attend graduate school, so $G_i = 0$ if $C_c = 0$. In period 4 and later periods, all individuals work.

Earnings in period 1 are $y_1(M, A_1)$ where $A_1$ is a vector including both ability (including innate ability and skills as of $t = 1$ and preferences of $i$ as of $t = 1$. Both ability and preferences evolve over time, so the distribution of $A_t$ depends on $A_{t-1}$. Preferences matter for earnings because they affect occupation choice and work hours. Earnings in period 2 are $y_2(C, A_2)$, where $y_2(0, A_2)$ are earnings for individuals who leave school. Earnings in period 3 are $y_3(C, G, A_3)$ where $C = G = 0$ for college dropouts and $G = 0$ if $i$ obtains a bachelor's degree but does not go to graduate school. Finally, from $t = 4$ to $t = T$, schooling is no longer an option in the simple model although it is an option in the empirical work. The individual earns $y_t(C, G, A_t)$. The expected present discounted value (PDV) of earnings between $t = 4$ and retirement at $t = T$ is

$$Y_4(C,G;A_3) = \sum_{t=4}^{T} \beta^t E(y_t(C,G,A_t)|A_3)$$

where $\beta$ is the discount rate. It depends on $c$ and $g$ as well as the distribution of $A_t$ conditional on $A_3$.

The flow value of utility is the sum of the discounted value of $y_t$ and a non-pecuniary utility component. When in college, the non-pecuniary components are $nu_1(M,A_1)$ and $nu_2(C,A_2)$. When in graduate school, the component is $nu_3(C,G,A_3)$. When the individual is out of school, the component is $nu_t(C,G,A_t)$. The latter depends on the combination of undergraduate and graduate degrees, as well as on ability and preferences.

The functions $nu_t(C,G,A_t)$ and $y_t(C,G,A_t)$ both reflect the utility maximizing job choice given trade offs between the productivity of the worker in a given job and non-pecuniary aspects of the work. The set of job opportunities the worker faces and preferences over them are affected by $C$ and $G$ as well as by the ability and preference vector $A_t$.

We assume people are indifferent to the timing of consumption and face perfect credit markets. Any rate of time preference over nonpecuniary aspects is embedded in the $nu_t$ functions. The value function in period 4 is

$$V_4(C,G;A_3) = Y_4(C,G;A_3) + NU_4(C,G;A_3)$$

where

$$Y_4(C,G;A_3) = \sum_{t=4}^{T} \beta^t E(y_t(C,G,A_t)|A_3)$$

and

$$NU_4(C,G;A_3) = \sum_{t=4}^{T} E(nu_t(C,G,A_t)|A_3)$$

The student's optimization problem and educational decisions are characterized by the following recursive formulation. First, before period 3, conditional on the college degree outcome and information available, student chooses $G$ to maximize expected utility:

$$V_3(C;A_2) = \begin{cases} \max_{g\in\mathcal{G}} \left\{\beta^3 E[y_3(C,g,A_3)|A_2] + E[nu_3(C,g,A_3)|A_2] + E[V_4(C,g;A_3)|A_2]\right\} & \text{if } C \neq 0 \\ \beta^3 E[y_3(0,0,A_3|A_2] + E[nu_3(0,0,A_3)|A_2] + E[V_4(0,0;A_3)|A_2] & \text{if } C = 0 \end{cases} \quad (2)$$

The sum of the first two terms inside the brackets on the right side of (2) is expected utility from earnings and nonpecuniary factors that accrues in period 3 conditional on choice of $g$ given $C$. The third term is

the continuation value, which is expected utility from earnings and nonpecuniary factors from $t = 4$ to $T$ conditional on choice of $g$ and the distribution of future values of $A_t$ given $A_2$. The optimal graduate degree choice is $G = G(C, A_2)$. The distribution of $A_2$, $f(A_2|C, A_1)$, induces the education transition probabilities $P_g(C, A_1)$, where $P_g$ is the probability that $G = g$.

Second, before period 2, conditional on major choice in period 1 and information available, the student chooses $C$ to maximize

$$V_2(M; A_1) = \max_{c \in \mathcal{C}} \left\{ \beta^2 E[y_2(c, A_2)|A_1] + E[nu_2(c, A_2)|A_1] + E[V_3(c; A_2)|A_1] \right\}. \tag{3}$$

The optimal bachelor's degree attainment is $C = C(M, A_1)$, and the cross sectional heterogeneity in ability and preferences, $f(A_1|M, A_0)$ induces the transition probability $P_c(M, A_0)$ where $P_c$ is the conditional probability that $C =$ given choice of major.

Finally, before period 1, conditional on information available, the student chooses college major to maximize expected value:

$$V_1(A_0) = \max_{m \in \mathcal{M}} \{ \beta E[y_1(m, A_1)|A_0] + E[nu_1(m, A_1)|A_0] + E[V_2(m; A_1)|A_0] \} \tag{4}$$

The optimal major choice is $M = M(A_0)$. Let $gpa_0$ be an element of $A_0$. Students for whom $gpa_0$ exceeds the threshold for transfer into the business major have the opportunity to do so. The cross sectional heterogeneity in abilities and preferences induces the major choice probabilities $P_m$.

## 4.2 The Return to Majoring in Business.

For each individual $i$, we define the return to majoring in business as the increase in earnings in period $t$ as a result of majoring in business:

$$R_{bt}(A_0) = \sum_{c \in \mathcal{C}} \sum_{g \in \mathcal{G}} E[P_g(c, A_2) P_c(b, A_1) y_{it}(c, g, A_t)|A_0] - \sum_{c \in \mathcal{C}} \sum_{g \in \mathcal{G}} E[P_g(c, A_2) P_c(M'(A_0), A_1) y_{it}(c, g, A_t)|A_0] \tag{5}$$

where $M'(A_0)$ is the optimal choice if $b$ is not an option. That is, we focus on the earnings return to $b$ relative to a weighted average of the alternative outcomes, $M'(A_0)$, including effects that operate subsequently through $C$ and $G$. This is the return parameter that is identified in our empirical work, in which we get at $R_{bt}(A_0)$ using a fuzzy RD design based on GPA (an element of $A_0$) crossing the minimum GPA for transfer

into business major. The weighted average is determined by the distribution of $A_0$ for those who are near the GPA threshold to transfer into business and who also satisfy other criteria that we discuss below.

### 4.3 The Role of Graduate School Options in the Ex Ante Return to a Major (Preliminary)

Let

$$Y_1(m, A_0) = \beta E[y_1(m, A_1)|m, A_0] + \beta^2 \sum_{c \in \mathcal{C}} E[P_c(m, A_1) y_2(c, A_2)|m, A_0]$$
$$+ \sum_{t=3}^{T} \beta^t \sum_{c \in \mathcal{C}} \sum_{g \in \mathcal{G}} E[P_g(c, A_2) P_c(m, A_1) y_t(c, g, A_t)|m, A_0]$$

The function $Y_1(m, A_0)$ is the expected present value of earnings net of monetary costs between period 1 and $T$ for choosing $m$ in prior to period 1 assuming optimal future choice of $C$ prior to period 2 conditional on $m$ and the realization $A_1$, optimal future choice of choice of $G$ prior to period 3 conditional on $C$ and the realization of $A_2$, and the flow of future earnings conditional on $C$, $G$, $A_3$ and future values of $A_t$. We define the value of the option to major in business for earnings as the expected value of all the future payoffs that this decision enables. In particular, this is defined as

$$OV(b, A_0) = Y_1(b, A_0) - Y_1(M'(A_0), A_0) \tag{6}$$

where $M'(A_0)$ is the optimal choice of $M$ when $b$ is not in the choice set.[8]To isolate the contribution of graduate school pathways to the ex ante value of majoring in business, we construct a counterfactual where majoring in business still affects the college degree distribution, but does not shift the likelihood of graduate degree attainment. We call this counterfactual "nograd" (NG). To be precise, the conditional probability $P_c^{\bar{G}}(M, A_1) = P_c(M, A_1)$, so that the effects of majoring in business on college degree attainment is held fixed. However, we shut down the effect college has on graduate degree attainment:

$$P_g^{\bar{G}}(C, A_2) = \begin{cases} \frac{\sum_{c \in \mathcal{C}} P_g(c, A_2) P_c(M, A_1)}{\sum_{c \neq 0} P_c(M, A_1)} & \text{if } C \neq 0 \\ 0 & \text{if } C = 0 \end{cases}$$

This definition of $P_g^{\bar{G}}$ implies that (1) the probability of choosing $G = g$ does not depend on $C$ as long as $C \neq 0$ and (2) the marginal probability of getting any graduate degree conditional on $C \neq 0$ is the same for

[8]This differs from Stange's (2012) definition of option value, which focuses on the value of *delaying* decision makings to after more information is revealed.

any $m$.

The option value $OV^{Grad}$ from graduate school for majoring in business is defined as:

$$\begin{aligned} OV^{Grad}(b, A_0) &= Y_1(b, A_0) - Y_1^{NG}(b, A_0) \\ &= \sum_{t=3}^{T} \beta^t \{ \sum_{c \in \mathcal{C}} \sum_{g \in \mathcal{G}} E[P_g(c, A_2) P_c(b, A_1) y_t(c, g, A_t) | b, A_0] \\ &- \sum_{c \in \mathcal{C}} \sum_{g \in \mathcal{G}} E[P_g^{NG}(c, A_2) P_c(b, A_1) y_t(c, g, A_t) | b, A_0] \} \end{aligned} \tag{7}$$

# 5 Econometric Specifications and Methods

We describe the empirical strategy for estimating the return to business, noting that the strategy for engineering is the same except when noted. We continue to use the notation from 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, $M_b = 1$ indicates choosing business as one's major as of the beginning of junior year, and $C_b = 1$ 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.

## 5.1 Regression Discontinuity (RD) Design Using GPA Cutoffs for Internal Transfer

Identifying the returns to majoring in business and engineering is difficult for two reasons. The first is that education choices depend on unobserved portions of $A_0$, $A_1$, and $A_2$. The second is that these elements affect the returns to college majors and graduate degrees.

To identify the causal return to majoring in business, we leverage minimum GPA requirements for internal transfers into business majors. 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 $\text{gpa}_{ijt}^0$. A simple RD specification for majoring in business is

$$P(M_b = 1) = \beta_0 + f(\text{gpa}_{ijt}^0; Z_{jt}) + \beta_1 \times z_{ijt} + \beta X_{ijt} + \epsilon_{ijt} \tag{8}$$

where $f(\cdot)$ is a piece-wise quadratic function of students' GPA around the cutoff $Z_{jt}$, and $z_{ijt}$ is the indicator

for crossing the cutoff:

$$z_{ijt} = 1(\text{gpa}^0_{ijt} \geq Z_{jt})$$

Throughout, we maintain standard assumptions for fuzzy RD designs:[9]

**Assumption A1 (Continuity)**. Potential outcomes are continuous in the running variable, $\text{gpa}^0_{ijt}$ around the cutoff $Z_{jt}$.

**Assumption A2 (Monotonicity)**. Crossing the GPA cutoff weakly increases the probability of majoring in business so that no students become less likely to major in business when eligible.

**Assumption A3 (Local Randomization)**. Conditional on a smooth function of GPA and other controls, $A_0$, $A_1$, and $A_2$ are orthogonal to the crossing of the cutoff, $z_{ijt}$.

**Assumption A4 (Exclusion)**. Crossing the cutoff only affects degree outcomes and earnings through its effect on major choice.

Under these assumptions, the parameter $\beta_1$ identifies the effect of crossing the GPA threshold on the probability of majoring in business for all students.

#### 5.1.1 Identifying Relevant Students Using Course Selection

Not all students are interested in majoring in business. As a result, the effect of crossing the GPA threshold on transferring into business would 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 major. 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 (8) to

$$\begin{aligned} P(m=1) = {} & \beta_0 + g(\text{coh}^1_{ijt}) + \beta X_{ijt} \\ & + 1(\text{coh}^1_{ijt} < \underline{\text{coh}}_{jt}) \times [f_1(\text{gpa}^1_{ijt}) + \lambda_t \times z_{ijt}] \\ & + 1(\text{coh}^1_{ijt} \geq \underline{\text{coh}}_{jt}) \times [f_2(\text{gpa}^1_{ijt}) + \gamma_t \times z_{ijt}] + \epsilon_{ijt} \end{aligned} \tag{9}$$

[9] See Cattaneo et al. (2024) for a discussion of fuzzy RD methods.

The term $1(\text{coh}^1_{ijt} < \underline{\text{coh}}_{jt}) \times [f_1(\text{gpa}^1_{ijt}) + \lambda_t \times z_{ijt}]$ 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 is 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 the 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 (9) is modified accordingly for engineering:

$$\begin{aligned} P(m=1) = \beta_0 + g(\text{coh}^1_{ijt}) + \beta X_{ijt} \\ + 1(C_{ijt}=0) \times [f_1(\text{gpa}^1_{ijt}) + \lambda_t \times z_{ijt}] \\ + 1(C_{ijt}=1) \times [f_2(\text{gpa}^1_{ijt}) + \gamma_t \times z_{ijt}] + \epsilon_{ijt} \end{aligned} \tag{10}$$

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 $Z_{jt}$.

### 5.1.2 Incorporating Multiple Transition Periods

In practice, students have multiple opportunities to transfer from non-business majors to business majors. Students can transfer as early as after their first semester in freshman year, and as late as after their second semester in sophomore year.[10] 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 some additional notation. Denote $M_b^{01}$, $M_b^{02}$, $M_b^{03}$, $M_b^{04}$ , $M_b^{05}$ as the indicators for a student entering his first, second, third, fourth, and fifth semester as a business major. Similarly, let $\text{gpa}^{0s}_{ijt}$ and $\text{coh}^{0s}_{ijt}$ be a student's GPA and coherence level entering semester $s$. Let $z^s_{ijt}$ be an indicator for crossing the GPA cutoff in semester $s$. While students at any of the transition points are assumed to face the same cutoff GPA, the minimum coherence

[10] Transfers that occur after junior year are already captured by the model with decision on $C$.

levels we consider are $s$-specific. In particular, $\underline{\text{coh}}^s_{jt}$ is defined as the median coherence level among students for whom $M_b^{0s} = 0$ and $M_b^{0(s+1)} = 1$. We adjust equation (9) to model the student's conditional probability of transferring into business for each transition period:

$$\begin{aligned}\phi_{is} &= P(M_b^{0(s+1)} = 1 | M_b^{0s} = 0) \\ &= \beta_{0s} + g_s(\text{coh}_{ijt}^{0s}) + \beta_s X_{ijt} \\ &+ 1(\text{coh}_{ijt}^{0s} < \underline{\text{coh}}^s_{jt}) \times [f_{1s}(\text{gpa}_{ijt}^{0s}) + \lambda_{ts} \times z^s_{ijt}] \\ &+ 1(\text{coh}_{ijt}^{0s} \geq \underline{\text{coh}}^s_{jt}) \times [f_{2s}(\text{gpa}_{ijt}^{0s}) + \gamma_{ts} \times z^s_{ijt}] + \epsilon_{ijts}\end{aligned} \tag{11}$$

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

$$\begin{aligned}\Phi_i &= P(M = b) \\ &= 1 - P(M = 0) \\ &= 1 - \Pi_{s=1}^4 (1 - \phi_{is})\end{aligned} \tag{12}$$

The main assumption for modeling transfers into business majors with a survival model is the following.

**Assumption A5 (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 $s \in \{1, 2, 3, 4\}$:

$$P(M_b = 0 | M^{0s} = 1) = 0$$

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%) are still a business (engineering) major at 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.[11]

We calculate $\hat{\Phi}_i = 1 - \Pi_{s=1}^4 (1 - \hat{\phi}_{is})$, where $\hat{\phi}_{is}$ is the predicted value following equation (11). We also

[11] If the assumption is false, then in principle one could improve efficiency by constructing separate instruments for transferring into business after the first semester, after the second semester, etc. but we prefer the more parsimonious approach. Note if the causal 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 a discussion of LATE in the context of multiple instruments, see Mogstad, Torgovitsky, and Walters (2021). We lack the statistical power to estimate separate treatment parameters.

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 (11) but excluding the RD variation in GPA for those with $\text{coh}_{ijt}^{0(s+1)} \geq \underline{\text{coh}}_{jt}^{s+1}$ :

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

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.[12] We do not want identification to come from nonlinear effects of $X_{it}$ and the $f(gpa_{ijt}^{0s})$ functions operating through $\hat{\Phi}_i$.

We also use an alternative empirical specification that does not rely on Assumption 1 and accounts for optimal bandwidth for the RD procedure. We modify equation (11) to

$$\begin{aligned}\tilde{\phi_{is}} &= P(m^{0(s+1)} = 1 | m^{0s} = 0) \\ &= \beta_0 + g_s(\text{coh}_{ijt}^{0s}) + \beta X_{ijt} \\ &+ 1(\text{coh}_{ijt}^{0s} < \underline{\text{coh}}_{jt}^{s}) \times [f_{1s}(\text{gpa}_{ijt}^{0s}) + \lambda_{ts} \times z_{ijt}^{s}] \\ &+ 1(\text{coh}_{ijt}^{0s} \geq \underline{\text{coh}}_{jt}^{s}) \times [f_{2s}(\text{gpa}_{ijt}^{0s}) + \gamma_{ts} \times z_{ijt}^{s}] \\ &+ 1(\text{coh}_{ijt}^{0s} \geq \underline{\text{coh}}_{jt}^{s}) \times 1(-b^s \leq \text{gpa}_{ijt}^{0s} \leq b^s) \times [f_{3s}(\text{gpa}_{ijt}^{0s)}) + \omega_{ts} \times z_{ijt}^{s}] + \epsilon_{ijts}\end{aligned} \tag{13}$$

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 $1(\text{coh}_{ijt}^{0s} \geq \underline{\text{coh}}_{jt}^{s}) \times 1(-b^s \leq \text{gpa}_{ijt}^{0s} \leq b^s) \times z_{ijt}^{s}$ for each $s$ as the excluded instruments and include the remaining terms in $\tilde{\phi_s}$ as controls.[13] 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.[14] The main disadvantage of the linear-RD approach

[12] In the engineering case, we replace $1(\text{coh}_{ijt}^{0s} < \underline{\text{coh}}_{jt}^{s})$ with $1(C_{ijt} = 0)$ and $1(\text{coh}_{ijt}^{0s} \geq \underline{\text{coh}}_{jt}^{s})$ with $1(C_{ijt} = 0)$.

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

[14] Another difference with the main specification is that the polynomial $f_{ts}$ are local linear functions instead of piece-wise quadratic functions.

is that it leads to larger standard errors, due to the inclusion of piece-wise linear terms for all transition periods. Note that this approach is similar in spirit to the dynamic RD method used in Cellini, Ferreira, and Rothstein (2010).

## 5.2 Estimating Returns to Majors

As in Section 4, we define the return to majoring in business as the causal effect of declaring as a business major (by junior year) on an individual's earnings. The earnings model for the return is:

$$y_{it} = a_0 + a_1 M_{bi} + a_2 \bar{\Phi}_i + aX_{it} + \epsilon_{it} \tag{14}$$

where $M_{mi}$ is instrumented with $\hat{\Phi}_i$. $X_{it}$ includes a gender specific cubic age profile, ethnicity, GPA, credits accumulated, high school test scores, institution fixed effects, 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, $[1(\text{coh}^{0s}_{ijt} \geq \underline{\text{coh}}^{s}_{jt}) \times \gamma_{ts} \times z^{s}_{ijt}]$, to identify the effects of majoring in business.

Given Assumptions A1-A5, $a_1$ identifies $R_b$, the causal effect of majoring in business (at the beginning of junior year) on earnings for the complier group $\Omega$.

### 5.2.1 Compliers and Counterfactuals

We define the complier group as:

$$\Omega = \{i | M(A_{i0}, z_{ijt} = 1) = 1, M(A_{i0}, z_{ijt} = 0) = 0\},$$

These are students who are induced into majoring in business if $z_{ijt} = 1$ and do not major in business if $z_{ijt} = 0$.

The return parameter we estimate is the average return for $\Omega$. The counterfactual group identified are students who are similar to those who declared major in business but ended up declaring other majors. Therefore, it is the return to majoring in business relative to a weighted average of alternative majors.

Since we only have one instrument, $\hat{\Phi}$, we cannot separately estimate the return relative to each counterfactual major. However, we provide evidence on who the compliers are and what the counterfactual majors might be. In section 6, we report comparisons of the compliers to the overall population over several observ-

able characteristics. In addition, we report the RD estimates of the effects of majoring in business on the attainment of a BA in each field, which shed light on the relative weights of different counterfactual majors.

### 5.3 Estimating Degree Outcomes and Time to Degrees

When making education decisions, students face uncertainty about the educational outcomes they will lead to. In this paper, we study three important dimensions of uncertainty. First, $C$ might not equal $b$ even if $M = b$. This reflects the possibility that students might drop out of college and or change majors after reaching junior year status.[15] Second, students may take varying number of years to complete their undergraduate degrees. For example, an engineering degree typically requires more credit hours than liberal arts degrees, perhaps requiring more effort and lengthier enrollment. Third, different majors could lead to different graduate school options. For example, 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 estimate the effects of majoring in business on the likelihood of various undergraduate and graduate degree outcomes. This corresponds to the transition probabilities $P_c(m)$ and $P_g(c)$ from the model in section 4. In addition, we break down periods 2 and 3 of the model in Section 4 into years. Empirically, we estimate the likelihood of attaining a BA in field $c \in \mathcal{C}$ for $y \in \{2, 3, \cdots, 8\}$ using

$$C_{ci}^{y} = \beta_0^{cy} + \beta_1^{cy} M_{bi} + \beta_2^{cy} \bar{\Phi} + \beta^{cy} X_{it} + \epsilon_{cit}\,, \tag{15}$$

where $M_{bi}$ is instrumented with $\hat{\Phi}$. The parameter $\beta_1^{cy}$ is the causal effect of declaring as a business major (by the beginning of junior year) on the probability of attaining a BA in $c$. These parameters indicate what the likely counterfactual majors are for students who are on the GPA margin for transferring into business. For example, if $\beta_1^{\text{engineering,y}}$ is significantly negative, this indicates that compared to treated students who declared business as their major, the counterfactual students are more likely to end up majoring in engineering. This would imply that engineering is an important counterfactual major for the marginal business students.

Finally, we estimate the likelihood of attaining a graduate degree in field $g \in \mathcal{G}$ for $y \in \{4, 5, \cdots, 8\}$ using

$$G_{gi}^{y} = \beta_0^{gy} + \beta_1^{gy} M_{bi} + \beta_2^{gy} \bar{\Phi} + \beta^{gy} X_{it} + \epsilon_{git} \tag{16}$$

where, again, $M_{bi}$ is instrumented with $\hat{\Phi}$.

[15] Dropping out of college after reaching junior year status is 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 include students who transfer to an out of state institution and complete their degree.

The equations for engineering have the same form as (15) and (16), but the parameters and error terms are different and we replace $M_{bi}$ with$M_{ei}$, where, as a reminder, $e$ denotes engineering.

# 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 returns to majoring in business and engineering. Section 6.3 considers the effects of majoring in business and engineering on degree outcomes and time to degrees. Section 6.4 and 6.5 presents results from alternative specifications and explores differences in returns across groups. Section 6.6 combines the return estimates, the effects on time to degrees, and the cost of enrollment to calculate present discounted values (PDV) of majoring in business and engineering. Section 6.6 also computes the option values of graduate school for majoring in business and engineering. Finally, section 6.7 provides a preliminary examination of the option value of industry access.

## 6.1 Effects of Crossing the GPA Cutoffs on Majoring in Business and Engineering.

Figures 2-3 present the probabilities of transferring into business 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.[16] 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 and 3 are essentially the "first stage" figures for fuzzy RD following equation (8). Meanwhile, figure 3 reports results for students with coherence levels greater or equal to the median coherence among students who successfully transferred into the business major in the transition period of interest. From figure 2, we observe that the probability of internally transferring into business 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 the business major 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. 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.

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

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 (when few would have met the course requirements) 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.

#### 6.1.1 Balance Tests

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 (11) 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. As in the main analyses, we restrict the sample to students who did not matriculate as business majors when examining the effects of crossing the business cutoffs, and restrict to students who did not matriculate as engineering majors when examining the effects of crossing the engineering cutoffs. We also impose the same minimum restrictions on course coherence that we impose in the main analysis. In the balance tests for students' first declared major, we use separate dummy variables for whether the student's first major was engineering or social sciences for business cutoffs. We use dummy variables for whether the student's first major was business and sciences for engineering cutoffs. Students who matriculated without a declared major are included in the analyses and have 0 values for the dummies.

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, and the point estimates are small in all but that case. 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) is statistically significant.[17] However, the estimates are noisy.

In addition, we also perform balance tests on the predicted likelihood of being a business / engineering major in the first semester of junior year. The likelihood is predicted using a linear probability model that includes all of the observable characteristics mentioned above. The results are reported in column (7) of table 3, and shows that crossing the GPA cutoffs for either business or engineering is not associated with discontinuity in the regression index.

### 6.1.2 Characteristics of the Compliers

As mentioned in the introduction, the effects of majoring in business and engineering estimated using the variation from crossing the GPA cutoffs are estimates of the LATE parameters 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.[18] For a binary 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.

## 6.2 Estimates of the Return to Business and to Engineering

Table 5 reports the returns to business and engineering on log earnings. The instrumental variable (IV) estimate shows a 0.13 (0.03) return for majoring in business. The OLS estimate for the return is somewhat

[17] 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.

[18] For example, for return to majoring in business, 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.

smaller at 0.09 (0.004). The fact that the IV estimate is larger than OLS may be due to a higher return for the marginal students identified with the IV specification.

Columns (3) and (4) of table 5 report the return for engineering. The IV estimate shows a 0.28 (0.08) return for majoring in engineering. The OLS estimate is somewhat smaller at 0.24 (0.01), but also shows a large return.

Table 6 reports results for the 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%.[19]

Table 6a shows a higher return for females. The IV estimates of the return for females — 0.17 (0.02) — is 30% higher than that for males — 0.13 (0.02). The same pattern is present in the OLS estimates. Note, however, that in the IV case the gender difference is not statistically significant.[20] Table 6b shows that economically disadvantaged students have a lower return to business. The 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). The differences in the IV estimates are not statistically significant, but the same pattern is present in the OLS estimates, which are precise.

Table 6d shows significant heterogeneity in returns across ethnicity. Non-Hispanic whites have the highest return — 0.20 (0.02). Hispanic and black students have lower returns — 0.14 (0.03). Asian students have the lowest return — 0.05 (0.03). Finally, table 6c shows that students in selective institutions have a substantially higher return to business. The point estimate is 67% higher — 0.15 (0.02) vs. 0.09 (0.03) — and the difference is statistically significant at the 10 percent level

Table 7 reports heterogeneity results for the 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. The return is 0.410 (0.164) higher for females — 0.50 (0.13) vs. 0.09 (0.10) The standard errors are large, but the difference is significant at the 5 percent level. However, the OLS estimates of the return are 0.252 (0.016) for females and 0.229 (0.011) for males, suggesting a smaller female advantage.

[19] Among 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.

[20] We investigated whether the gender difference in returns arises because females and males major in 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 shares of male and female 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 a higher return for male students because finance is the highest earning sub-field in business.

## 6.3 Estimates of 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, which corresponds to the six-year graduation time frame often used by colleges to report degree completion rates. Several patterns can be observed. First, the results for the full sample in column 2 of 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. For comparison, the average graduation rate of students who reach junior status is around 80%. 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 suggest that the option value of attaining a graduate degree, and a business degree in particular, is likely a significant part of the return to majoring in business. In section 6.5, we estimate the graduate school option value.

### 6.3.1 Engineering

Table 10 reports the effects of majoring in engineering on college degree outcomes four years after reaching junior status. First, majoring in engineering increases the likelihood of attaining an engineering bachelor's degree by 0.98 (0.03). Second, the most prevalent counterfactual majors for engineering students are science

and "other". Interestingly, the IV estimate is only -0.03 (0.03) for business, indicating that the marginal students who are affected by crossing the GPA threshold and who have taken the required courses to transfer do not come from business (The OLS estimate is larger, -0.14 (0.01). This contrasts with the large role of engineering as a counterfactual degree in analysis of business in Table 8. Third, similar to the case for business, gender heterogeneity in degree outcomes can help explain the higher return to engineering for females. 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 (but not statistically significant) for males.

Table 11 presents the effects of majoring in engineering on graduate degree outcomes eight years after junior year. In contrast to 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 indicate that graduate degree attainment is likely not as important for 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 time to degree. Anecdotal evidence suggests that engineering is a particularly demanding course of study. Engineering programs require more credits, with requirements concentrated in STEM coursework. This may increase time to degree. [21] 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 4 year "on-time" graduation. Comparing the fourth rows of table 13 and Table 10 suggests that a large share of students who transfer into the engineering major do not complete a bachelor's degree in four years. Majoring in engineering increases the probability of earning an engineering degree by 0.19 (0.03) two years after reaching junior status, which compares to 0.98 (0.03) four years after junior status. In comparison, the corresponding values for the effect of majoring in business on earning a business undergraduate degree are 0.48 (0.01) at 2 years and 0.998 (0.009) at four years. 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). Taken together, these results indicate that the added demands of engineering programs translate into meaningfully longer times to degree, whereas business majors face no such penalty and are, if anything, somewhat more likely to graduate

[21] For instance, a bachelor's degree in mechanical engineering at Texas A&M University requires 128 semester credit hours, compared to the university-wide minimum of 120. The 2025-26 edition of the University Catalog 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.

on time.

## 6.4 Robustness to Alternative RD Specifications

Here we show that our results are robust to 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. The value 0.3 is the optimal bandwidth calculated for both business and engineering following Calonico, Cattaneo, and Titiunik (2014a and 2015b).[22] 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 separately includes the RD variation 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 to facilitate for comparison. The results for business show that our main estimate (0.13) is very similar to restricting to students whose GPAs are within 0.3 of the cutoffs (0.14) and to using the linear-RD model (0.14). As expected, the survival-RD model has the advantage of having more precision compared to the linear-RD approach. The results for engineering show that our main estimate (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 differences are not large compared to the standard errors.

## 6.5 Accounting for Differences in the Estimates

Before turning to the results on graduate school option values we address two questions. First, can we explain the differences in estimates of the effects on earnings between OLS and survival-RD with the differences in the OLS and survival-RD estimates of the effects on degree attainment? Second, and similarly, can we explain the differences in estimates of the effects on earnings for different populations with the corresponding group differences in estimates of the effects on degree attainment?

We try to predict the 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 degree. Specifically, we predict the returns by computing the linear combination $\sum_{i=1}^{6} \hat{a}_{1c}\hat{\beta}_1^{c4}$ separately business and for engineering, where the $\hat{a}_{1c}$ are OLS estimates of the major-specific BA earnings premiums for the population as a whole or for each of the sub populations that we consider.[23] The $\hat{\beta}_1^{c4}$ are either OLS

[22] Specifically, for each transition period, the procedure estimates local-linear regression discontinuity models using different bandwidths and chooses the bandwidth that minimizes the mean squared error of the model, balancing the reduction in sampling variance from including more observations against the increase in bias from observations farther from the cutoff. We obtained values close to 0.3 for each transition period and for both business and engineering. As a result, we choose 0.3 as the optimal bandwidth.

[23] The BA field specific earnings premiums $\hat{a}_{1c}$ are obtained from OLS estimation of

or survivalr-RD-based estimates of the effect of majoring in business (engineering) on the $C_{ci}$ reported in Table 8 (Table 10).

The predicted 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 returns to majoring in business. The results in columns 1 and 2 show that the estimates from both the OLS and survival-RD models (0.09 and 0.13) are approximated reasonably well by the predicted returns (0.11 and 0.16). The results in columns 3-9 show that the returns estimates from the survival-RD models for different populations (e.g., females, males, economically disadvantaged) are also approximated reasonably well by the predicted returns for each population. Table 16 report results for the returns to majoring in engineering. The results in columns 1 shows that the return estimate from the OLS model (0.24) is reasonably close to the predicted return (0.29). The return estimates from the survival-RD models for the full sample, female, and male students (0.28 (0.08), 0.50 (0.13), and 0.09 (0.10)) are not as well approximated (0.39 , 0.40, and 0.38). The gap between the predicted return and RD estimate is large for males, but the discrepancies for the combined sample and for females are not large compared to the standard errors of the return estimates.

Overall, the estimates of the effects on earnings are broadly consistent with the estimates of the effects on degree attainment. In particular, the returns to majoring in business, and to a lesser extent engineering, can for the most part be predicted by the effects of majoring in business and engineering on undergraduate degree attainment. It is important to note, however, that graduate degree attainment remains a potentially significant component of the returns to majoring in business and engineering. This is because the earnings premiums of college degrees implicitly incorporate the option value of graduate degrees. In the next subsection, we examine the present discounted values of majoring in business and engineering and quantify the option values of graduate degrees.

## 6.6 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

$$y_{it} = a_0 + \sum_{c=1}^{6} a_{1c} C_{ci} + aX_{it} + \epsilon_{it} \tag{17}$$

where $C_{ci}$ 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 × cohort combination. We estimate (17) separately for each sub population. Note that 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.

graduate school? We answer these questions by calculating the actual and counterfactual present discounted values (PDV) of majoring in business and engineering.

### 6.6.1 Procedure for Calculating PDVs

We use the following procedure to calculate the PDVs. Consider business. First, we extend equations (15) and (16) 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:

$$d_{io}^{y} = \delta_0^{oy} + \delta_1^{oy} M_{bi} + \delta_2^{oy} \bar{\Phi} + \delta^{oy} X_{it} + \epsilon_{it} \tag{18}$$

where $d_{oi}^{y} = 1$if $i$ has the degree combination $o$ in year $y$ and $M_{bi}$ 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 no sooner than 3 years after junior year. In addition, we include college enrollment and graduate enrollment as possible outcomes.[24]

Second, we predict the actual and counterfactual probabilities of each outcome for 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 $P_{oy}^{Counter} = \hat{\delta}_0^{oy} + \hat{\delta}_2^{oy} \bar{\bar{\Phi}} + \hat{\delta}^{oy} \bar{X}_{it}$.[25]

Third, following section 4.3, 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) $P_{cgy}^{ActualCollege} / \sum_{o \in O_c} P_{oy}^{ActualCollege} = P_{cgy}^{Counter} / \sum_{o \in O_c} P_{oy}^{Counter}$, where cg is college degree c and graduate degree g, 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

[24] 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 $c$ × graduate degree in field $g$ — 48 outcomes.

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

$y \in \{9, 10, \cdots, 39\}$ by assuming 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. To accommodate estimation of earnings at high values of $y$ we do not restrict the earnings sample 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 6.5 — that we can predict the returns with reasonable accuracy using IV estimates of the effects on degree attainment and OLS estimates of the earnings premiums of degrees — suggests the issue is likely not severe, at least for business and for the combined sample for engineering.

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 $C_{iy}$ for the first 2 years and $C_{i4}$ for years 3 and 4 for persons who attain 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 estimate 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.

### 6.6.2 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 actual 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. Differences by gender align with what we see in the return estimates — females have substantially higher PDV gains.

The bottom panel presents results for engineering majors. The actual PDV gain for engineering major is 32.0%. The PDV gain is 30.3% when we assume no effect of majoring in engineering on graduate enrollment and graduate degree attainment. Thus, in the engineering case the option value of graduate education contributes only 6% of the PDV gains to majoring in engineering.

### 6.7 Option Value of Industry Access

Majoring in different fields in college may also create option value by leading students into different labor-market pathways. While the Texas administrative data do not collect individuals' occupation information, we do observe the industry in which they are employed. In this subsection, we provide a preliminary examination of how much of the value of majoring in business and engineering comes from access to higher-paying industries compared to higher earnings within a given industry. We call this the option value of industry access.

The approach we take to answer this question is parallel to our examination of the option value of graduate education. First, we aggregate industries into 8 categories — "Technology", "Finance", "Engineering", "Legal", "Education", "Healthcare", "Trade, Logistics, or Operations", and "Consumer or Local Services". Second, we use the survival-RD specification to estimate how majoring in business and engineering affects a student's likelihood of being employed in one of the 8 industry categories.[26] Third, we combine individuals' college degree fields and industry categories and estimate a richer outcome model using the survival-RD specification. This produces predicted actual and counterfactual probabilities for an individual to end up in a specific college degree $\times$ industry category. Fourth, we compute another set of probabilities where we allow the distribution of college degrees to follow the actual distribution but restrict the industry distribution to follow the counterfactual distribution. Fifth, we use OLS with rich controls to predict the labor market value of each college degree $\times$ industry category. Finally, we compute the PDV of each of the three scenarios — Counterfactual, Actual, and ActualCollege.

Table B1 reports OLS and survival-RD estimates for the industry outcomes. For business, the RD estimates indicate a large increase in the probability of working in finance — 0.340 (0.022) — and a smaller increase in trade, logistics, or operations — 0.084 (0.019). Majoring in business reduces the likelihood of working in the education industry — -0.205 (0.023). For engineering, the RD estimates show a large increase

[26] For each individual, we use the most common industry category among all of the quarters we observe employment. In a future draft, we will separately categorize an individual's industry by career stages.

in working in the engineering industry — 0.511 (0.073) — and large decreases in the likelihood of working in finance — -0.178 (0.065) — education — -0.110 (0.049) — and healthcare — -0.181 (0.042). Interestingly, majoring in engineering does not lead to a significant change in the probability of working in the technology industry.

Table B2 reports the PDV under the three scenarios described. Note that, similar to the discussion of option value of graduate education, the option value of industry access is the PDV difference between the Actual and ActualCollege scenarios. The results suggest that around 12% of the total PDV gain from majoring in engineering comes from the shift in industry distribution while the share is only 3.5% for business. This is consistent with the interpretation that, compared to engineering, business generates more of its value through earnings gains that are relatively transferable across industries.

# 7 Conclusion

In this paper, we leverage GPA cutoffs for internal transfers into business and engineering majors and use RD designs to estimate the returns to majoring in business and engineering in college. The return to business is around 0.12, while that for engineering is 0.28. 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 23% of the PDV gain from majoring in business comes from the option value of graduate schools, the share is only around 6% for engineering. In contrast, our preliminary work on the role of industry suggests that the value of leading students into higher-paying industries is more important in the PDV gain from majoring in engineering (12%) compared to majoring in business (3.5%). These results point to a broader interpretation of the value of college majors. The value of a college major is not fully captured by a single returns estimate. Rather, it reflects the set of subsequent educational and labor market options that the major makes available and the economic returns associated with those options.

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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

**Panel A. Final Major Equals Major of Bachelor's Degree**

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

**Panel B. Final Major Equals Major at Junior Year**

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

*Notes:* 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 panel a and (2)-(5) for panel b report the share of students who transitioned to their final major after the semester in the second row. Panel a takes students' final major as their BA degree major, while Panel b takes students' final major as their junior year major.

Table 3: Balance Tests for the Regression Discontinuity

| | **Business** | | | | | | |
|---|---|---|---|---|---|---|---|
| | HS Math Percentile (1) | HS Reading Percentile (2) | Not Econ. Disadv. (3) | Male (4) | First Major Engineering (5) | First Major Social Sciences (6) | Predicted Probability of Transfer (7) |
| Semester 1-2 | -0.57 | -0.88 | 0.02 | 0.00 | 0.01 | -0.01 | 0.001 |
| | (0.78) | (0.62) | (0.02) | (0.00) | (0.01) | (0.01) | (0.001) |
| Semester 2-3 | -1.12 | -0.17 | 0.00 | 0.00 | 0.01 | 0.01 | -0.000 |
| | (1.02) | (0.82) | (0.03) | (0.00) | (0.01) | (0.01) | (0.001) |
| Semester 3-4 | 0.93 | 0.67 | 0.02 | 0.00 | 0.02 | 0.01 | -0.002 |
| | (1.08) | (0.96) | (0.03) | (0.00) | (0.02) | (0.01) | (0.002) |
| Semester 4-5 | 0.94 | 0.74 | 0.09 | 0.00 | 0.02 | 0.02 | 0.000 |
| | (1.22) | (1.05) | (0.03) | (0.00) | (0.02) | (0.02) | (0.002) |
| | **Engineering** | | | | | | |
| | HS Math Percentile (8) | HS Reading Percentile (9) | Not Econ. Disadv. (10) | Male (11) | First Major Business (12) | First Major Sciences (13) | Predicted Probability of Transfer (14) |
| Semester 2-3 | 8.37 | -8.45 | -0.55 | 0.00 | 0.14 | 0.20 | 0.035 |
| | (11.89) | (10.52) | (0.41) | (0.00) | (0.17) | (0.34) | (0.022) |
| Semester 3-4 | 0.28 | 3.75 | 0.27 | 0.00 | -0.28 | -0.07 | -0.014 |
| | (5.35) | (4.62) | (0.19) | (0.00) | (0.08) | (0.15) | (0.010) |

*Notes:* This table presents results from balance tests for the RD using GPA cutoffs for internal transfer. They are based on the first stage equation for majoring in business (panel a) or majoring in engineering (panel b), replacing the major indicators $M_{bi}$ or $M_{ei}$ with dependent variables for the tests listed in the first row of each panel. As in the main analyses, we restrict to students who did not matriculate as business majors when examining the effects of crossing the business cutoffs, and restrict to students who did not matriculate as engineering majors when examining the effects of crossing the engineering cutoffs. The variables are high school standardized math test score percentile, high school standardized reading test score percentile, binary indicator for whether the 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. In the last column, column (7), we also report balance tests where the dependent variables are the predicted probability of majoring in business / engineering using a linear probability model that includes all variables from columns (1)-(6). Results in the top panel are for business cutoffs, and use the survival-RD specification based on equation (11) and (12). Results in the bottom panel are for engineering cutoffs. They use the survival-RD specification replacing $1(\text{coh}_{ijt}^{0s} < \underline{\text{coh}}_{jt}^{s})$ with $1(C_{ijt} = 0)$ and $1(\text{coh}_{ijt}^{0s} \geq \underline{\text{coh}}_{jt}^{s})$ with $1(C_{ijt} = 0)$ in (11). 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 the Full Sample

| | Business | | | | |
|---|---|---|---|---|---|
| | HS Math $>$ 80th percentile (1) | HS Reading $>$ 80th percentile (2) | Female (3) | Economically Disadvantaged (4) | Non-Hispanic White (5) |
| Business | 1.07 | 1.05 | 0.91 | 0.97 | 0.99 |
| Engineering | 1.08 | 1.01 | 0.42 | 0.96 | 0.63 |

*Notes:* This table shows the relative likelihood of various characteristics in the complier groups compared to the overall population. The column headings list the binary characteristics we examine: dummy variables for whether an individual scored above the 80th percentile in their high school standardized math test and 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: Returns to Majoring in Business and Engineering

| | Business | | Engineering | |
|---|---|---|---|---|
| | OLS | IV | OLS | IV |
| Returns | 0.093 | 0.125 | 0.235 | 0.277 |
| | (0.004) | (0.026) | (0.009) | (0.077) |
| Observations | 590,528 | | 317,651 | |

*Notes:* This table reports the returns to declaring major in business and engineering by the beginning of the junior year. Columns (1) and (3) report OLS results, and columns (2) and (4) report IV results with the survival-RD model and the earnings equation (14). 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 using a 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: Heterogeneity in the Return to Business

**Panel A. Gender**

| | OLS | | | IV | | |
|---|---|---|---|---|---|---|
| | Female | Male | Difference | Female | Male | Difference |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Returns | 0.110 | 0.096 | 0.014 | 0.169 | 0.127 | 0.042 |
| | (0.005) | (0.006) | (0.008) | (0.024) | (0.024) | (0.034) |
| N | 214,337 | 142,874 | – | 214,337 | 142,874 | – |

**Panel B. Economic Disadvantage Status**

| | OLS | | | IV | | |
|---|---|---|---|---|---|---|
| | Disadvantaged | Not Disadvantaged | Difference | Disadvantaged | Not Disadvantaged | Difference |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Returns | 0.060 | 0.104 | -0.044 | 0.095 | 0.160 | -0.065 |
| | (0.009) | (0.005) | (0.010) | (0.044) | (0.020) | (0.048) |
| N | 78,672 | 215,967 | – | 78,672 | 215,967 | – |

**Panel C. Selective versus Non-Selective Institutions**

| | OLS | | | IV | | |
|---|---|---|---|---|---|---|
| | Selective Institutions | Non-Selective Institutions | Difference | Selective Institutions | Non-Selective Institutions | Difference |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Returns | 0.095 | 0.079 | 0.016 | 0.146 | 0.087 | 0.059 |
| | (0.005) | (0.007) | (0.009) | (0.021) | (0.026) | (0.033) |
| N | 200,527 | 156,684 | – | 200,527 | 156,684 | – |

**Panel D. Ethnicity**

| | OLS | | | | |
|---|---|---|---|---|---|
| | Non-Hispanic White | Hispanic/Black | Asian | White − Hispanic/Black | White − Asian |
| | (1) | (2) | (3) | (4) | (5) |
| Returns | 0.121 | 0.075 | 0.050 | 0.046 | 0.071 |
| | (0.006) | (0.006) | (0.011) | (0.008) | (0.013) |
| N | 147,480 | 159,506 | 34,485 | – | – |
| | IV | | | | |
| | Non-Hispanic White | Hispanic/Black | Asian | White − Hispanic/Black | White − Asian |
| | (6) | (7) | (8) | (9) | (10) |
| Returns | 0.196 | 0.139 | 0.054 | 0.057 | 0.142 |
| | (0.022) | (0.034) | (0.025) | (0.040) | (0.033) |
| N | 147,480 | 159,506 | 34,485 | – | – |

*Notes:* This table reports the return to declaring major in business by the beginning of the junior year for different subgroups. Table 6a compares females and males, table 6b compares economically disadvantaged students and those who are not, table 6c compares students in selective versus non-selective institutions, table 6d compares non-Hispanic white students, hispanic/black students, and Asian students. For each table, we report the OLS estimates and the IV estimates from the survival-RD model following equations (14). We also report the differences between the estimates of the subsamples. 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, $\tilde{\Phi}_i$, and control, $\bar{\Phi}_i$ are included in the bootstrap procedure.

Table 7: Heterogeneity in the Return to Engineering by Gender

| | Dependent Variable: Log Earnings | | | | | |
|---|---|---|---|---|---|---|
| | OLS | | | IV | | |
| | Female | Male | Diff | Female | Male | Diff |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Returns | 0.252 | 0.229 | 0.023 | 0.501 | 0.091 | 0.410 |
| | (0.016) | (0.011) | (0.019) | (0.129) | (0.102) | (0.164) |
| N | 214337 | 142874 | - | 214337 | 142874 | - |

*Notes:* This table reports the returns to declaring major in engineering by the beginning of the junior year 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 equation (14). 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, $\hat{\Phi}_i$, and control, $\bar{\Phi}_i$ are included in the bootstrap procedure.

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

| Bachelor's Degree in... | OLS | IV | | | | |
|---|---|---|---|---|---|---|
| | Full Sample (1) | Full Sample (2) | Female (3) | Male (4) | Econ Disadv (5) | Not Econ Disadv (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 |

*Notes:* 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 (15). 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, $\hat{\Phi}_i$, and control, $\bar{\Phi}_i$ are included in the bootstrap procedure.

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

| Graduate Degree in... | OLS | IV | | | | |
|---|---|---|---|---|---|---|
| | Full Sample (1) | Full Sample (2) | Female (3) | Male (4) | Econ Disadv (5) | Not Econ Disadv (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 |

*Notes:* 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 fields 8 years after the beginning of the junior year. Column (1) reports OLS results and columns (2) — (6) report IV estimates following equation (16). 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, $\hat{\Phi}_i$, and control, $\bar{\Phi}_i$ are included in the bootstrap procedure.

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

| Bachelor's Degree in... | OLS | IV | | |
|---|---|---|---|---|
| | Full Sample (1) | Full Sample (2) | Female (3) | Male (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 |

*Notes:* 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 (15). 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, $\hat{\Phi}_i$, and control, $\bar{\Phi}_i$ are included in the bootstrap procedure.

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

| Graduate Degree in... | OLS | IV | | |
|---|---|---|---|---|
| | Full Sample (1) | Full Sample (2) | Female (3) | Male (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 |

*Notes:* 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 (16). 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: Two Years Post Junior

| Bachelor's Degree in... | OLS | IV | | | | |
|---|---|---|---|---|---|---|
| | Full Sample (1) | Full Sample (2) | Female (3) | Male (4) | Econ Disadv (5) | Not Econ Disadv (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 |

*Notes:* 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 (15). 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: Two Years Post Junior

| Bachelor's Degree in... | OLS | IV | | |
|---|---|---|---|---|
| | Full Sample (1) | Full Sample (2) | Female (3) | Male (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 |

*Notes:* 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 (15). 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 Returns to Majoring in Business and Engineering

| | **Panel A. Business** | | | |
|---|---|---|---|---|
| | OLS | IV | | |
| | Full Sample | Survival | Survival–0.3 BW | Linear |
| | (1) | (2) | (3) | (4) |
| | 0.093 | 0.125 | 0.144 | 0.142 |
| | (0.004) | (0.026) | (0.026) | (0.091) |
| N | 590528 | 590528 | 98078 | 590528 |
| | **Panel B. Engineering** | | | |
| | OLS | IV | | |
| | Full Sample | Survival | Survival–0.3 BW | Linear |
| | (5) | (6) | (7) | (8) |
| | 0.235 | 0.277 | 0.235 | 0.328 |
| | (0.009) | (0.077) | (0.093) | (0.198) |
| N | 317651 | 317651 | 71869 | 317651 |

*Notes:* This table reports the returns to declaring major in business and engineering by the beginning of the junior year using multiple empirical specifications. Columns (1), (2), (5), and (6) reproduce the OLS and IV estimates in Table 5. Columns (3) and (7) report IV results with the survival-RD model following equation (14), 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 a 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, $\hat{\Phi}_i$, and control, $\bar{\Phi}_i$ are included in the bootstrap procedure.

Table 15: Estimated and Predicted Returns to Majoring in Business

| | Business Major | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 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) |
| Return (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) | |
| Return (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 return to declaring major in business. The first row reports estimates from the OLS and survival-RD models. The second row reports return estimates calculated using the procedure described in section 6.5. In particular, let $\hat{a}_{1c}$ be the estimated earnings premium for college degree c estimated with OLS. Following the notation from equation (15), let $\hat{b}_1^{c4}$ 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 $\sum_{i=1}^{6} \hat{a}_{1c}\hat{b}_1^{c4}$. 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 and Predicted Returns to Majoring in Engineering

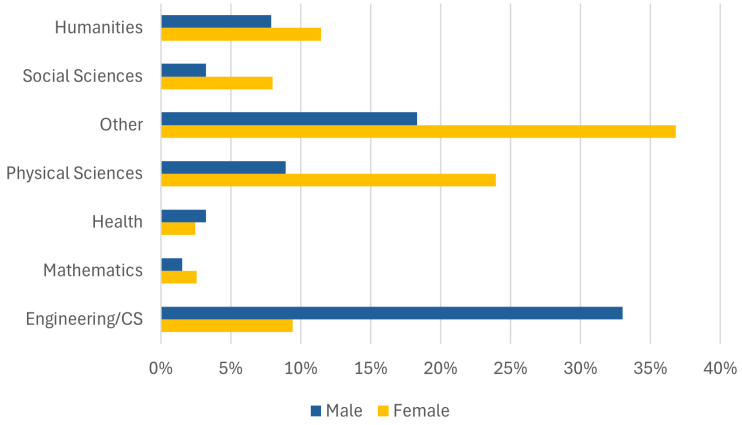
| | Engineering Major | | | |
|---|---|---|---|---|
| | OLS | IV | | |
| | Full Sample | Full Sample | Female | Male |
| | (1) | (2) | (3) | (4) |
| Returns (Estimated) | 0.235 | 0.277 | 0.501 | 0.091 |
| | (0.009) | (0.077) | (0.129) | (0.102) |
| Returns (Computed) | 0.290 | 0.385 | 0.397 | 0.381 |
| N | 317651 | 317651 | 192094 | 125557 |

*Notes:* This table reports the returns to declaring major in engineering. The first row reports estimates from the OLS and survival-RD models. The second row reports returns calculated using the procedure described in section 6.5. In particular, let $\hat{a}_{1c}$ be the estimated earnings premium for college degree c estimated with OLS. Following the notation from equation (15), let $\hat{b}_1^{c4}$ 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 $\sum_{i=1}^{6} \hat{a}_{1c}\hat{b}_1^{c4}$. 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.

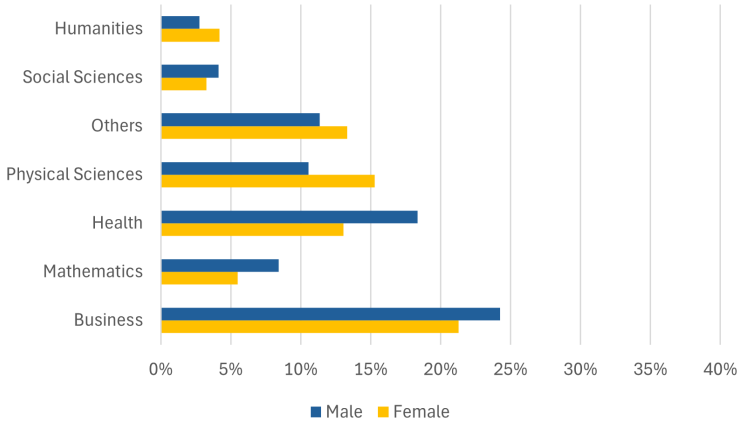
Table 17: Present Discounted Values of Majoring in Business and Engineering

| | Counterfactual | Actual College | Actual |
|---|---|---|---|
| **Panel A. Business** | | | |
| Overall | 1,047,782 | 1,150,765 | 1,180,882 |
| | | (9.8%) | (12.7%) |
| Female | 902,893 | 1,006,599 | 1,045,803 |
| | | (11.5%) | (15.8%) |
| Male | 1,234,442 | 1,308,606 | 1,345,768 |
| | | (6.0%) | (9.0%) |
| **Panel B. Engineering** | | | |
| Overall | 1,173,318 | 1,528,307 | 1,548,806 |
| | | (30.3%) | (32.0%) |
| Female | 1,038,402 | 1,281,877 | 1,317,040 |
| | | (23.4%) | (26.8%) |
| Male | 1,313,660 | 1,712,210 | 1,733,056 |
| | | (30.3%) | (31.9%) |

*Notes:* This table reports the PDVs calculated for various scenarios and subsamples using a discount rate of 0.05 As discussed in section 6.6.1, 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).



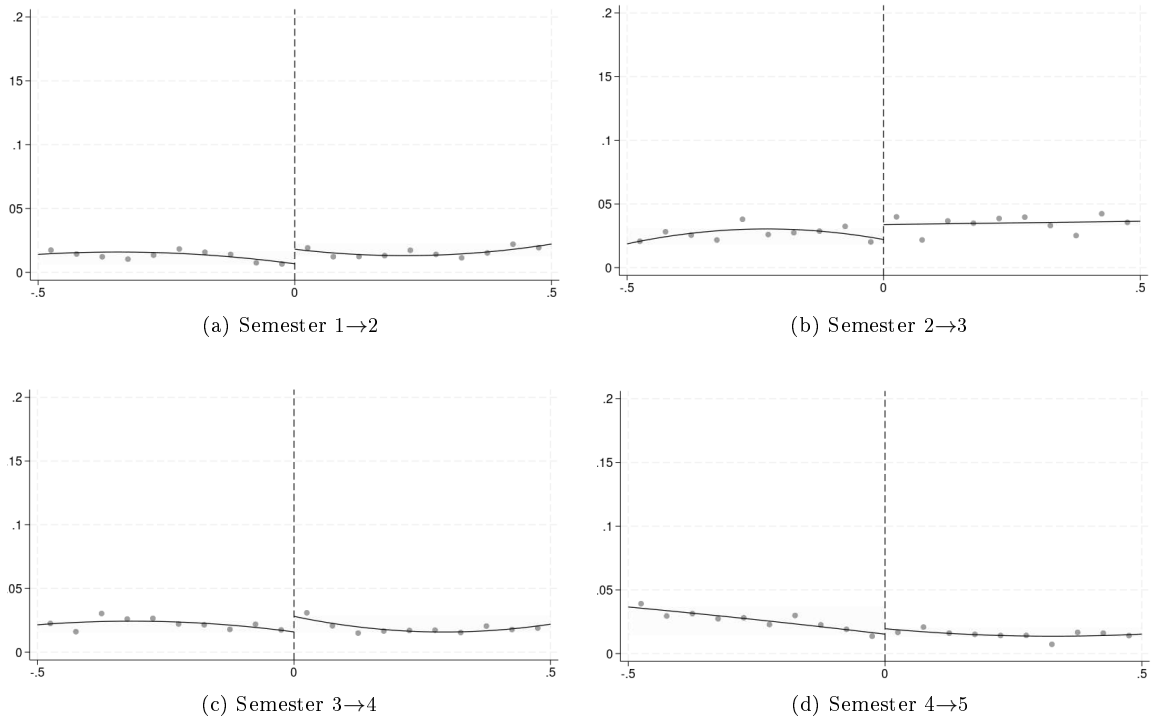

(a) Business




(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

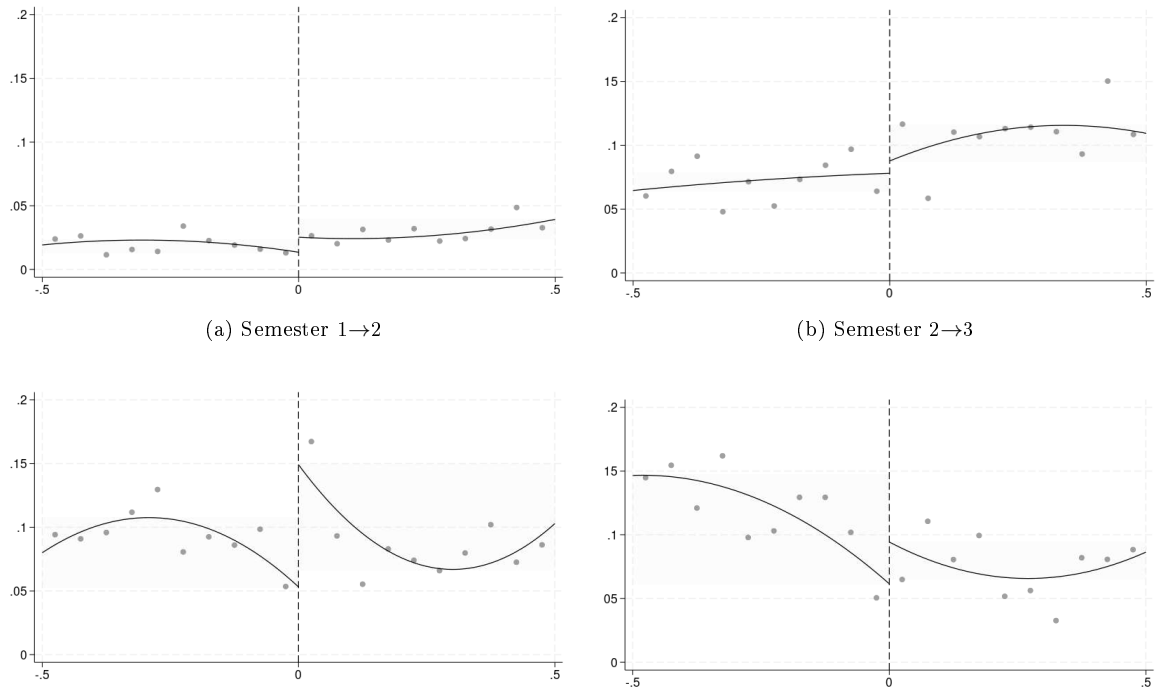
(b) Semester 2→3

(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. The curves on the two sides of the cutoffs are separate quadratic fits of the probability of transfer estimated using observations below and above the cutoffs.




(a) Semester 1→2

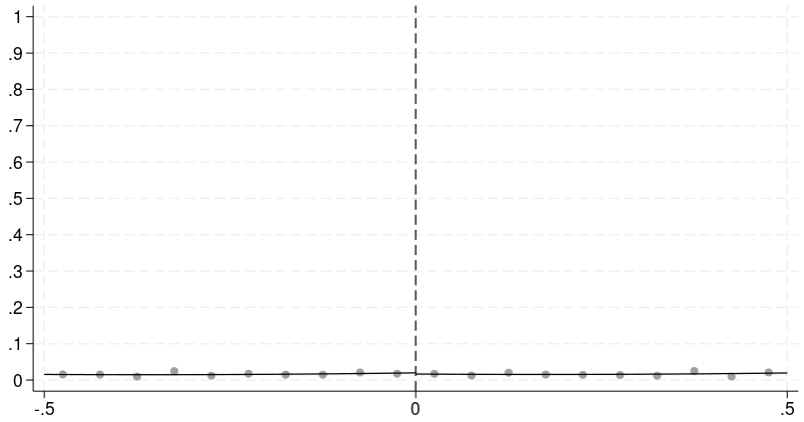
(b) Semester 2→3

(c) Semester 3→4

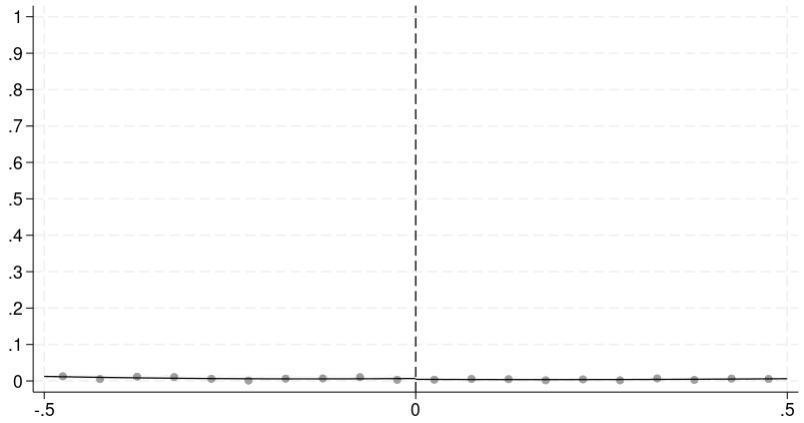
(d) Semester 4→5

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. The curves on the two sides of the cutoffs are separate quadratic fits of the probability of transfer estimated using observations below and above the cutoffs.



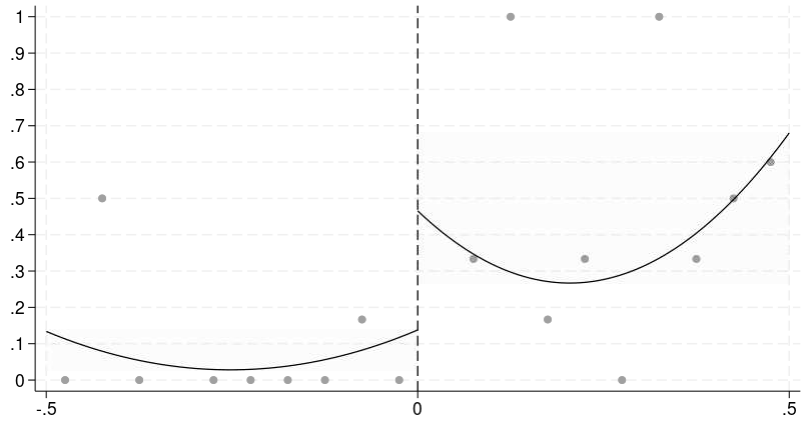

(a) Semester 2→3



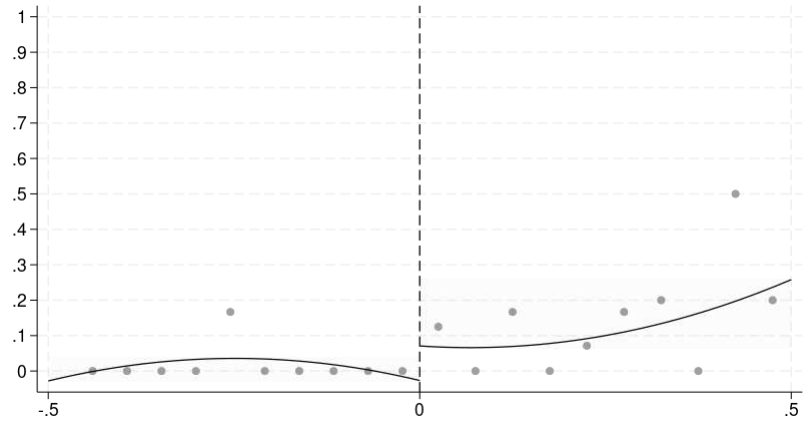

(b) Semester 3→4

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. The curves on the two sides of the cutoffs are separate quadratic fits of the probability of transfer estimated using observations below and above the cutoffs.




(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 completed all required pre-transfer courseworks for engineering by the start of the corresponding transition period. The horizontal axis represents the difference between students' GPA and the cutoff GPA for internal transfer into engineering majors. The curves on the two sides of the cutoffs are separate quadratic fits of the probability of transfer estimated using observations below and above the cutoffs.

# Appendix A: Additional Tables and Figures

Table 1: Summary Statistics of Analysis Samples

| | HS Math | HS Reading | Not Econ. Disadv. | Male | BA On Time | BA in 6 Years | Adv Degree |
|---|---|---|---|---|---|---|---|
| **Business Sample** | | | | | | | |
| Mean | 80.00 | 83.54 | 0.45 | 0.41 | 0.40 | 0.91 | 0.10 |
| | (18.12) | (13.99) | (0.50) | (0.49) | (0.49) | (0.29) | (0.31) |
| **Engineer Sample** | | | | | | | |
| Mean | 82.84 | 82.68 | 0.45 | 0.55 | 0.37 | 0.99 | 0.19 |
| | (16.47) | (14.48) | (0.50) | (0.50) | (0.48) | (0.12) | (0.39) |

*Notes:* This table shows the mean and standard deviation of high school test scores, demographic status, and degree attainment for the analysis samples. Business sample consists of students who reach junior status, did not matriculate as business majors, and enrolled in one of the institutions for which we have business GPA cutoffs. Engineering sample consists of students who reach junior status, did not matriculate as engineering majors, and enrolled in one of the institutions for which we have engineering GPA cutoffs. HS Math / Reading Percentiles are students percentile ranking among their cohorts in Texas state administered standardized Math / Reading exams in high school. BA on time is a dummy variable for whether a student attained BA degree within 2 years after reaching junior status. BA 6 yrs is a dummy variable for whether a student attained BA degree within 4 years after reaching junior status. Adv Degree is a dummy variable for whether a student attained advanced degrees within 8 years after reaching junior status.

Table 2: Summary Statistics of Business Coherence

| Category | Semester 1 | Semester 2 | Semester 3 | Semester 4 |
|---|---|---|---|---|
| Started as a Business Major | 0.183 | 0.355 | 0.506 | 0.626 |
| | (0.083) | (0.130) | (0.155) | (0.169) |
| Transferred into Business | 0.135 | 0.272 | 0.426 | 0.567 |
| | (0.070) | (0.120) | (0.155) | (0.170) |
| Not a Business Major | 0.101 | 0.180 | 0.234 | 0.271 |
| | (0.062) | (0.102) | (0.129) | (0.148) |
| Total | 0.113 | 0.206 | 0.278 | 0.330 |
| | (0.071) | (0.123) | (0.165) | (0.200) |

*Notes:* This table shows the mean and standard deviation (in parentheses) of business coherence levels in semesters 1-4. The table shows the statistics separately for those who started college as a business major, those who did not start as a business major but transferred into business major in or before semester 5, and those who are not a business major by semester 5.

# Appendix B: Option Value of Industry

Table 1: Effects of Majoring on Industry Outcomes

| | Business | | Engineering | |
|---|---|---|---|---|
| Industry | OLS | RD | OLS | RD |
| Tech | -0.007 | 0.014 | 0.078 | -0.008 |
| | (0.005) | (0.014) | (0.015) | (0.051) |
| Finance | 0.202 | 0.340 | -0.064 | -0.178 |
| | (0.008) | (0.022) | (0.015) | (0.065) |
| Engineering | -0.036 | 0.004 | 0.250 | 0.511 |
| | (0.006) | (0.016) | (0.019) | (0.073) |
| Legal | -0.006 | -0.016 | -0.013 | -0.003 |
| | (0.003) | (0.009) | (0.005) | (0.023) |
| Education | -0.166 | -0.205 | -0.139 | -0.110 |
| | (0.006) | (0.023) | (0.011) | (0.049) |
| Healthcare | -0.083 | -0.022 | -0.102 | -0.181 |
| | (0.004) | (0.018) | (0.008) | (0.042) |
| Trade, logistics, or operations | 0.076 | 0.084 | 0.001 | 0.031 |
| | (0.007) | (0.019) | (0.015) | (0.060) |
| Consumer or local services | 0.013 | -0.020 | -0.019 | -0.051 |
| | (0.006) | (0.019) | (0.010) | (0.040) |

*Notes:* This table reports the effects of majoring in business and engineering (by the beginning of the junior year) on the probability of being employed in different industry categories. We take the industry in which a student is observed the most quarters. Column (1) and (3) report OLS results and columns (2) and (4) report IV estimates following equation (15). 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, $\hat{\Phi}_i$, and control, $\bar{\Phi}_i$ are included in the bootstrap procedure.

Table 2: Present Discounted Value Decomposition of Industry Option Value

| Major | Counterfactual | Major - No Industry Shift | Major | Total PDV Gain | Industry Option Value | Share of Gain |
|---|---|---|---|---|---|---|
| Business | 1,068,528 | 1,203,039 | 1,207,704 | 139,176 (13.0%) | 4,665 | 3.5% |
| Engineering | 1,255,654 | 1,476,833 | 1,506,802 | 251,148 (20.0%) | 29,969 | 11.9% |

*Notes:* This table reports the PDVs calculated for various scenarios and subsamples using a discount rate of 0.05 As discussed in section 6.7, the Counterfactual scenario (column 1) is computed assuming that the probability of various educational $\times$ industry 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 $\times$ industry 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 industry categories follow those in the Counterfactual case. The percentage gain compared to the Counterfactual scenario is reported in parentheses in columns (2) and (3).