Grading Policies and College Major Choice with Ability Learning

Hyunkyeong Lim*

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Abstract

Universities worldwide have experienced substantial grade inflation. At some U.S. institutions, nearly half of all grades are now A's, with inflation particularly pronounced in non-STEM fields. This paper studies how uneven grade inflation affects students' course-taking, major choice, and sorting by comparative advantage. I develop a dynamic model of college course and major choices that features two key mechanisms: students' concern for maintaining a high GPA and their learning about unobserved, major-specific ability from course grades. The model is matched to the grade distribution and educational outcomes of the administrative data from a large public university in Texas. To separately identify GPA concerns from ability learning, I exploit the temporary expansion of pass/fail grading during the COVID-19 pandemic. Counterfactual analyses show that equalizing grading standards to non-STEM levels increases STEM graduation by 2–10% and reduces dropout by 10–22%. It also narrows the gender gap in STEM graduation by about 8%. However, grade inflation weakens sorting: about 15% of students with low relative STEM ability remain in STEM.

*University of Wisconsin-Madison. hyunkyeong.lim@wisc.edu. The conclusions of this research do not necessarily reflect the opinions or official position of the Texas Education Agency, the Texas Higher Education Coordinating Board, the Texas Workforce Commission or the State of Texas.

1 Introduction

University grading standards have experienced a steady rise in recent decades. Average grade point average (GPA) of undergraduate students has risen from 2.8 to 3.15 (12% increase) between 1990 and 2020 (U.S. Department of Education, National Center for Education Statistics 2024a,b). Importantly, such grade inflation has been much more pronounced in less quantitative fields. For instance, the share of A's approached 50% in 2019 compared to 42% in 2012 in Texas public universities (Nieswiadomy and Kim (2024)), and the share of A's increased by 12% in Humanities and 11% in Sociology, whereas it only increased by 4–5% in Math, Chemistry, and Engineering.

How does uneven grade inflation across departments affect students' educational decisions in college? In particular, how does it affect how students sort into majors based on their comparative advantage, and consequently their outcomes? On the one hand, the inflated course grades result in less informative signals, diverting students' subsequent course and major choices away from maximizing the payoff from college experience. On the other hand, students' concern for maintaining a high GPA can deter students from experimenting and gathering information about their fit, especially from fields with more stringent grading policy. Lenient grading raises GPAs across all fields and compresses GPA differences between them, reducing the penalty for enrolling in a potentially mismatched field. In other words, the uneven grading policy across fields generates a trade-off for students in deciding which course to take: the risk of drawing a bad grade versus the value of information they can obtain from the course grades about their unknown major-specific ability.

To quantify how grading policies interact with students' learning about their academic fit to different majors and how they eventually sort into different fields, this paper develops a rich individual decision-making model of college course and major choices. The model incorporates the key trade-offs: students' taste for maintaining a high GPA versus the process of learning about major-specific ability, alongside the traditional factors that affect college major choice emphasized in the literature: such as interest in the field, returns to human capital, and time to graduation. I allow for gender differences in key preference parameters, such as the taste for GPA, to explore observed gender gap in college major choice and how grade inflation interacts with it.

The model captures the main trade-off between the informativeness of GPAs as signals versus the preference over better GPA as follows. First, students are heterogeneous in their major-specific ability to learn in college and are informed about their major-specific ability only up to their subject SAT scores and demographic characteristics, with some uncertainty left. The model largely consists of two stages. In the first stage, students take courses not only to accumulate human capital and complete the degree, but also to gain information about their major-specific ability. In the second stage, students commit to a major. The chosen major renders graduation payoff to students. Depending on the history of courses students have taken in the first part, students may have to stay in college more to complete the degree, where these extra time in college is costly to students. The model allows students to "switch" majors by changing their course-taking decisions in the first stage. If one decides to "switch" major, this will cause longer time to stay in college at the end, which acts as a switching cost.

Second, the cumulative GPA determines graduation payoffs along with one's interest in the chosen major, major-specific ability, and how much one specialized course taking in that field. The importance of cumulative GPA in the graduation payoff reflects how much students care about maintaining their GPA high. Major-specific ability is unobserved, so students form beliefs about their own major-specific ability, and thus the graduation payoff. There is also a match effect between one's ability and major: the graduation payoff increases if you specialize more in a field where you perform well.

The main identification challenge when mapping the model to the data also comes from this main trade-off. Let's consider a student who is observed to take much more non-STEM courses than STEM courses. It could be that she has strong preference over maintaining high GPA. At the same time, the same pattern can be all explained by the adjustment of her belief after receiving high grades in non-STEM. To isolate the effect of students' taste for maintaining a high GPA on major choice from the role of beliefs, I use a policy variation that expanded the pass/fail grading option during the COVID-19 pandemic at large public universities in Texas. In Spring 2020, almost all schools across the nation attempted to reduce the burden of schoolwork by introducing very lenient pass/fail grading options with little restriction on the set of courses which the option can be applied to. Often, colleges extended the deadline to opt in to pass/fail grading to the end of the semester and even allowed students to make the decision after observing their course grade. This reduced the risk of disclosing bad grades. After Spring 2020, however, some schools decided to continue the expanded pass/fail option, while others reverted to their original policies, where the option could only be applied to electives for a limited number of courses.

Using this variation in policy adoption after Spring 2020, I provide causal evidence that students have a positive taste for maintaining a high GPA. The probability of taking a STEM course, which typically yields harsher grades, increased on average by about 1.2–1.7 percentage points (or 1.5–2.0 percent). The response was larger among female students (1.3–2.0 percentage points or 2.4–3.7 percent) and non-STEM students (2.2–3.0 percentage points or 4.1–5.6 percent). I simulate the expanded pass/fail policy in the model to match students' course choices observed in the data, and then use indirect inference to estimate the key parameter in the model that reflects students' willingness to maintain a high GPA.

This paper does not take a specific stance on why students value maintaining their GPA high. However, there have been ample prior research on what might be driving students' concern for GPA in college. First, GPA matters for labor market signaling, especially at the entry level (Piopiunik, Schwerdt, Simon, and Woessmann (2020), Hansen, Hvidman, and Sievertsen (2024)) and resume screening process (Petersheim, Lahey, Cherian, Pina, Alexander, and Hammond (2022)). Second, GPA can broaden opportunities such as internship that lead to successful labor market entry (Nunley, Pugh, Romero, and Seals Jr (2016), Jaeger, Nunley, Seals Jr, Shandra, and Wilbrandt (2023)). Independent of direct returns on the labor market, students can still value GPA for behavioral and psychic reasons, which still matters for how they make choices.

The model estimates align well with economic intuition and findings from prior studies. First, gender differences are most pronounced in the taste for GPA, consistent with the reduced evidence that female students reacted more sensitively to the expansion of pass/fail grading option. The stronger taste for GPA by female students is also in line with the theory that female students anticipate discrimination on the labor market and works harder to signal their ability (Lepage, Li, and Zafar (2025), Exley, Fisman, Kessler, Lepage, Li, Low, Shan, Toma, and Zafar (2024)). Second, the payoff of having a high STEM ability is strongly positive in graduating with a STEM degree, whereas the payoff of non-STEM ability is less positive in graduating with a non-STEM degree, echoing the findings of Arcidiacono (2004) that math ability is more decisive for major choice and labor-market outcomes than verbal ability. Lastly, time-to-graduation parameters reflect rigid, sequential course structures in STEM and more flexible requirements in non-STEM, producing sensible differences in degree completion dynamics. Overall, the model fits the data well, replicating the skewness of GPA distributions, the under-representation of women in STEM, and realistic dropout and graduation patterns.

Given the estimated model, I conduct the following counterfactual simulations. The first set simulates counterfactual grading policies: equalizing STEM grading policy to the level of non-STEM and equalizing both majors' grading policies to the level where an average STEM student would receive a B in a STEM course. Then I evaluate how different grading policies affect educational outcomes such as GPA, major choice, time to graduation, and dropout. Using the same set of counterfactual simulations, I also examine ability sorting, measuring how closely students' major choices align with their comparative advantage in STEM versus non-STEM under alternative grading policies. Lastly, I examine how grading policies affect the resolution of uncertainty by comparing the model results with uncertainty in ability to the full-information benchmark.

The results show that equalizing grading standards to non-STEM levels substantially increases STEM participation and graduation by 1.5-4 percentage points (2-10 percent) while reducing dropout by 0.59-0.64 percentage points (10-22 percent). By contrast, equalizing to a deflated grading scheme, where an average student will on average receive B in STEM courses, decreases STEM graduation by 1.7-2.0 percentage points (2-3 percent) due to significant increase in dropout by 3.1-4.6 percentage points (51-155 percent). However, grade inflation weakens alignment between major choice and comparative advantage, especially among low-ability STEM students. Compared to an equalization of grading policies to a deflated grading standards, where the sorting in to major based on comparative advantage is the strongest, up to 15 percent of low-comparative-advantage students remain in STEM under grade inflation. Finally, equalizing grading policies to the current non-STEM level do increase female STEM graduation rates (4 percentage points or 10 percent), but the reduction in the gender gap is modest (about 4 percentage points): even under the most favorable scenario, the gap remains above 27 percentage points.

These results align with the two mechanisms (the GPA-preference channel and the ability learning channel) that govern how uncertainty in ability interact with different grading policies. When grades are inflated and similar across fields, students who know their strengths and those who do not behave similarly, because GPA differences provide little discipline. On the other hand, stricter grading makes grades more informative, so uncertainty about ability has larger effects on major choice. Interestingly, these dynamics result in more similar choices of students between the full-information benchmark and the model with uncertainty in ability when grading policies are more lenient.

The findings of this paper implies that grade inflation is not unambiguously harmful or beneficial: it raises attainment and reduces attrition, but reduces sorting into majors based on comparative advantage. However, the taste of GPA strongly governs students' choices, reducing the difference between behavior under uncertainty and under full information when there is grade inflation. Finally, while it improves female representation in STEM, the gender gap remains substantial even under the most generous grading regimes, suggesting that grading policy alone cannot fully resolve long-standing disparities.

Related Literature This paper contributes to the following four strands of literature. First, I add to the college major choice literature, by incorporating two additional mechanisms that significantly interact with grade inflation and grading policies: taste for a high GPA and ability learning. Prior work on college major choice has highlighted several factors influencing major choice: students' interest in the field, returns to human capital, time to graduation, and comparative advantage—whether they are relatively better in one subject versus another

(Arcidiacono (2004), Zafar (2013), Wiswall and Zafar (2015), Hsu (2018), Thomas (2024)). This paper is the closest to Hsu (2018), which models dynamic course taking where students learn about their match to college majors, considering the graduation requirement. His paper focuses on quantifying the importance of major course requirements and ability sorting in major choice, and finds that the path dependency from course requirements largely drive major choice. This paper models graduation requirements in a more reduced form way, and focuses on understanding how grading policies affect student choices.

Second, this paper relates to the literature of decision under uncertainty and learning, which is pioneered by Erdem and Keane (1996) and has been widely applied in various fields of economics (Crawford and Shum (2005), Conlon, Pilossoph, Wiswall, and Zafar (2018), Guvenen, Kuruscu, Tanaka, and Wiczer (2020)). The key contribution in this paper lies in modeling how course grades send signals about students' academic ability. The structure of grading policies can be crucial for determining how much students learn about themselves from grades. It has been well documented in the economics literature that there is substantial uncertainty in educational decisions in college, based on structural models (Stinebrickner and Stinebrickner (2014), Bordon and Fu (2015), Aucejo, Maurel, and Ransom (2024)). These papers emphasize the value of exploration and self-learning in college. Similar to their approaches, in this paper, students are Bayesian learners about their own major-specific ability. However, often in the literature, grading policies are modeled as signals with normally distributed noise. This can create problems when the model is matched to the data, as higher average grades mechanically reduce the variance of noise in grades. In other words, such models would predict that everyone receiving an A obtains a more accurate signal about their ability. In this paper, I adopt Binomial and Beta distributions to capture the signal-to-noise ratio of course grades, while keeping the learning model computationally feasible.

Third, this paper explicitly allows for gender differences in key preference parameters, and explore how grading policies affect the gender gap in college major choice. The literature has examined the sources of the persistent gender gap in college major choice. Prior work explains the gender gap with gendered job-attribute preferences (Wiswall and Zafar (2018)), different expectations about career and family outcomes by gender (Wiswall and Zafar (2021)), or greater sensitivity to grades among women (Ugalde (2022), Ahn, Arcidiacono, Hopson, and Thomas (2024)). This paper is the closest to Ahn, Arcidiacono, Hopson, and Thomas (2024), which argues that harsher STEM grading policies deter women disproportionately from taking STEM courses and finds that equalizing average grades across classes shrink the STEM gender gap. In their model, the sensitivity to grades is identified by sorting into courses by comparative advantage, *within* department across courses with different grading policies. They model how professors set grading policies and study the equilibrium effect where professors adjust workload in a course, in response to the equalization of grading policies. This paper focuses on students' decision but with an additional channel of ability learning. Moreover, I identify the sensitivity to grades using the grading policy variation that lowered the risk of disclosing bad grades, adding to the evidence of gender difference in sensitivity to grades. Finally, this paper models both course *and* major choice, with students' concern for time to graduation, while Ahn, Arcidiacono, Hopson, and Thomas (2024) focus on course choices, fixing students' major in their counterfactual analyses.

Finally, this paper adds to the literature of understanding how grading policies affect students' educational outcomes. I provide a unified framework to study the implications of grade inflation on various educational outcomes, such as course and major choices, time to graduation, and degree completion. Denning, Eide, Mumford, Patterson, and Warnick (2022) find that much of the increase in graduation rates after 1990s can be explained by grade inflation rather than improved student preparation or institutional inputs, in line with the result of this paper that grade inflation increases degree completion. Other papers documented that course enrollment react to grading policies: enrollment rises in courses where grading is more lenient (Bar, Kadiyali, and Zussman (2009), Butcher, McEwan, and Weerapana (2014)). Using regression discontinuity designs, Main and Ost (2014) find no evidence of letter grades on subsequent course taking in economics major, while Tan (2023) find a significant effect of letter grades on labor market outcomes and course taking behavior.

Organization The rest of the paper is organized as follows. Section 2 introduces the Texas Education Research Center (ERC) data and presents data patterns motivating ability learning and the role of GPA in academic exploration. Section 3 describes the structural model of dynamic course and major choices with ability learning. Section 4 outlines the estimation strategy. Section 5 presents the estimates of the model primitives. In Section 6, I discuss the implications of grade inflation and alternative grading policies for students' educational outcomes, gender differences in major choice, and ability sorting. It also analyzes how the GPA-preference and learning channels interact with grading policies and the resolution of uncertainty in ability. Section 7 concludes.

2 Data

2.1 Texas Education Research Data

In this project, I use the administrative education data of Texas housed by the University of Texas-Dallas Education Research Center (UTD ERC). The UTD ERC data provides rich information about demographic characteristics, college enrollments, course enrollments, course grades, and major choice at the individual-semester level for students who are enrolled at one of the public post-secondary institutions in Texas. This information is linked to graduation and degrees conferred through a unique individual identifier. For those who enrolled in a 4-year public university of Texas, the UTD ERC data also contain college application data, from which I can obtain SAT or ACT scores whenever they are reported.

A crucial information I can observe in the UTD ERC data for this project is the course enrollment and grade data. The course enrollment data lists all the courses an individual took in a given semester. It provides the course number, section number, and the Classification of Instructional Programs (CIP) code of the course. For now I group them into STEM and non-STEM fields using the CIP code of the courses, where the wage differential upon graduation and acquired skills are the most different[1]. The data also provide the letter grade each student received in each course and a complete list of courses that students took. However, I do not observe the exam scores in each course which the letter grade is based off of. I assume that students also only observe the letter grades[2].

In this project, I primarily focus on the first-time undergraduate (FTUG) students entered the University of Texas-Austin (UT Austin) during the 2014/2015 - 2019/2020 academic years. All of these students have demographic information, course taking and major choice information. I pull the subject SAT scores from the university application data for a subset of these students. Less than 10% of students have a missing information on SAT scores. Table 2.1 provides the summary statistics of the sample by gender. Males take more STEM courses (19.81) and are more likely to declare a STEM major (67.16% vs. 39.97% for females), conditional on not dropping out in the first three years. Around ten percent of students switch majors between STEM and non-STEM. On average, students take about 1.68-1.75 semesters to graduate after enrolling for 6 semesters. Both male and female students earn higher GPAs in non-STEM courses (3.46, 3.59) than in STEM courses (3.14, 3.17). Despite having lower average SAT scores than males, female students tend to earn higher GPAs in both fields, consistent with broader findings on gender differences in academic performance.

[1] In the future, plan to extend this by considering four different groups: Natural Science, Engineering & Computer Science, Humanities, Business & Economics. The purpose of grouping majors is for the tractability of the model which is discussed in Section 3.

[2] Students typically see numeric exam/assignment scores (0–100) on the course website that instructors enter per assignment. Relative performance is available but optional and to a limited degree: the course websites provide students with information such as the mean/median, upper and lower quartile score for each assignment if the instructor doesn't hide it. The final reporting is in letter grades.

Table 2.1. Summary Statistics

	Male		Female	
	Mean	SD	Mean	SD
SAT Math	695.52	73.28	650.88	72.54
SAT Reading	660.87	75.86	645.92	75.63
SAT Math missing (%)	9.44		8.80	
SAT Reading missing (%)	9.06		6.93	
High parental edu. (%)	84.68	36.02	81.42	38.90
Parental edu.missing (%)	1.43		1.40	
Dropout (%) in 3 yrs	6.53	24.71	4.15	19.94
STEM (%) | ∼dropout in 3 yrs	67.16	46.96	39.97	48.99
non-STEM (%) | ∼dropout in 3 yrs	27.41	44.61	56.45	49.58
Switched major (%)	12.62	33.21	11.60	32.02
Extra time to graduate after 3 yrs	1.75	0.54	1.68	0.60
Total N of courses				
in STEM	19.81	10.00	13.77	9.95
in non-STEM	13.11	9.06	19.17	9.97
GPA				
in STEM	3.14	0.64	3.17	0.65
in non-STEM	3.46	0.51	3.59	0.42
N Obs.	18,212		21,948	

2.2 Descriptive Investigation of Ability Learning

A frequent major switching rate between STEM and non-STEM suggests that students are learning about their field-specific abilities while in college. This is consistent with a large body of literature which finds that students face substantial amount of uncertainty about their learning abilities (Arcidiacono (2004),Stinebrickner and Stinebrickner (2012), Bordon and Fu (2015), Aucejo, Maurel, and Ransom (2024), Fu, Grau, and Rivera (2022)). This section adds to the literature by investigating how residualized course grades correlate to students' major choice. Specifically, I closely follow the exercise of Fu, Grau, and Rivera (2022). First, for each field (STEM and non-STEM), I regress field-specific GPA on individual fixed effects (α_i) and academic seniority dummies ($\eta_{s(it)}$), fully interacted with whether you took any course in a field in a given semester (DQ_{imt}), and course portfolio fixed effects ($\rho_{q(imt)}$).

$$GPA_{imt} = \alpha_i + \eta_{s(it)} + \beta_0 \, DQ_{imt} + \sum_{k=2,\cdots,6} \beta_k \left(1(a(it) = k) \cdot DQ_{imt}\right) + \rho_{q(imt)} + \varepsilon_{imt} \qquad \text{for } m = 1, 2 \tag{1}$$

$s(it) = k$ if time t is the $k-th$ semester of individual i and DQ_{imt} takes 1 if i took any course in major m (STEM or non-STEM) in a calendar semester t. I set the GPA to be zero in a semester t where i has taken zero course from field f, but controls for DQ_{imt}. The sample is subset to those who did not drop out until the 6th semester.

Furthermore, I also include course portfolio fixed effects ($\rho_{q(imt)}$) in the spirit of Dale and Krueger (2002), since the unobserved motivation and effort allocation effect can bias the correlation between grades and major choice upward. Specifically, I construct course portfolios based on the number of courses students have taken in each field in semester t. The idea is that these course portfolios capture the unobserved level of interest students have in each field. In addition, effort allocation should be similar among students taking a similar set of courses.

After controlling for individual-specific and seniority-specific factors, the residual ε_{i1t} and ε_{i2t} likely capture the deviation of one's GPAs in each field from their expected level. Then, I regress a dummy of whether one declared STEM major in the 7th semester on the averages of the shocks for each field and individual level control variables.

$$STEM_i = \theta_1 \sum_t \left(\frac{\hat{\varepsilon}_{i1t}}{6} \right) + \theta_2 \sum_t \left(\frac{\hat{\varepsilon}_{i2t}}{6} \right) + X_i' \Gamma + \nu_{it} \text{ for } m = 1, 2 \tag{2}$$

$STEM_i$ takes 1 if i reported STEM as one's declared major in semester 7 and X_i is a set of individual characteristics, including SAT math and reading scores, gender, and parental education level. Table 2.2 shows the coefficients $\{\hat{\theta}_k\}_{k=1,2}$. The estimated coefficients on the averages of lagged GPA residuals are highly positive and significant. Compared to the effect of other control variables, such as SAT subject scores or gender, the effect is sizable. A 1 standard deviation increase in the average residualized STEM GPA (standard deviation: 0.84) leads to 27.34 percentage point increase in STEM major choice, whereas a 1 standard deviation increase in the average residualized non-STEM GPA (standard deviation: 0.69) decreases STEM major choice by 12.96 percentage point. This is consistent with the story that students learn about their field-specific ability through grades by taking courses in college. However, readers should be cautious in interpreting these results, as these patterns could be driven by other explanations such as motivation and effort allocation. For instance, if one's interest in field m changes overtime and affects both one's GPA and major choice decision, ε_{imt}'s can be correlated with ν_{it}.

2.3 The Role of GPA Concerns in Course Selection

2.3.1 Pass/Fail Grading Option at UT-Austin

In this section, I provide evidence that course selection in college is affected by how much students value maintaining a high GPA. Ideally, one would like an environment where only

Table 2.2. Final Major and Average Lagged GPA Residuals

θ_1	0.326***
	(0.002)
θ_2	-0.189***
	(0.003)
SAT Math	0.054***
	(0.002)
SAT Reading	0.016***
	(0.002)
Female	-0.064***
	(0.004)
High Parental Edu.	-0.015***
	(0.005)
Constant	0.300***
	(0.012)
Mean	0.579
SD	0.494
R^2	0.627
N	32517

Notes: SAT subject scores are standardized by subject. * indicates p-value < 0.1, ** p-value < 0.05, and *** p-value < 0.001.

the face value of course grades or GPA is changed and the amount of information students obtained about their ability from the course grades is unchanged. Thus, even if there is an exogenous change in grading policies, this may not isolate the channel of students acting risk-averse in course taking to maintain their GPA high: change in grading policies also changes the information content of the course grades. In this paper, I exploit the policy change which allowed students to conceal bad course grades during the COVID-19 pandemic. During the COVID-19 pandemic, students from UT-Austin were able to opt in to conceal the grades *after* observing their course grades. This helps separately identifying how students' taste for high GPA affected their course choices from their incentive to take courses to acquire information about their unobserved ability.

At UT-Austin, students have the option to convert up to two elective courses per semester to be graded on a pass/fail basis, provided they had completed 30 hours of college credits. Students always had this option throughout the sample period. The pass/fail decision had to be made before students received their final grades, typically within the first 12 class days[3]. If a student opted for pass/fail and earned a grade of D- or higher, the course appear on the transcript as "credit earned" without affecting the GPA. However, a failing grade (F) would

[3] After the first 12 class days, students were required to consult their academic advisor to change the grading status to pass/fail. The deadline, usually before the 12th week of the semester, is specified in the academic calendar.

Table 2.3. UT-Austin Pass/Fail Grading Policy

	Eligibility	Commitment	Course limit
Pre-pandemic	After 30 credits	Before grades	Two electives
Spring 2020	Everyone	After grades	Unlimited
Fall 2020 - Spring 2021	Everyone	After grades	Total three

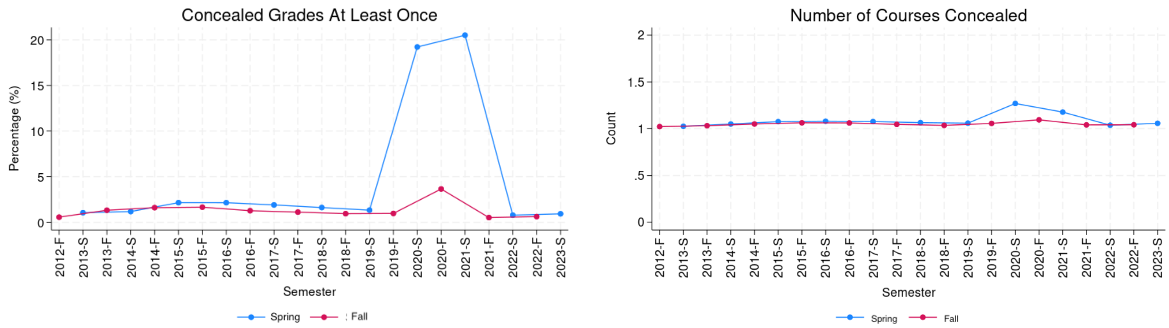
be recorded on the transcript and factor into the GPA. However, given the restriction on the type of courses students could apply this policy, only around 1% of students used the pass/fail option on eligible courses in a semester.

During the COVID-19 pandemic, UT-Austin introduced additional opportunities to reduce academic pressure by allowing students to withhold their grades in addition to the original pass/fail option. In Spring 2020, the deadline to change a class to or from pass/fail was extended from April 6 to May 29, and there was no limit on the number of courses eligible for pass/fail grading. Even core and required courses could be taken pass/fail. Crucially, students were allowed to decide to convert a grade to "credit earned" after viewing their final grades, in addition to the original pass/fail option. However, for the 2020-2021 academic year, the policy remained unclear until November 2020, leaving students uncertain about the continuation of the COVID-19 pandemic pass/fail options. But there was ongoing effort by the UT Student Government to support the expansion of pass/fail in Fall 2020 and Spring 2021. Eventually, the university permitted students to apply the pass/fail grading to up to three courses in total, including core and required ones, without penalty for the 2020/2021 academic year. This additional pass/fail flexibility ended after the Spring 2021 semester and was no longer available starting in the summer of 2021.

Figure 2.1 shows how often the pass/fail grading option was used by students both before and after the COVID-19 pandemic policy change. On average, around 1.4% of students concealed a letter grade at least once to "credit earned" from Fall 2012 through Fall 2019. In Spring 2020, with the additional COVID-19 pandemic amendment, it increases to 19.2%, followed by 3.7% and 20.5% in the next two semesters with the modified COVID policy[4]. It falls down to 0.5% in Fall 2021. Conditional on concealing any letter grade to "credit earned", the intensive margin of number of courses with a concealed letter grade stays at around 1 with a slight increase to 1.2 during the COVID-19 pandemic period.

[4]The sudden drop in Fall 2020 seems to be driven by the detail of the policy where students could conceal 3 courses *in total* in the 2020/2021 academic year. Students were potentially waiting to see what happens in Spring 2021, unless it was a really bad grade that had to be concealed.

Figure 2.1. Concealing Choice



2.3.2 Empirical Strategy

I exploit overtime variation in the change of Pass/Fail policy at UT-Austin similar to Jiang, Chen, Hansen, and Lowe (2021). Specifically, Equation 3 compares UT-Austin students who have spent the same number of semesters in college (i.e. academic seniority is the same), took similar amount of courses, and received similar course grades, but different in terms of being exposed to the COVID-19 Pass/Fail policy. i denotes student and t denotes calendar semester. Y_{it} is either (1) whether i has completed any STEM course in semester t or (2) the share of completed STEM courses of student i in semester t[5]. The goal is to test whether the expansion of a generous Pass/Fail grading option allowed students to take more risk in course taking, leading them to take more STEM courses where grading tend to be harsher.

$$Y_{it} = \alpha + \beta_0 Expect_{it} + \beta_1 PF_{it} + \gamma_i + \delta_{sm(it)} + S'_{it}\Lambda + \varepsilon_{iat} \qquad (3)$$

First, $Expect_{it}$ takes 1 for the Fall 2020 semester when students had the expectation for the extension of the policy. In many schools, including UT-Austin, student representatives were working to persuade the faculty that the Pass/Fail expansion should be extended to Fall 2020. But in most cases, the extension decision was not announced until around November of 2020. Hence, β_0 might be positive if students acted based on the expectation that the Pass/Fail expansion policy will be continued in Fall 2020. Second, PF_{it} takes 1 for the Spring 2021 semester. This was after the announcement around November 2020 of whether the generous Pass/Fail option will continue to exist for the 2020-2021 academic year. Thus, students were exactly aware of whether they can use the expanded Pass/Fail option at the end of the semester when they were making course choices.

[5] I exclude retakes when constructing Y_{it} and subset the sample to those who stayed in college for at least 8 semesters.

To isolate the effect of the policy changes, I include student level fixed effects (γ_i) to control for individual level traits such as timing of college entry, academic preparedness, family background, and risk aversion. Thus, β_0 and β_1 are identified using the within-individual variation of course choice. In other words, student composition change overtime at UT-Austin will not drive β_0 or β_1. δ_{sm} are the academic seniority fixed effects by major. δ_{sm} takes 1 if one has spent s number of semesters in college at time t in major m. S_{it} is a vector of time-varying covariates, such as semester fixed effects (i.e. Fall or Spring), cumulative credit hours earned in each field until $t-1$, and cumulative GPA earned in each field until $t-1$. δ_{sm} and S_{it} capture how much a student is knowledgeable about institutional policies and any effects from required curriculum (e.g. need to complete certain number of credits in certain fields before becoming a junior). They help isolate the policy effect from having more or less students at certain stage of their college experience during Fall 2020 - Spring 2021. After 2021, no school continued to have the expanded Pass/Fail option and they went back to the pre-pandemic Pass/Fail options.

2.3.3 Result

Table 2.4 shows that the expectation of a Pass/Fail extension (*Expect*) increased the probability of taking at least one STEM course by 1.7 percentage points (2.1% relative to the mean of 0.797) for the full sample, while the actual Pass/Fail policy (*PF*) raised this probability by 1.2 percentage points (1.5% from the mean). Comparing females and males highlights a stronger response among female students: for example, *Expect* boosted female students' probability of taking a STEM course by 2.0 percentage points (3.7% from a mean of 0.545), relative to 1.3 percentage points (1.5% from a mean of 0.867) for males. Similarly, non-STEM majors exhibit larger increases than STEM majors, with *Expect* yielding a 3.0 percentage-point increase (5.6% from a mean of 0.539) among non-STEM students, compared to 0.7 percentage points (0.7% from a mean of 0.976) among STEM majors.

Turning to the actual Pass/Fail policy (*PF*), the results in Table 2.4 also show an appreciable impact on course-taking behavior. Overall, *PF* increased the probability of taking at least one STEM course by 1.2 percentage points—equivalent to about 1.5% relative to the baseline mean of 0.797. Compared to males, who saw a 1.0 percentage-point increase (1.2% of their baseline), female students experienced a 1.3 percentage-point increase (approximately 2.4% of their baseline). This pattern is consistent with the idea that GPA protection encourages more risk-taking in course selection for students who are less certain about their ability in STEM fields.

Looking at students by their major, non-STEM majors exhibit the largest relative gain under *PF*: a 2.2 percentage-point increase (roughly 4.1% of the mean of 0.539) in enrolling

Table 2.4. Effect of Grade Concealing on Course Taking - Extensive Margin

	(1)	(2)	(3)	(4)	(5)
Sample	All	Female	Male	non-STEM	STEM
Expect	0.017***	0.020***	0.013***	0.030***	0.007***
	(0.003)	(0.005)	(0.004)	(0.007)	(0.002)
PF	0.012***	0.013***	0.010***	0.022***	0.004*
	(0.003)	(0.005)	(0.004)	(0.007)	(0.002)
Mean	0.797	0.545	0.867	0.539	0.976
SD	0.402	0.441	0.340	0.498	0.154
R^2	0.557	0.545	0.547	0.539	0.283
N of obs.	194,492	103,401	91,091	79,582	114,910

Notes: Standard errors are clustered at the individual level. * indicates p-value < 0.1, ** p-value < 0.05, and *** p-value < 0.001.

in at least one STEM course. By contrast, STEM majors show a more modest increase of 0.4 percentage points (0.4% of their 0.976 baseline). Overall, these results reinforce the conclusion that providing a formal mechanism to conceal poor grades in the short run reduces the perceived GPA risk of STEM enrollment and particularly encourages non-STEM and female students to explore unfamiliar fields.

Table 2.5 presents analogous results for the share of STEM courses taken. Here, *Expect* increased the share of STEM courses by 0.7 percentage points (1.3% from a mean of 0.523) overall and 0.6 percentage points (1.4% from a mean of 0.437) for females, compared to 0.8 percentage points (1.3% from a mean of 0.620) for males. Again, students initially enrolled in non-STEM fields respond more strongly, with *Expect* increasing their share of STEM courses by 0.5 percentage points (2.4% from a mean of 0.213). Across both margins, the larger effect for female and non-STEM students is consistent with the idea that these students are more reluctant to take harshly graded STEM courses unless the risk to their GPA is mitigated. In other words, when grades can be concealed, these groups appear more willing to "explore" academically by enrolling in more STEM courses, supporting the interpretation that GPA concerns drive course-taking decisions.

A similar pattern emerges in Table 2.5, which reports how students' share of STEM courses changes under *PF*. Across the full sample, the policy leads to a gain of 0.6 percentage points, translating to roughly 1.2% relative to the mean share of 0.523. Female students see an increase of 0.4 percentage points (about 0.9% relative to their baseline mean of 0.437), whereas males experience an increase of 0.7 percentage points (1.1% relative to 0.620).

As before, the strongest response appears among initially non-STEM majors: *PF* raises their share of STEM courses by 0.6 percentage points (a 2.8% increase from a mean of 0.213).

Table 2.5. Effect of Grade Concealing on Course Taking - Intensive Margin

	(1)	(2)	(3)	(4)	(5)
Sample	All	Female	Male	non-STEM	STEM
Expect	0.007***	0.006**	0.008**	0.005	0.007***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
PF	0.006***	0.004	0.007**	0.006**	0.003
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Mean	0.523	0.437	0.620	0.213	0.737
SD	0.357	0.349	0.341	0.245	0.250
R^2	0.711	0.713	0.669	0.538	0.426
N of obs.	193,597	102,906	90,691	79,086	114,511

Notes: Standard errors are clustered at the individual level. * indicates p-value < 0.1, ** p-value < 0.05, and *** p-value < 0.001.

By contrast, among those already majoring in STEM, the share of STEM coursework rises by only 0.3 percentage points (about 0.4% from the 0.737 mean). These findings confirm that access to a pass/fail grading option in later semesters influences students' willingness to enroll in more challenging STEM courses, further highlighting the role of GPA concerns in shaping course-taking decisions.

To confirm whether the effect of the expanded pass/fail grading option on course choices carried over to major choice in the long term, I also examine students' major choice using an event-study framework in Appendix B. For the 2019 cohort, who were affected by the policy change during their sophomore year, the STEM graduation rate increased by 1.58%. The effect is limited, since the policy could only influence students' choices for one year (by concealing at most three courses). Nevertheless, this evidence suggests that students face an exploration–exploitation trade-off due to GPA concerns, and that this trade-off has the potential to shape their ultimate major choice.

2.3.4 Placebo Test

Out of 30 public universities in Texas, some schools extended the expansion of Pass/Fail option after Spring 2020 and others didn't. However, individual institutions are inherently heterogeneous in terms of their curriculum, student quality and characteristics, and educational policies. For instance, University of Houston adopted a grade forgiveness policy starting the 2018/2019 cohort, and Texas A&M had a significant change in their automatic entry to a major process for Engineering students around 2017-2018. This makes it difficult to use difference-in-differences type of analysis to validate the effect of COVID Pass/Fail policy on students' course choices. Instead, I run Equation 3 with different schools separately as

Figure 2.2. Placebo Test - Extensive Margin

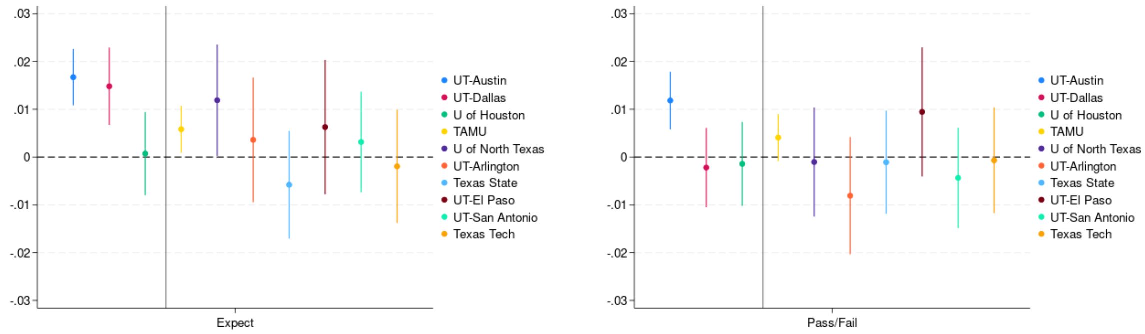
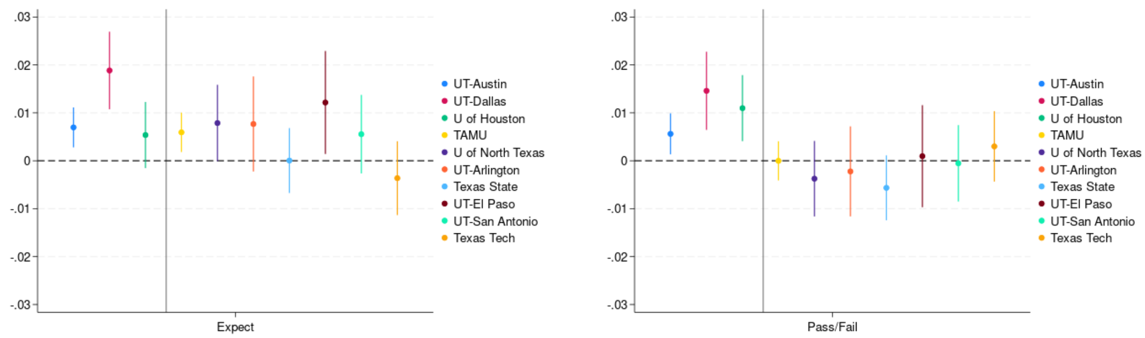


Figure 2.3. Placebo Test - Intensive Margin



a placebo test. This will sidestep the pitfalls of comparing fundamentally different schools, which can undermine the validity of the diff-in-diff approach. But this helps verify that the observed treatment effect isn't an artifact of common time trends or unaccounted-for school-level shocks. By showing that the same model applied to non-treated schools yield null results, it reinforces the causal interpretation of the policy effect.

I have collected data on how the Pass/Fail policy was implemented during Spring 2020–Spring 2021 for the top 10 public universities in Texas by enrollment size. Among them, UT-Austin, UT-Dallas, and the University of Houston extended the expanded Pass/Fail options through Spring 2021, with the official announcement occurring around November 2020. In contrast, the remaining institutions only implemented the Pass/Fail expansion in Spring 2020 and did not continue the policy thereafter.

In Figure 2.2–Figure 2.3, I plot β_0 (left panel) and β_1 (right panel) of Equation 3 for each university. The leftmost three schools in the figures—UT-Austin, UT-Dallas, and the University of Houston—are those that extended the Pass/Fail expansion through Spring 2021. Reassuringly, these institutions show an increase in STEM course-taking in Spring 2021, supporting the idea that extending the Pass/Fail policy encouraged continued engagement in STEM courses. Conversely, schools that did not extend the Pass/Fail expansion experienced either no effect or a slight decline in STEM enrollment relative to other semesters.[6]

The figures illustrate the impact of the COVID-19 Pass/Fail expansion on STEM course-taking at both the extensive margin (probability of enrolling in any STEM course) and the intensive margin (share of STEM courses, including zero values). The results suggest that students at institutions that extended the Pass/Fail option were more likely to increase their STEM enrollment across both dimensions. Additionally, the coefficient on "Expect" are positive at some universities that did not ultimately extend the Pass/Fail option, reflecting students' initial expectations before policy decisions were finalized.

Among institutions that extended the policy, UT-Austin and UT-Dallas exhibit stronger effects compared to the University of Houston, possibly due to U of Houston's grade forgiveness policy, introduced for the 2018/2019 cohort, which may have influenced students' risk assessments regarding grades. Furthermore, unlike in Spring 2020, UT-Austin and UT-Dallas restricted the Pass/Fail option to a maximum of three courses during Fall 2020–Spring 2021, a policy students were fully aware of at the time. This likely explains the somewhat muted effect of the expanded Pass/Fail options in Spring 2021, as students had more certainty about their grading options and thus may have adjusted their course selection strategies accordingly.

3 Model

3.1 Primitives

Students are characterized by gender (X_i), parental education level (Z_i), major-specific multidimensional abilities ($\vec{a}_i$), prior beliefs on abilities ($\vec{\mu}_i, \vec{\sigma}_i$) and academic interests where i denotes individuals. Let $\vec{q}$ denote a course bundle, and m denote a major (1=STEM, 2=non-STEM). An outside option of dropping out is available to all students in all periods except the first period.

To allow for rich heterogeneity in gender that can potentially explain the gender gap observed in college major choice, all parameters governing pre-college learning ability and preferences—such as the flow cost of enrollment and course taking, the graduation payoff, and the cost of staying longer in college—are gender specific. In contrast, institutional features such as grading policies and the mapping from course taking to time-to-degree are assumed to be homogeneous across gender. The idea is that evaluation of students' performance or course requirements for graduation should be the same across gender.

[6] Appendix A provides the regression tables corresponding to Figure 2.2-Figure 2.3.

3.1.1 Student Characteristics

A student comes from a family with parental education level of $Z_i \in \{Low, High\}$, and has a two-dimensional major-specific ability $\vec{a}_i = (a_{i1}, a_{i2})$. a_{im} reflects one's pre-college human capital level and it determines how much one can learn in each major in college. a_{im} is drawn independently from a Beta distribution that is demographic specific (gender X_i and parental education level Z_i). The heterogeneous ability distribution reflects systematic differences in pre-college experience and interest across demographic groups. True ability ($\vec{a}_i$) is unobserved to the students.

Since one's own major-specific ability is unobserved to the students, they form beliefs. I characterize the belief on ability m (a_{im}) using a Beta distribution, which is characterized by two shape parameters $(\alpha_{imt}, \beta_{imt})$[7]. The parameters $(\alpha_{imt}, \beta_{imt})$ evolve over time as students receive information through course grades. The signal structure of course grades and how exactly $(\alpha_{imt}, \beta_{imt})$ evolve are described in the sub-sections below. Beliefs on ability are independent across major[8].

The initial beliefs on ability, characterized by Beta$(\alpha_{im1}, \beta_{im1})$, are a function of demographic characteristics and subject SAT scores (math and reading). Before they start college, individuals observe subject SAT scores and update their prior where the prior comes from the population ability distribution of one's demographic group[9]. Subject SAT scores reflect one's major-specific ability to learn in college.

$$SAT_{im} \sim \mathcal{N}(\mu_{im}^{SAT}, (\sigma_m^{SAT})^2) \ \mid \ 200 < SAT_{im} < 800 \tag{4}$$

$$\mu_{im}^{SAT} = 200 + \frac{600}{1 + \exp(-(\alpha_m^{SAT} + \beta_m^{SAT} \cdot a_{im}))} \quad (m = 1, 2) \tag{5}$$

More specifically, a subject SAT score is drawn from a Truncated Normal distribution where the mean is a function of students' major-specific ability as in Equation 4. The mean of math SAT score (SAT_{i1}) is a function of STEM ability and the mean of reading SAT score (SAT_{i2}) is a function of non-STEM ability. Equation 5 describes the relationship between the mean of subject SAT scores and major-specific abilities. β_m^{SAT} governs how strongly one's pre-college ability is reflected on her subject SAT score. σ_m^{SAT} governs the noise of subject

[7]For a random variable that follows Beta distribution with parameters (α, β), its mean is $\alpha/(\alpha+\beta)$ and the variance decreases in $\alpha + \beta$. Thus, relatively higher α implies a higher mean of the ability distribution, whereas a large $\alpha + \beta$ indicates a tight ability distribution.

[8]Aucejo, Maurel, and Ransom (2024) allows correlated ability and learning. Since the ability distribution and beliefs are modeled as Beta distribution, allowing correlation across majors (or fields) is not straightforward. Future extension of this model may allow correlated ability and learning using a copula function.

[9]Appendix C describes in detail the updating rule of the population ability distribution upon observing subject SAT scores.

SAT scores. Thus, subject SAT scores provide a more accurate signal one's ability when β_m^{SAT} is high and σ_m^{SAT} is low.

3.1.2 Course Grades in College

Denote c a single course. A grade g_{imc} that individual i will receive in field m in course c follows a Binomial distribution with $N = 4$ and the success probability equal to $a_{im}^{c_m}$. Each course grade is drawn independently from the same individual-field specific distribution. I interpret receiving an A from a course equal to drawing $g_{imc} = 4$ and receiving an F from a course equal to drawing $g_{imc} = 0$. The mapping between the letter grade and g_{imc} is provided in Table 3.1. A plausible interpretation is to think of each course consisting 4 challenges and students who successfully complete all 4 challenges receive the highest grade.

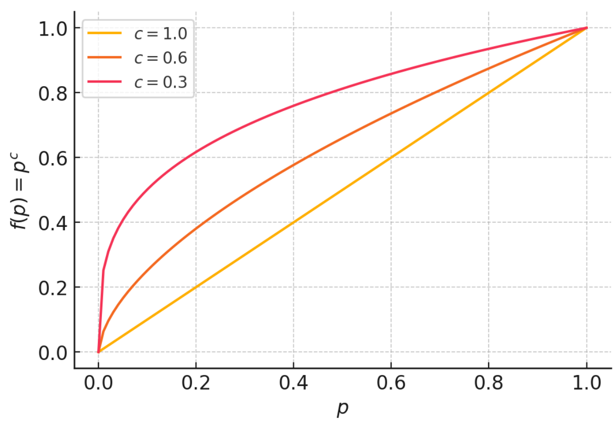


Figure 3.1. How c_m Distorts the Relationship Between p_{im} and g_{imc}

$$a_{im} \sim \text{Beta}(\alpha_m(X_i, Z_i), \beta_m(X_i, Z_i)) \tag{6}$$

$$\alpha_m(X_i, Z_i) = \overline{\alpha}_m + \pi_{1m}^A X_i + \pi_{2m}^A Z_i, \quad \beta_m(X_i, Z_i) = \overline{\beta}_m + \pi_{1m}^B X_i + \pi_{2m}^B Z_i \tag{7}$$

$$g_{imc} \sim \text{Binomial}(N = 4, a_{im}^{c_m}) \tag{8}$$

To reflect field specific grading practices, Equation 8 introduces a distortion of how one's field specific ability, a_{im} affect the realization of course grades through a parameter, $c_m \in (0, 1]$. Observe that when c_m is small, $a_{im}^{c_m}$ is larger than a_{im}, which leads to a higher probability of drawing a high grade in Equation 8, holding one's ability a_{im} constant. Thus, c_m represents the grading policy of field m. It is a simple but convenient way of capturing how lenient a grading policy is in each field. The caveat of this model is that it forces higher distortion in the middle range of a_{im} as shown in Figure 3.1. Also, it breaks the conjugacy between Beta prior and Binomial likelihood. I discuss further below how the updating of belief is modeled.

Table 3.1. Mapping of Letter Grade - g_{imc} - Grade Points

Letter Grade	g_{imc}	Grade Points
A	4	4.0
B	3	3.0
C	2	2.0
D	1	1.0
F	0	0.0

Remark There are 12 different grades one can receive in a letter graded course at UT-Austin: from A through F with +/- grading. To reduce the computational burden, I ignore the +/- grading and only allow A, B, C, D, and F to be realized in the model, which leads to setting $N = 4$. This simplification results in a reduced amount of information that each grade can give to students about their abilities, if in reality students learn something about their abilities from the +/- grades.

Notice that $N = 4$ is a fixed constant, which in theory can also be a parameter to be estimated. However, identifying both c_m and N will have to heavily rely on functional form assumption, as they both affect the within and across individual variation in observed grades. More practically, when $N > 4$, the mapping between the letter grades in the data and the model course grades is not straightforward and requires additional integration when calculating beliefs to solve the model. This means that the interpretation of ability distribution and grading policy parameters only hold up to the normalization of N. Across field comparison should always go through qualitatively regardless of N, but the cardinal levels of these parameters are hard to interpret.

3.1.3 Learning

Students update beliefs on ability in a Bayesian manner every time they receive a course grade. As mentioned earlier, the belief on ability m (a_{im}) is characterized by a Beta distribution with two shape parameters $(\alpha_{imt}, \beta_{imt})$. Denote the posterior density of individual i in period $t+1$ in major m as f_{im}^{t+1}. Upon observing a course grade $g_{imc} = g$, individuals will update their α_{imt} and β_{imt} that best match the mean and variance implied by the actual posterior described in Equation 9[10].

$$f_{im}^{t+1}(a) \quad \propto \quad \underbrace{a^{\alpha_{imt}-1} \times (1-a)^{\beta_{imt}-1}}_{\substack{\text{Contribution from} \\ \text{the prior}}} \times \underbrace{\{(a^{c_m})^{g_{imc}} \times (1-a^{c_m})^{N-g_{imc}})\}}_{\substack{\text{Contribution from} \\ \text{the grade } g_{imc} \text{ likelihood}}} \tag{9}$$

More specifically, the mean and variance of the Beta distributed posterior belief should match the mean and variance described in Equation 10-Equation 12.

$$\mathbb{E}_{t+1}(a_{im}) = \int a \cdot f_{im}^{t+1}(a)da, \quad \mathbb{V}_{t+1}(a) = \int (a - \mathbb{E}(a))^2 \cdot f_{im}^{t+1}(a)da \tag{10}$$

$$\alpha_{im,t+1} = \mathbb{E}_{t+1}(a_{im}) \cdot \left(\frac{\mathbb{E}_{t+1}(a_{im}) \cdot (1 - \mathbb{E}_{t+1}(a_{im}))}{\mathbb{V}_{t+1}(a_{im})} - 1 \right) \tag{11}$$

$$\beta_{im,t+1} = (1 - \mathbb{E}_{t+1}(a_{im})) \cdot \left(\frac{\mathbb{E}_{t+1}(a_{im}) \cdot (1 - \mathbb{E}_{t+1}(a_{im}))}{\mathbb{V}_{t+1}(a_{im})} - 1 \right) \tag{12}$$

The logic of typical Bayesian learning goes through in this model. First, high initial values of α_{imt} and β_{imt} indicate a strong or highly precise prior, suggesting that additional information from grades has limited impact on one's beliefs. Second, c_m, the grading policy parameter, determines the speed of learning about ability. When c_m is high, the likelihood of grades become more variable across individuals and within-individual variance in grades decreases, which means grades are more informative of one's ability in field m. Therefore, the posterior variance of a_{im} is smaller when c_m is high. Finally, c_m also affects the across-individual average grade. When c_m is close to one, there is little amplification of success probability conditional on ability. This means a high grade received when c_m is close to one is a more positive signal than when c_m is close to zero. Thus, the posterior mean of a_{im} is higher when c_m is high. Figure 3.2 visualizes the relationship with an example of how the mean and variance of posterior belief differs when a student with prior Beta(2,2) receives a letter grade B, under different grading policies. The x-axis is the parameter that governs grading policy (c_m in Equation 8). The blue line plots how the posterior mean varies as the grading policy changes and the red line plots how the posterior variance varies as the grading policy changes.

Discussion Two important aspects are considered when modeling grades and ability. First, grades should have a finite support (i.e. $-\infty$ or ∞ cannot be realized as grades). Often times grades or GPA are modeled to follow a Gaussian distribution with an infinite support. However, having an infinite support for grades can distort the amount of information conveyed through grades about one's ability, since course grades are typically discrete and top-coded.

[10] A Beta distribution is a conjugate prior of a Binomial likelihood. However, the introduction of grading policies through c_m breaks the conjugacy.

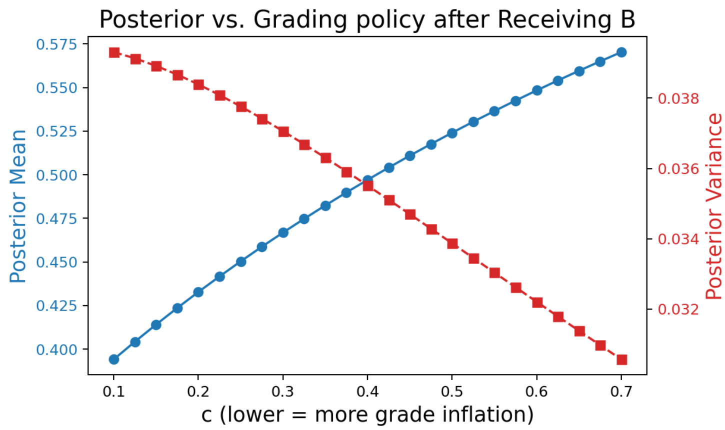


Figure 3.2. Relationship Between Posterior Belief and Grading Policy

Specifically, departments that on average give higher grades will look like they have smaller noise-to-signal ratio, meaning their grades are very *informative*. However, everyone receiving an A, in fact, means that the grade is very *uninformative*. To correctly capture the information structure of discrete and top-coded course grades, grade distributions should have a finite support.

Second, a continuous variable to measure one's ability introduces rich heterogeneity to the model, but calculating the posterior belief upon receiving signals can easily make solving the model computationally intractable. A potential solution to this problem is to use a conjugate prior that can give a closed-form expression for the posterior given a likelihood function, or a signal distribution. However, there is a limited scope of distributions that have a conjugate relationship, especially with bounded supports[11]. When the conjugacy breaks, one can still take numerical approaches to either correctly calculate or approximate the posterior belief. For instance, one can find parameters that characterize the posterior belief to match observed moments in the data.

The Binomial and Beta distributions ensure finite support and well capture the information structure of top-coded grade signals. Moreover, the numerical approximation of posterior beliefs allows computationally feasible characterization of belief evolution.

3.1.4 Course Bundle and Flow Utility

Students take courses to graduate and receive the graduation payoff which is a function of courses taken. Students choose from a set of course bundles where a bundle of course ($\vec{q}$) is

[11]Assuming normal prior on ability and normal grade signal is useful in this sense, as normal prior and likelihood have a conjugate relationship. However, the conjugacy does not hold if we introduce bounded supports by using distributional assumptions such as ordered probit on the grade signal.

the number of courses taken in each field, q_1 (STEM) and q_2 (non-STEM). In each period 1-6, students receive flow utility from taking a bundle of courses. The flow utility reflects the net cost of college enrollment and course taking. Equation 13 describes the net flow utility[12]. γ_0 is the enrollment cost, and γ_1 and γ_2 are the net marginal cost of taking a course in field 1 (STEM) and 2 (non-STEM), respectively.

$$U_t(\vec{q}, X_i) = \gamma_0(X_i) \cdot 1\{q_1 + q_2 \neq 0\} + \gamma_1(X_i) \cdot q_1 + \gamma_2(X_i) \cdot q_2 \tag{13}$$

The set of course bundles has a restriction: $3 \leq q_1 + q_2 \leq 6$. Conditional on this restriction, it consists of all possible combinations of (q_1, q_2), which comes down to 22 discrete bundles in total. The purpose of the restriction is to keep the model computationally tractable. Also, only 8% of students take courses with the total number of courses taken outside of the above range in a semester. Notice that this creates convexity in the cost of course taking in the sense that a course bundle outside of the above range incurs infinite cost that no one would choose to do so.

3.1.5 Graduation Payoff

In the last period, students decide whether and in which major to receive a degree. The terminal payoff from dropping out and not receiving a degree ($m = 0$) is normalized to be zero. The payoff from graduating with a degree in major m is a function of one's cumulative GPA, major-specific abilities ($\vec{a}_i = (a_{i1}, a_{i2})$), and the share of total number of courses taken in that field in period 1-6 (S_{im}).

$$\begin{aligned} U_m(X_i, G_{iT}, a_i, S_{im}) = &\beta_{0m}(X_i) + \beta_1(X_i)\, G_{iT} \\ &+ \beta_{2m}(X_i)\, a_{im} + \beta_{3m}(X_i)\, S_{im} + \beta_{4m}(X_i)\, (a_{im} \cdot S_{im}) \end{aligned} \tag{14}$$

$$U_0 = 0 \tag{15}$$

β_{0m} measures how much students like to graduate with major m, independent of their GPA, ability, and course taking. and β_1 reflects how much students value a high cumulative GPA. When β_1 is high, students are less likely to get out of their comfort zone to explore different fields, because they care about the final GPA, and she has only finite amount of time to recover when a bad grade is drawn. β_{2m} measures how much your ability in major m increases the graduation payoff. If β_{2m}'s are positive, students will sort into fields where they have comparative advantage. β_{3m} reflects the returns from specializing of course taking in

[12] In the future, I plan to extend this by allowing the utility of a bundle to depend on the interaction of number of courses taken in different fields, to allow for potential complementarity or substitutability across fields.

the field one is graduating with. Finally, β_{4m} captures whether there is match effect between one's major-specific ability and the specialization of course taking in one's majoring field. If β_{5m} is large and positive, one would want to figure out where her comparative advantage lies as soon as possible, so she can specialize in that field as much as she can within limited amount of time.

Discussion The graduation payoff reflects both the labor market return and psychic return. The earnings data linked to the UTD ERC data have limited information on occupation, which makes it hard to isolate the labor market returns to human capital accumulation consisted of major-specific ability (a_{im}) and course taking (S_{im}) from individuals' preferences and consumption value correlated with these measures. Moreover, it is hard to find an exogenous variation in the cumulative GPA to pin down its return on the labor market. The COVID-19 pandemic pass/fail policy could be a potential option, although students selected into concealing grades. However, it only happened around 2021, which doesn't allow researchers to observe the labor market outcomes of the students who are affected by the policy yet. For these reasons, I take an approach of identifying the graduation payoff based on students' revealed preference, rather than directly tying it to observed variables such as labor market outcomes.

3.1.6 Cost of Extra Time in College

The extra time to graduation, after spending 6 semesters in college, is probabilistically based on the major chosen and the number of courses taken across fields up to period 6. Denote T_{im} the extra number of semesters one has to stay in college to graduate with a degree in major m. Let Q_{i1T} and Q_{i2T} be the total number of courses one has taken in STEM (1) and non-STEM (2) up to period T=7. The extra number of semesters to graduate follows a Poisson distribution described in Equation 16. The mean of extra semesters for graduation (λ_{im}) is a function of total number of courses taken so far in the graduating major (Q_{imT}), in other major fields (Q_{i-mT}), and the interaction between the two.

$$\begin{aligned} T_{im}(Q_{i1T}, Q_{i2T}) &\sim \text{Poisson}(\lambda_{im}) \text{ for } m = 1, 2, \;\; T_{i0} = 0 \\ \log(\lambda_{im}) &= \tau_{0m} + \tau_{1m} \cdot Q_{imT} + \tau_{2m} \cdot Q_{i-mT} + \tau_{3m} \cdot (Q_{imT} Q_{i-mT}) \end{aligned} \tag{16}$$

For each extra semester, students incur marginal cost of $C(X_i)$ every semester. This captures the extra tuition, foregone earnings, and psychic cost of staying in college. Taking too many courses in a field one does not intend to major will cause more extra semesters to graduate. However, given the general education requirements at play, one can reduce the extra time in college by taking courses in other major fields. Equation 16 is a reduced form way of capturing these graduation requirements.

3.1.7 Timeline

The model consists of 7 periods. Each of the first 6 periods corresponds to a semester in the data. During the first 6 periods, individuals decide how many courses to take from each field $m \in \{1, 2\}$: $\vec{q} = (q_1, q_2)$ where q_1 is the number of courses in STEM and q_2 is the number of courses in non-STEM. Or individuals can also choose to drop out except for the first semester. By taking courses, individuals learn about their ability through grades and accumulate GPA, which determines graduation payoff in the last period. In the final period (period 7), if an individual has not dropped out yet, she will choose which major to graduate with or to drop out[13].

$$\text{State space: } \Omega_{it} = \{ \overbrace{X_i}^{\text{Gender}}, \overbrace{\vec{\mu}_{it}}^{\substack{\text{Mean of} \\ \text{Belief on Ability}}}, \overbrace{\vec{\sigma}_{it}}^{\substack{\text{Variance of} \\ \text{Belief on Ability}}}, \overbrace{\vec{Q}_{it}}^{\substack{\text{N of courses} \\ \text{taken}}}, \overbrace{G_{it}}^{\substack{\text{GPA} \\ \text{in period t}}} \} \tag{17}$$

Equation 17 describes the state space. In each period t, the model keeps track of the gender of individual i (X_i), mean of belief on ability in each field ($\vec{\mu}_{it}$), variance of beliefs on ability in each field ($\vec{\sigma}_{it}$), the number of courses taken in each field up to the beginning of period t ($\vec{Q}_{it}$), and cumulative GPA at the beginning of period t (G_{it})[14]. The mapping from the shape parameters of beliefs ($\alpha_{imt}, \beta_{imt}$) to $\vec{\mu}_{it}$ and $\vec{\sigma}_{it}$ is as follows: $\vec{\mu}_{it} = (\frac{\alpha_{imt}}{\alpha_{imt}+\beta_{imt}})_{m=1,2}$ and $\vec{\sigma}_{it} = (\alpha_{imt} + \beta_{imt})_{m=1,2}$[15]. Notice that $\vec{\mu}_{it}$, $\vec{\sigma}_{it}$, and $\vec{Q}_{it}$ are a 2 by 1 vector where each element corresponds to each field: STEM (1) and non-STEM (2). Figure 3.3 summarizes the per-period decision loop and the evolution of the state space.

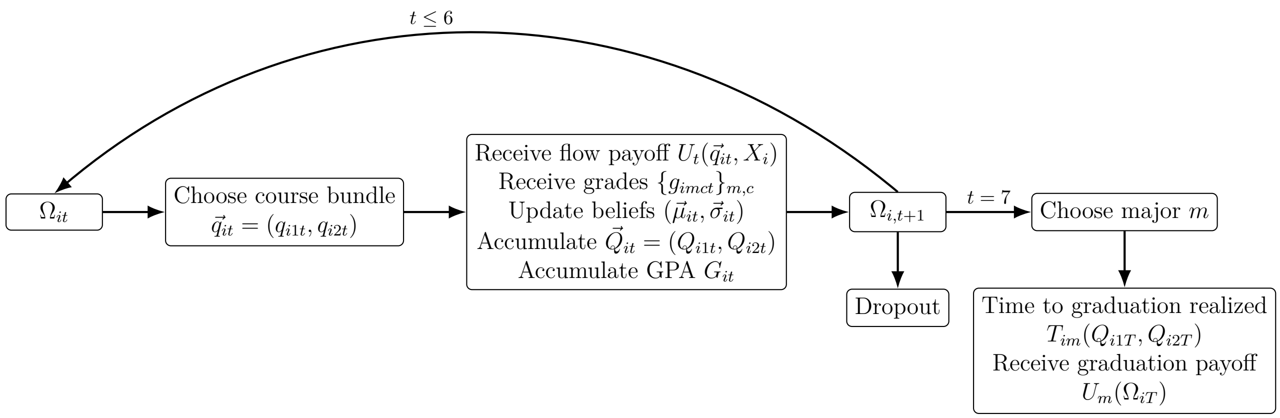
Discussion The model focuses on the first six semesters in college followed by a major commitment decision. Typically, college students in US public universities have to declare their major by the end of the second year. In the data, it is observed that some students still switch their majors after the second year, but fewer than 1% of students switch after the junior year. A non-negligible number of students (roughly 15%) even graduate in fewer than four years, as some enter with dual credits or AP credits earned in high school. For these reasons, the model focuses on how forward-looking students choose their courses in the first six semesters, considering the returns after graduation and the time to graduation.

[13]The decision is made before the extra time to stay in college is realized.

[14]Heterogeneity across other demographic dimension, such as parental education level, is not accounted for. The purpose is to keep the state space as simple as possible. Furthermore, after controlling for ability differences, there is no significance difference in major choice across the parental education level, while gender difference remains significant.

[15]One could instead keep track of α_{imt} and β_{imt} separately. The choice was made so that it is easier to keep track of the state space since μ_{it} is bounded between 0 and 1.

Figure 3.3. Per-Period Decision Loop and State Transition



3.2 Optimization Problem

This subsection solves the students' optimization problem backwards.

3.2.1 Major Choice

After the first six periods in college, student i observes her idiosyncratic preferences $(\xi_{i1}, \xi_{i2}, \xi_{iD})$, and decides which major to graduate with or to drop out. The value of dropping out is normalized to be zero. Given gender, beliefs on ability, total number of courses taken, and GPA, a student's final-period problem is described in Equation 18

$$\max\{\max_{m\in\{1,2\}} \mathbb{E}_{\Omega_{iT}}[\ \underbrace{U_m(\Omega_{iT})}_{\substack{\text{Graduation}\\ \text{payoff}}} - C(X_i) \cdot \underbrace{T_{im}}_{\substack{\text{Extra}\\ \text{time to}\\ \text{graduate}}}\ ] + \xi_{im}\},\ \xi_{iD}\} \tag{18}$$

$$F_{\boldsymbol{\xi}}(\xi_D, \{\xi_m\}_{m\in\{1,2\}}) = \exp\left(-e^{-\xi_D} - \left(\sum_{m\in\{1,2\}} e^{-\xi_m/\lambda_M}\right)^{\lambda_M}\right) \tag{19}$$

where the idiosyncratic preference shocks are drawn from Equation 19. The preference shock has a nested structure where the first nest is dropout versus graduation, and the second nest only exists if one graduates over different majors[16]. The scale of the shock is normalized to one and λ_M is the dissimilarity parameter within the graduation nest. If the student chooses to continue and graduate, she will draw how much longer she needs to stay in college to graduate (T_{im}), and enjoy the graduation payoff $U_m(\Omega_{iT})$. Any extra time taken to graduate is costly (C_i). If she chooses to drop out at the beginning of the last period, she will no

[16]Dropout decision is different from choosing majors (or course bundles described in the next sub-section) in its nature. For instance, health shocks, financial shocks, or family related shocks matter more for the decision of whether to enroll in college or not than the decision of which course bundle to take.

longer stay in school ($T_{im} = 0$) and receive a payoff of zero from dropping out right away.

3.2.2 Course Bundle Choice

In the first six periods in college, a student chooses a course bundle or to drop out as described in Equation 20

$$\max\{\{\max_{\vec{q}} \overbrace{U_t(\vec{q}, \Omega_{it})}^{\substack{\text{Flow cost of} \\ \text{taking bundle } \vec{q}}} + 0.95 \cdot \overbrace{\mathbb{E}_{\Omega'_{i,t+1}}[V_{t+1}(\Omega'_{i,t+1})|\Omega_{it}, \vec{q}]}^{\text{Continuation value}} + \eta_{i\vec{q}t}\},\ \eta_{iDt}\} \quad \text{for} \quad 1 \leq t \leq 6 \quad (20)$$

$$F_{\boldsymbol{\eta_t}}(\eta_{Dt}, \{\eta_{\vec{q}t}\}_{\vec{q}\in\mathcal{Q}}) = \exp\left(-e^{-\eta_{Dt}/\nu} - \left(\sum_{\vec{q}\in\mathcal{Q}} e^{-\eta_{\vec{q}t}/(\nu\lambda_Q)}\right)^{\lambda_Q}\right) \quad \text{for} \quad 1 \leq t \leq 6 \qquad (21)$$

where the idiosyncratic preference shocks are drawn from Equation 21. Again, the preference shock has a nested structure where the first nest is dropout versus enrollment, and the second nest only exists upon enrollment over different bundles of courses. ν is the scale of the shock and λ_Q is the dissimilarity parameter within the enrollment nest[17]. Upon choosing a course bundle ($\vec{q}$), a student updates her beliefs based on the realized grades from the course bundle she chose, and evaluates the expected continuation value based on the updated beliefs. At the beginning of the period, no grades are realized yet, so she forms an expectation on what grades will be realized for each course bundle based on her beliefs in period t.

Remark I restrict the dropout payoff in all periods to be zero since there is not enough data to identify the dropout payoff at different points in time. The assumption behind this is that students who drop out face the same labor market as high school graduates, where their knowledge about ability to learn in college and courses they took in college do not matter. It rules out the case where the amount of partial training in college is valuable. Under this specification, the value of partial training is captured in the net utility of enrollment and course-taking, as well as graduation payoff minus cost of staying longer in college.

3.2.3 Computational Details

Two aspects of the model make solving it computationally challenging. First, the choice set expands quickly with the number of fields and the total number of courses allowed. For example, with 2 fields and a maximum of 6 total courses, there are 22 possible choices. Increasing the maximum to 10 courses raises the number of choices to 60. With 4 fields and

[17]Scale of the preference shock for major choice is normalized to be one. The course bundle choice set size is very different from major choice. There are 22 different course bundles to choose from, where as there are only two majors. To account for this I allow the scale of the preference shock to differ for course and major choices.

a maximum of 10 courses, the number of choices grows to 986. This is the main reason why the model groups majors into STEM and non-STEM, the most distinctive dimension among college majors. In addition, I restrict students to taking 3–6 total courses, since it is rare to observe anyone outside this range in the data[18].

Second, the state space includes multiple continuous state variables, which makes solving the value function difficult. To address this, I use the interpolation method proposed by Keane and Wolpin (1994). Grids are constructed for the continuous state variables, which serve as the basis for projecting the continuation value in periods 1–5[19]. Although Q_{it} is not continuous, the set of possible combinations of Q_{it} expands rapidly over time, even with only two fields. To manage this, I randomly select grid points for Q_{it}. I then use linear and quadratic terms of the state variables at these points as basis functions, and project the continuation value onto these bases to construct the interpolation model[20].

4 Estimation

4.1 Identification

There are two crucial sets of parameters in this model: parameters related to ability and beliefs, and the parameter that measures the preference to maintaining a high GPA. This section discusses how these key parameters of the model are identified.

First, it is assumed that students' prior beliefs are given from the population distribution of ability. The parameters that measure the population distribution of ability are $\{\pi^A_{1m}, \pi^A_{2m}, \pi^B_{1m}, \pi^B_{2m}, \overline{\alpha}_m, \overline{\beta}_m\}_{m\in\{1,2\}}$. Identification of these parameters, as well as c_m, is obtained through multiple observations of grades in different fields for each individuals. a_{im} is unobserved, but the persistency in observed grades in field m help identify the unobserved ability of individuals, in the spirit of Kotlarski's theorem (Kotlarski (1967)). Moreover, the across-individual variation in observed grades will identify the ability distribution. It is important to note that most students take some courses in STEM and non-STEM almost every semester, which reduces the concern of selection when identifying the population ability distribution.

The panel observation of grades for each individuals in both fields also help identify c_m's, the grading policy parameters. The additional feature of the data that pins down c_m is the within-individual variation in observed grades. Notice that, conditional on one's ability a_{im},

[18] About 8% of students take courses outside of that range in a semester. I exclude if a student ever took courses outside of the range in the first 6 semesters, which becomes about 30% of the sample.

[19] In period 6, the continuation value is exactly calculated without interpolation.

[20] The R^2 of the projection is typically around 0.8–0.9.

the variance in observed grade is a function of c_m: $N \cdot a_{im}^{c_m}(1 - a_{im}^{c_m})$. Furthermore, since c_m distorts the effect of true ability on grades the most in the middle range, if students with SAT scores in the middle range particularly have received high grades, c_m will be smaller.

The other key parameter is β_1, which measures how much students value maintaining a high GPA. Thus, it governs how risk averse students are with respect to their cumulative GPA. When β_1 is high, students will take courses in fields with lenient grading and where they have a tighter prior on ability with a higher mean. The challenge is that course grades enter both a cumulative GPA and the posterior beliefs. Hence, when students take more courses and choose a major in a field where they receive high grades, it's hard to separately identify the effect of preference on a high GPA and beliefs on ability (and thus returns to human capital). To separately identify the preference on a high GPA (β_1), I exploit the COVID-19 Pass/Fail option expansion and how students reacted to the policy in terms of risk taking in their course choices. Recall that the expansion of Pass/Fail option during Fall 2020 and Spring 2021 increased STEM course taking at UT-Austin, especially for female and non-STEM students. I reflect the policy change in the model and simulate course choices accordingly to target the change in course taking observed in the reduced form results.

During this period, the fraction of students who concealed at least one letter grade jumped from 1.4% to around 3.7% and 20.5% in Fall 2020 and Spring 2021, respectively. However, the number of courses concealed upon concealing any course remained at around 1.2. Given this observation, as well as to simplify computation of the simulated model, I replicate the policy change by allowing students to choose *whether* to conceal grades or not. To be more specific, after students choose which bundle of course to take, grades will be realized and students will decide whether or not to conceal grades based on the state variables and realized grades. Upon choosing to conceal, her GPA will be boosted up as a function of her current state variables and realized grades. The boost-up in the GPA reflects reduced risk of drawing bad grades. Matching the change in students' course choices under the Pass/Fail expansion policy and the original model to the data moments will identify β_1. Appendix D explains more in detail how I incorporate the expansion of Pass/Fail option in the model.

The rest of the parameters include those that determine the terminal payoff other than β_1, marginal cost of extra time to graduate, the parameters that determine the extra time to graduate, and the flow utility of taking courses. Notice that given the initial belief and the stream of grade signals, everything becomes observable in the model. Thus, the returns to human capital in the terminal payoff ($\beta_{2m}, \beta_{3m}, \beta_{4m}$) are identified by observing how students sort into each major based on their belief and the share of courses they have taken in each field. Then the rest of the difference in the fraction of students choosing each major pins down the gender-specific average payoff of each major (β_{0m}). Similarly, the marginal cost of extra time to graduate and the parameters that determine the extra time to graduate are identified from how students with different number of courses taken (in level terms) sort into each major and how much longer it takes for them to graduate, which is observed in the data. Furthermore, the overall average number of courses students take in each field pins down the flow utility of taking courses. Finally, with dropout utility normalized to zero, the fraction of students who dropout identifies the per-semester utility from enrolling in college.

4.2 Estimation

The model is estimated sequentially in two stages. In the model, students' unobserved ability only affects their choices through realized course grades. Thus, initial beliefs and the sequence of course grades are sufficient to control for selection into courses and observed grades. With these ingredients, the population ability distribution and grading-policy parameters are identified by observing a panel of course grades for each student [21]. Thus, in the first stage, I estimate the parameters of grade equation and ability distribution using simulated maximum likelihood. In the second stage, the flow utility parameters $(\overline{\gamma}, \gamma_{1m}, \gamma_{2m})$, major choice parameters $(\beta_{0m}, \beta_1, \beta_{2m}, C)$, and extra time to graduate parameters $(\tau_{0m}, \tau_{1m}, \tau_{2k}, \tau_{3k})$ are estimated using an indirect inference (II), taking the first-stage estimates as given. Below I formally describe the likelihood function of the first stage, and what auxiliary moments are used in the indirect inference of the second stage.

Subsetting the Sample I apply several additional rules to construct the sample for estimating the model primitives. First, I only focus on 2015 and 2016 cohorts as these students are not affected by the COVID-19 pandemic during their first 3-4 years of college experience (12,529 individuals). Second, I drop those who graduate within 5 semesters (12,453 individuals left). Third, I only keep those with SAT subject scores (11,060 individuals left). Third, for the model to be computationally tractable for an estimation, I restrict the choice set of course bundles in period 1-6: I only allow students to take 3-6 courses in total in each semester. This leaves 7,839 individuals[22]. Table 4.1 reports the summary statistics of the sample used for model estimation.

Compared to the full sample used in Section 2, the model sample has slightly lower SAT scores (about 0.75-1.69%). But they dropout at a lower rate in the first three years (31.02-33.67% less) and graduate in STEM more, conditional on not dropping out in the first three

[21] If an unobserved type of individuals is added to the model that affect students' choices, the two-step estimation strategy does not work anymore. See Aucejo, Maurel, and Ransom (2024) for a related issue.

[22] The other option is to treat the rest of the course bundle as like an outside option. However, it is unclear how to summarize the average effect of the outside option bundle on learning and GPA. Since this is an individual decision model, I focus on the subsample of students who choose course bundles that are relatively popular among students.

years (5.24-6.05%). However, they graduate in non-STEM less (3.11-22.22%), which means they drop out more after three years. Students of the model estimation sample take less courses in general (13.70-26.66%) but earn slightly higher GPA (0.69-1.78%), and they take longer to graduate: extra time to graduate after 3 years is 15.54-23.51% higher.

Table 4.1. Summary Statistics of the Sample for Model Estimation

	Male		Female	
	Mean	SD	Mean	SD
SAT Math	690.30	70.24	645.57	68.44
SAT Reading	650.39	73.41	635.02	72.45
High parental edu. (%)	82.56	37.95	82.09	38.35
Dropout (%) in 3 yrs	4.51	20.75	2.75	16.36
STEM (%) | ∼dropout in 3 yrs	74.01	43.86	42.39	0.49
non-STEM (%) | ∼dropout in 3 yrs	22.33	41.65	54.69	0.50
Extra time to graduate after 3 yrs	2.16	0.94	1.94	0.90
Total N of courses				
in STEM	16.73	7.53	11.89	7.96
in non-STEM	9.62	6.32	14.86	7.36
GPA				
in STEM	3.20	0.64	3.22	0.60
in non-STEM	3.49	0.53	3.61	0.39
N Obs.	3,550		4,289	

First Stage In the first stage, I estimate the grade equation and ability distribution using simulated maximum likelihood. The parameters to be estimated include ability distribution parameters $\{\pi^A_{1m}, \pi^A_{2m}, \pi^B_{1m}, \pi^B_{2m}, \overline{\alpha}_m, \overline{\beta}_m\}_m$, SAT subject score parameters $\{\alpha^{SAT}_m, \beta^{SAT}_m, \sigma^{SAT}_m\}_m$, and the grading policy parameters $\{c_m\}_m$. Since an individual's field-specific ability is unobserved, the likelihood of course grades must be integrated over the latent ability distribution. Note that field-specific abilities are assumed to be independent across fields. Moreover, conditional on ability, SAT score shock and grade shocks are also assumed to be independent. Let d_{it} denote the decision of individual i in period t (representing the course bundle chosen and/or dropout choice), and $\{g_{ifct}\}_{f,c,t}$ represent the grades received by individual i in each period and field. The full set of parameters to be estimated in the first stage is:

$$\Theta_a = \{\pi^A_{1m}, \pi^A_{2m}, \pi^B_{1m}, \pi^B_{2m}, \overline{\alpha}_m, \overline{\beta}_m, \alpha^{SAT}_m, \beta^{SAT}_m, \sigma^{SAT}_m, c_m\}_{m\in\{1,2\}}$$

The likelihood contribution of individual i is characterized in Equation 22. The key observation is that since unobserved ability only affects students' decisions through *realized* grades, the likelihood of SAT and grades can be separated from the likelihood of choices ($\{d_{it}\}_{i,t}$), and the latter does not need integration over unobserved ability. Notice that each likelihood term inside the integral can be calculated as a product of Truncated Normal distribution probability density and a series of Binomial distribution probability mass, conditional on ability (A_{if}) This follows from the assumption that SAT and grade shocks are idiosyncratic and that it follows Truncated Normal and a Binomial distribution, respectively, as discussed in Section 3.

$$\begin{aligned}
&L(\{SAT_i, g_{imct}\}_{m,c,t}|\Theta_a, (X_i, Z_i)) \\
&\quad = \int L(SAT_i|\Theta_a, (X_i, Z_i), A) \\
&\qquad\quad \times L(\{g_{imc1}\}_{f,c}|d_{i1}, SAT_i, \Theta_a, (X_i, Z_i), A) \\
&\qquad\quad \times L(\{g_{imc2}\}_{f,c}|d_{i1}, d_{i2}, \{g_{imc1}\}_{m,c}, SAT_i, \Theta_a, (X_i, Z_i), A) \\
&\qquad \cdots \times L(\{g_{imc6}\}_{m,c}|d_{i1}, \cdots, d_{i6}, \{g_{imc1}\}_{m,c}, \cdots, \{g_{imc6}\}_{m,c}, SAT_i, \Theta_a, (X_i, Z_i), A)\, dF_A.
\end{aligned} \tag{22}$$

To compute the integral in Equation 22, I simulate each individual's ability 30 times from Beta(α_{if}, β_{if}), conditional on their gender and parental education level. Given a drawn ability level, the likelihood function is computed as the product of the Binomial distribution probability mass function at the observed grades and the probability density function of the Beta-distributed ability, conditional on gender and parental education level. Finally, the log-sum of Equation 22 across all individuals is maximized to estimate the model parameters.

Second Stage In the second stage, I estimate the flow utility parameters ($\overline{\gamma}, \gamma_{1m}, \gamma_{2m}$), major choice parameters ($\beta_{0m}, \beta_1, \beta_{2m}, C$), and extra time to graduate parameters ($\tau_{0m}, \tau_{1m}, \tau_{2k}, \tau_{3k}$) using an Indirect Inference (II). I take the first-stage estimates as given in the second-stage estimation. Based on the identification argument, I match the moments from the auxiliary models described below. The intuition of which moments pin down which parameters is as follows[23]. Aux 1 and Aux 2 help identifying the graduation payoff parameters. Aux 3 and Aux 4 are targeted to pin down flow utility of taking courses and enrolling in college. Aux 5 identifies how costly it is to stay in college after $t = 6$. Aux 6 pins down the extra time to graduation parameters. Finally, Aux 7 isolates the preference for maintaining a high GPA.

Aux 1: Coefficients from regression of the form in Equation 23 using the sample of individuals

[23] In practice, all moments jointly identify the parameters as the auxiliary moments are calculated on selected sample based on students' decisions.

who did not drop out until $t = 7$.

$$
\begin{aligned}
DM_{im} = & \beta_0^M + \beta_1^M DM_{1m} + \beta_2^M DM_{2m} + \beta_3^M \left(DM_{0m} \cdot Cum\_GPA_i\right) \\
& + \beta_4^M \left(DM_{1m} \cdot \mathbb{E}_T(a_{i1})\right) + \beta_5^M \left(DM_{2m} \cdot \mathbb{E}_T(a_{i2})\right) \\
& + \beta_6^M \left(DM_{1m} \cdot S_{i1}\right) + \beta_7^M \left(DM_{2m} \cdot S_{i2}\right) \\
& + \beta_8^M \left(DM_{1m} \cdot \mathbb{E}_T(a_{i1}) \cdot S_{i1}\right) + \beta_9^M \left(DM_{2m} \cdot \mathbb{E}_T(a_{i2}) \cdot S_{i2}\right) \\
& + \beta_{10}^M \cdot \left(DM_{1m} \cdot (Q_{i1T} + Q_{i2T})\right) + \beta_{11}^M \cdot \left(DM_{2m} \cdot (Q_{i1T} + Q_{i2T})\right) \\
& + \psi_i + \varepsilon_{im}^M
\end{aligned}
\tag{23}
$$

where DM_{im} is a dummy that takes 1 when i's chosen major after the first 6 semester in college is m, DM_{km} is a dummy that takes 1 when $m = k$, Cum_GPA_i is the cumulative GPA of i at the beginning of the 7th semester. $\mathbb{E}_T(a_{i1})$ and $\mathbb{E}_T(a_{i1})$ are model implied individuals' belief on ability in STEM ($m = 1$) and non-STEM ($m = 2$) at the beginning of the 7th semester. S_{i1} and S_{i2} are the share of courses taken in STEM ($m = 1$) and non-STEM ($m = 2$) by the beginning of the 7th semester. Q_{i1T} and Q_{i2T} are the total number of courses taken in STEM and non-STEM in 3 years, respectively, and thus $Q_{i1T} + Q_{i2T}$ is simply the total number of courses taken in STEM and non-STEM in 3 years. Finally, ψ_i is an individual fixed effect. This specification mimics the terminal period major choice in the model in a reduced-form OLS with individual fixed effects framework, similar to the first auxiliary model (Aux 1) of Biasi, Fu, and Stromme (2021).

Aux 2: Moments of share of students dropping out during $t = 2 - 6$.

Aux 3: Moments of share of students choosing each major in $T = 7$.

Aux 4: The average total number of courses taken in each field in $t = 1 - 6$ by one's chosen major chosen in $T = 7$.

Aux 5: Group students based on whether your math SAT is higher than reading SAT (group 1) or reading SAT is higher than math SAT (group 2). The average number of courses taken in each field in in each year by the group.

Aux 6: The average extra time to graduation by one's chosen major chosen in $T = 7$.

Aux 7: Coefficients from two regression of the form in Equation 24 sub-setting the sample to individuals who chose major $m \in \{1, 2\}$ in $T = 7$.

$$
\log(T_i + 1) = \beta_0^T + \beta_{1m}^T Q_{i1T} + \beta_{2m}^T Q_{i2T} + \beta_{3m}^T \left(Q_{i1T} \cdot Q_{i2T}\right) + \varepsilon_i^T \;\; \text{for } m = 1, 2 \tag{24}
$$

where T_i is the extra number of semesters taken after the 6th semester to graduate, Q_{i1T} is the total number of courses taken up to semester 6 in STEM, and Q_{i2T} is the total number of courses taken up to semester 6 in non-STEM. The regression is run separately for those who chose STEM ($m = 1$) and non-STEM ($m = 2$).

Aux 8: Change in the (1) average per semester fraction of students who take any STEM course, and (2) average per semester number of STEM courses taken, conditional on taking any STEM course. In addition, I match the average per semester fraction of students who choose to conceal the lowest grade when the option is available. These moments pin down the taste for GPA (β_1) in Equation 14 and the marginal cost of concealing grade for one course (β_5) in Equation 29. In the data, these moments come from Equation 3 and the average change in the fraction of students who conceal at least one grade during Spring 2020 - Spring 2021 plotted in Figure 2.1.

5 Results

5.1 Parameter Estimates

Table 5.1-Table 5.3 reports parameter estimates of the structural model. First, Table 5.1 presents parameter estimates that govern the ability distribution and grading policies. These parameters govern the ability learning process in the model. For STEM ability, the gap is about 0.15 and for non-STEM ability, the gap is about 0.12, both of which are larger than 1 standard deviation of the ability distributions. Students with a high parental education background has higher ability on average both in STEM and non-STEM. The average STEM ability is about 0.40 for male students and about 0.37 for female students. The variance of STEM ability is about 0.074 for male students and about 0.061 for female students. The average non-STEM ability is about 0.50 for male students and about 0.53 for female students. The variance of non-STEM ability is about 0.088 for male students and about 0.075 for female students. The gender gap exists but to a magnitude less than 0.5 standard deviation.

Math SAT score is more highly correlated with STEM ability than reading SAT score is with non-STEM ability ($1.295 > 0.765$) The size of noise is slightly higher in math SAT ($4.338 < 4.301$). Finally, grading policies are more lenient in non-STEM fields (0.103-0.120) than in STEM fields (0.166-0.178), as expected. There is a slight variation across years in how lenient grading policies are within a field, but the across-field difference is larger. The grading policy parameters imply that grading is significantly inflated in both fields, more so in non-STEM. For an average STEM student to receive B on average, c_1 should be around 0.30. For an average non-STEM student to receive B on average, c_2 should be around 0.42.

Table 5.2 reports flow utility parameters related to college enrollment and course taking,

Table 5.1. Estimates: Ability Distribution and Grading Policies

	STEM		non-STEM	
	Coeff	SE	Coeff	SE
Ability parameters				
α: mean	0.635	(0.075)	0.682	(0.067)
α: H parental edu.	0.289	(0.038)	0.229	(0.038)
α: female	0.174	(0.046)	0.319	(0.039)
β: mean	1.537	(0.076)	1.315	(0.074)
β: H parental edu.	-0.287	(0.081)	-0.399	(0.073)
β: female	0.446	(0.056)	0.093	(0.044)
SAT: intercept	0.884	(0.032)	0.692	(0.022)
SAT: slope	1.295	(0.057)	0.765	(0.033)
SAT: scale	4.338	(0.012)	4.301	(0.011)
Grading policy				
Year 1	0.166	(0.015)	0.120	(0.007)
Year 2	0.178	(0.016)	0.120	(0.007)
Year 3	0.166	(0.015)	0.103	(0.006)

and the graduation payoff parameters. The last row, marginal cost of concealing 1 grade, is the parameter that governs how often students conceal there grades when there is the option. The signs of the parameters are as expected. STEM courses are slightly more costly than non-STEM courses for female students, but overall the gender difference in flow utility is minimal.

The taste for GPA (β_1) is sizable and shows the largest gap between male and female students (male: 0.78 vs. female: 1.81), which is significantly larger than the gender gap in mean utility of choosing each major (male: 0.77 and 1.03 vs. female: 0.44 and 0.94 for STEM and non-STEM). This is, to some degree, in contrast to Wiswall and Zafar (2018) that finds tastes for fields are the main driving force of gender gap in major choice, particularly driven by non-wage amenities of jobs related to certain majors, which should be captured by the mean utility graduation payoff in this model. This result is in conjunction with Ahn, Arcidiacono, Hopson, and Thomas (2024) which finds the taste for grading policy (how rewarding the grading policy is to student effort) as the main driving force in the gender gap in college course choices.

Turning to the returns to major-specific ability and specialization in course taking, there is a significant match effect between one's ability in a major and specializing course taking in that major (β_{4m}). In other words, one's graduation payoff is higher if she specializes her course taking in a field where she has a higher ability. The match effect is larger for male students. Interestingly, the match effect is larger in STEM for male students than in non-STEM, but it's larger in non-STEM for female students than in STEM. The coefficients in

Table 5.2. Estimates: Flow Utility and Graduation Payoff

	Male STEM	Male non-STEM	Female STEM	Female non-STEM
Flow utility				
Enrollment (γ_0)	-1.67		-1.71	
	(0.036)		(0.017)	
per 1 course (γ_m)	-0.11	-0.07	-0.13	-0.12
	(0.023)	(0.001)	(0.075)	(0.001)
Graduation payoff				
Mean utility (β_{0m})	0.77	1.03	0.44	0.94
	(0.011)	(0.029)	(0.035)	(0.011)
Taste for GPA (β_1)	0.78		1.81	
	(0.019)		(0.024)	
Ability in my major (β_{2m})	-1.97	-2.03	-2.05	-2.29
	(0.012)	(0.004)	(0.042)	(0.040)
Share of courses (β_{3m})	3.57	3.30	3.79	3.22
	(0.024)	(0.031)	(0.027)	(0.060)
Ability $\times$ Share of courses (β_{4m})	13.85	7.44	10.72	7.94
	(0.013)	(0.015)	(0.081)	(0.032)
Cost of extra semester (C)	1.70		2.60	
	(0.048)		(0.012)	
Cost of concealing 1 grade	0.06		0.15	
	(0.0002)		(0.005)	

Note: Standard errors are in parentheses. I follow two-step estimators' standard error calculation as described in Newey and McFadden (1994), to account for the noise coming from keeping the first-stage parameter estimates as given when estimating the second-stage parameters in Section 4. See Appendix F for further discussion on calculating the standard error of the second-stage estimates.

front of ability in the chosen major is negative. However, combined with the match effect, if the share of courses taken in the chosen major is above certain level (above 14-30%), the marginal effect of higher ability is positive on the graduation payoff. Increased specialization in a field by taking more courses in the majoring field always increases the graduation payoff, and more so when one has higher ability in that field.

Finally, the cost of an extra semester in college is 53% larger for female students than for male students (male: 1.70 vs. female: 2.60). The marginal cost of concealing one course grade of female students is more than twice larger than that of male students (male: 0.06 vs. female: 0.15). A plausible story for these gender differences is that female students anticipate discrimination on the labor market and works harder to signal their ability through grades and on-time graduation (Lepage, Li, and Zafar (2025)).

Table 5.3 presents parameters that govern the extra time to graduation of Equation 16. A positive marginal effect of taking a STEM course on time to graduation reflects rigid

Table 5.3. Estimates: Extra Time to Graduation

	STEM		non-STEM	
	Coeff	SE	Coeff	SE
τ_0	0.368	(0.007)	1.490	(0.002)
τ_1	0.017	(0.0002)	-0.066	(0.0006)
τ_2	0.039	(0.0004)	-0.074	(0.0002)
τ_3	-0.002	(0.00001)	0.007	(0.00004)

Note: Standard errors are in parentheses.

Table 5.4. Estimates: Preference Shock

	Coeff	SE
ν_1	1.13	(0.006)
ν_2	0.87	(0.003)
ν_3	0.96	(0.007)
λ_Q	0.77	(0.002)
λ_M	0.29	(0.015)

Note: Standard errors are in parentheses.

and highly sequenced curricula of some STEM majors. Some majors within STEM have many required STEM courses and so students who have taken more STEM courses appear to have longer time to graduate in the data. Moreover, a synergy effect of taking courses both in STEM and non-STEM in reducing the time to graduation ($\tau_3 < 0$) reflects the general education requirements. Simply taking non-STEM courses wouldn't shorten time to graduation ($\tau_2 > 0$), but after taking enough STEM courses, it helps to reduce the time to graduation. The course requirement and time to graduation dynamic is a bit different in non-STEM graduation. Both STEM and non-STEM courses marginally reduce time to graduation ($\tau_1 < 0$ and $\tau_2 < 0$) if one hasn't taken too many courses in the other field ($\tau_3 > 0$). In STEM, the structure of extra time to graduation incentivizes students to take a more diverse set of courses across fields where as in non-STEM it incentivizes students to concentrate more on one field.

To provide a better context, I interpret the parameter estimates of the graduation payoff in terms of extra semesters to stay in college in Table 5.5. In other words, it is the willingness to pay by staying longer in college. The numbers come from dividing the coefficients of the graduation payoff by $C(X_i)$. Alternatively, given that an average per semester in-state tuition of a 4-year public university is about \$4,875, one can convert the extra time to stay in college into willingness to pay by multiplying \$4,875, ignoring any psychic cost of staying in college involved with an extra semester after 3 years of enrollment in college. For instance,

Table 5.5. Willingness to Stay in College

	Male		Female	
	STEM	non-STEM	STEM	non-STEM
1 SD GPA	0.12		0.15	
1 SD higher a_{im}*	2.28	1.03	1.44	1.09
1 SD higher S_{im}**	1.31	1.20	1.06	0.94
Concealing 1 grade	0.03		0.06	

*Evaluated at the average S_{im} among those who chose m.
**Evaluated at a_{im} among those who chose m.

1 standard deviation higher GPA (i.e. 0.21-0.27 higher GPA) is equivalent to staying 0.12 semester less in college for male students and 0.15 semester less in college for female students. Each semester is about 16 weeks, so it is about 14-17 days less in college. In monetary terms, this would be willingness to pay about $585-$731. The interpretation goes through similarly for the rest of the variables. Notice that the value of ability and specialization of course taking in a chosen major is higher in STEM, both for male and female students.

5.2 Model Fit

Table 5.6. GPA Model Fit

	Data		Model	
	STEM	non-STEM	STEM	non-STEM
Mean	3.21	3.56	3.23	3.58
Variance	0.38	0.21	0.38	0.19
Skewness	-1.16	-1.91	-1.06	-1.64
Percentiles				
25%	2.88	3.33	2.90	3.40
50%	3.33	3.67	3.36	3.71
75%	3.67	3.90	3.70	3.92

Table 5.6-Table 5.7 show that the model does a good job of capturing the grade distribution and key patterns in course-taking behavior and major choices by gender. First, Table 5.6 presents the distribution of GPA at the end of period 6 in the data and the model. The distribution of GPA not only reflects the grade distribution, but also the sorting of students by ability (i.e. who took which courses). The model captures the mean difference in the GPA across STEM and non-STEM very well. Both STEM and non-STEM GPA distribution are skewed to the left in the data, and in the model the distribution is slightly less negatively skewed. But the model captures well that non-STEM is much more negatively skewed than STEM.

Table 5.7. Selected Model Fit

	Male				Female			
	Data		Model		Data		Model	
Graduating major	STEM	non-STEM	STEM	non-STEM	STEM	non-STEM	STEM	non-STEM
SAT Math	690.30		667.34		645.57		665.67	
SAT Reading	650.39		639.97		635.02		643.55	
High parental edu. (%)	82.56		82.19		82.09		82.09	
Aux 2: Dropout (%) in 3 yrs	4.51		4.03		2.75		2.31	
Aux 3: Major choice (%)*	74.01	22.33	75.73	22.11	41.22	53.18	43.16	56.14
Aux 4: Total N of courses								
in STEM	20.39	7.08	20.24	7.43	19.81	6.19	19.63	5.88
in non-STEM	6.91	19.03	7.22	20.09	7.98	20.50	7.34	21.72
Aux 6: Extra semesters**	2.17	2.12	2.05	1.64	2.03	1.86	2.04	1.38
Aux 8: Grade concealing moments								
Δ in Prob(STEM $>$ 0) (%)	0.65		0.54		1.15		0.80	
Δ in share of STEM (%)	0.55		0.28		0.30		0.33	
Concealing grades (%)	40.30		35.92		30.07		26.46	

* Major choice for those who didn't drop out in the first 3 years.
** Extra semesters beyond 3 years of enrollment in college.

Table 5.7 shows the moments related to individuals' educational choices. The model replicates well how male and female students choose major differently in college. It also captures well the specialization of course taking in the field that students are graduating in. On average, students take about 2 extra semesters to graduate (i.e. total 8 semesters ro graduate), except that non-STEM female students take shorter time. Dropout rates match well. When grade concealing policy is available, students react to it less in the model compared to the data, but overall it well matches the pattern of increasing course taking in STEM field. Model fit of auxiliary moments 1, 5, and 7 are reported in Appendix E. Figure 5.1 also plots the data moments against the simulated moments to visualize the model fit.

6 The Role of Grading Policies in College Educational Outcomes and Major Sorting

Going back to the research questions, this section presents how different grading policies affect college students' course and major choices and how students sort based on comparative advantage into majors. In particular, I focus on analyzing the effect of grade inflation on students' educational outcomes and sorting patterns. Furthermore, I shed light on how grading policies affect the observed gender gap in major choices, particularly the under-representation of female students in STEM. In the analyses, I consider the following counterfactual grading

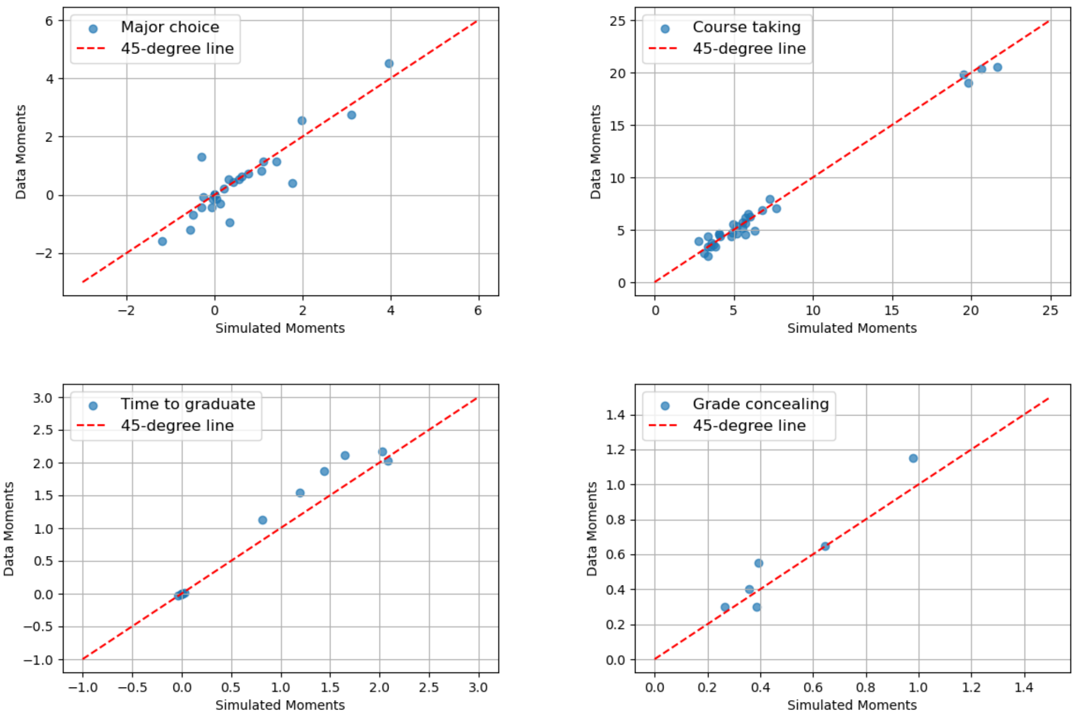


Figure 5.1. Model Fit

policies described in Table 6.1.

Table 6.1. Counterfactual Grading Policies

Scenario	**Grading policy** (c)
Status Quo	non-STEM < STEM < 1
Uniform inflation	non-STEM = STEM = 0.120
Uniform deflation	non-STEM = STEM = 0.303

The first is status quo-how grading policies are set in the data. The unique thing about this scenario is that the grading policies are different between STEM and non-STEM. This provides a cheap way for students to increase their GPA by taking courses in non-STEM where the grading policy is more inflated than in STEM. Second, I set the grading policies uniform to the non-STEM level observed in the data (uniform inflation). This is the most inflated grading policy scenario in the following counterfactual analyses. Third, I set the grading policies uniform to the level where a student with an average level of STEM ability would on average receive B (uniform deflation). Comparing the second and third counterfactual grading policies focus more on how the taste for GPA and ability learning affect student choices when there is no cheap way of increasing GPA by taking courses from a major with more lenient grading policy.

6.1 How do different grading policies affect educational outcomes?

The first set of counterfactuals examines how alternative grading policies affect students' educational outcomes such as course enrollment, graduation, GPA, dropout, and time to graduation. Table 6.1 reports average GPA, STEM completion rate, dropout rate, and time to graduation. It shows that aligning grading standards of STEM to non-STEM levels leads to particularly strong improvements in STEM degree completion. Under "uniform inflation," STEM graduation increases 2-4 percentage points (2-10 percent), with no meaningful delay in time to degree (an increase of only 0.01-0.04 semester which is less than a week). The dropout rate falls by 0.59-0.64 percentage points (10-22 percent).

By contrast, uniform deflation slightly decreases overall STEM graduation by 1-2 percentage points. This is mostly driven by increased dropout rates, reflecting that stricter grading discourages persistence among marginal students. For female students, the dropout rate increases more than twice. Conditional on not dropping out, however, male students' STEM choice slightly increases from 77.4 percent to 77.8 percent, while female students' STEM choice increases from 43.5 percent to 44.9 percent[24]. GPA also falls by 13 percent, consistent with the model's structure where higher c generates less inflated signals and, hence, lower average grades. These results highlight that the *unequal* grade inflation particularly pushes students away from taking STEM courses which negatively affects STEM degree completion[25].

Table 6.2. Counterfactual Grading Policies and Educational Outcomes

	Male			Female		
	Status Quo	Uniform inflation	Uniform deflation	Status Quo	Uniform inflation	Uniform deflation
GPA	3.36	3.49	2.90	3.47	3.56	3.01
Major = STEM (%)	72.68	74.18	70.64	42.16	46.22	41.47
Switched from Dropout (%)	-	0.69	0.09	-	0.58	0.04
Switched from non-STEM (%)	-	1.39	1.02	-	3.85	2.85
Dropout (%)	6.10	5.51	9.24	2.99	2.34	7.62
Time to graduation	1.96	1.97	1.96	1.67	1.71	1.68

Taken together, the results highlight the double-edged nature of grade inflation: while it potentially weakens the signal value of grades, it can improve persistence and reduce dropout. This echoes the results of Ahn, Arcidiacono, Hopson, and Thomas (2024), where more lenient grading increased course enrollment in harsher-graded STEM fields, particularly for female students.

[24] STEM graduation rate reported in 6.1 is an unconditional probability of choosing STEM.

[25] The conditional STEM choice probability under uniform inflation is 78.5 percent and 47.3 percent for male and female students, respectively

Gender Gap How effective are different grading policies in reducing the gender gap in STEM major choice? The model's structural parameters imply that female students' stronger GPA orientation should make them more sensitive to the implicit costs of enrolling in harsher-graded fields, deterring them from STEM participation. Simulation results in Table 6.2 confirm that female students are more responsive to inflated or lenient grading regimes. Under the status quo, the STEM graduation rate is 72.68 percent for males and 42.16 percent for females, leaving a 30.52 percentage-point gap. When grading is equalized to non-STEM standards (uniform inflation), female STEM graduation rises by 9.6 percent, compared to only 1.5 percent for males, narrowing the gap by 8.35 percent. Under uniform grading deflation, the gap falls by 4.4 percent. Taken together, these results demonstrate that while grading policies can meaningfully boost female representation in STEM, they are insufficient to eliminate the gender gap. Even in the most favorable scenario (uniform inflation), a gap of over 27 percentage points remains.

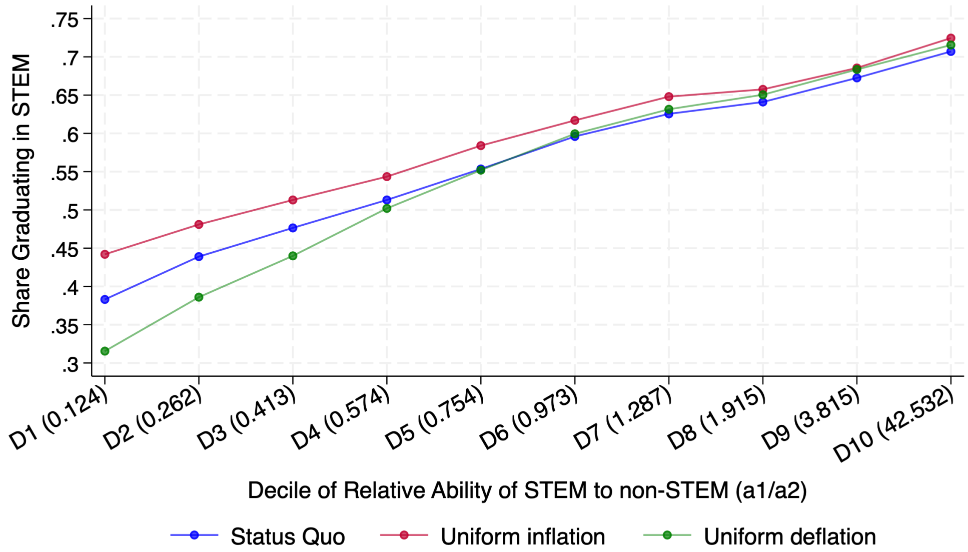
6.2 How do different grading policies affect ability sorting?

A second set of counterfactuals evaluates how grading policies affect the sorting of students into majors according to their comparative advantage. The graphical evidence in Figure 6.1 illustrates how grading policies shape sorting by comparative advantage. The graph plots the share of students majoring in STEM against the deciles of the relative ability of STEM to non-STEM (a_{i1}/a_{i2}), which measures one's comparative advantage in STEM. The numbers in parentheses in the x-axis are the deciles of the relative ability. A steep gradient of a line reflects strong sorting: as students move up the deciles of relative STEM ability, the probability of graduating in STEM rises sharply.

The status quo with more grade inflation in non-STEM is the benchmark. Grading policies that impose uniform grading to non-STEM standards increase overall STEM graduation, but at the cost of excessive participation among students with low STEM ability relative to non-STEM, which pulls the curve upward in the lower deciles by up to 15 percent. The slope also slightly flattens out, indicating weaker sorting with respect to comparative advantage. Uniform grade deflation steepens the slope relative to the other two. At the highest decile, STEM graduation rate increases by 1.2 percent (0.85 percentage points) and at the lowest decile, it decreases by 17.6 percent (6.75 percentage points). At the lower decile of relative STEM ability, lower graduation in STEM is largely driven by students dropping out. Out of 6.75 percentage point change, 5.45 percentage point is coming from students who used to graduate with a STEM degree dropping out instead under the uniform grade deflation.

Discussion The sorting pattern by comparative advantage has important labor-market im-

Figure 6.1. Counterfactual Grading Policies and Ability Sorting



plications. In their paper, Guvenen, Kuruscu, Tanaka, and Wiczer (2020) group skills into verbal, math, and social, and measure multidimensional skill mismatch in the NLSY 79 data that is implied by a dynamic model of skill acquisition and occupational choice. They find that workers choose to switch occupations so as to reduce their skill mismatch, and that occupational mismatch can reduce annual wages by roughly 11 percent. The above counterfactual results suggest that while grade inflation improves graduation rates, particularly in STEM, it does so partly by allowing weaker students to persist in majors where they are poorly matched, raising the likelihood of downstream mismatch in the labor market.

6.3 How does uncertainty in ability interact with different grading policies?

This section examines how grading policies shape students' major choices when their ability is uncertain. I compare two versions of the model: one in which students know their true ability in each field (full information), and one in which they learn about it over time through noisy grade signals (uncertainty). This comparison reveals two mechanisms:

1. a **GPA-preference** channel, through which grading policies alter the weight students place on maintaining a high GPA relative to matching by ability;

2. a **learning** channel, through which grades convey information about ability; and

Simulation results in Table 6.3-Table 6.5 highlight these mechanisms. Each column of

Table 6.3. STEM Graduation Rate: Full-information

Quantile of Relative Ability (a1/a2)	Q1	Q2	Q3	Q4
Uniform inflation	42.26	54.2	64.9	72.84
Uniform deflation	33.04	49.64	63.48	72.66

Table 6.4. STEM Graduation Rate: Uncertainty

Quantile of Relative Ability (a1/a2)	Q1	Q2	Q3	Q4
Uniform inflation	46.88	55.66	63.66	69.64
Uniform deflation	36.66	51.16	62.20	69.02

the graphs are the four quantile groups of the sample based on their relative STEM ability. Q1 is the lowest 25th percentile group and Q4 is the highest 25th percentile group. Each row represents two different grading policies: uniform inflation and uniform deflation. Table 6.3 and Table 6.4 report the fraction of student graduating in STEM by the grading policy and the ability quantile group when there is full information about ability and when there is uncertainty, respectively. Table 6.5 reports the percentage of students making different choices under full information and uncertainty by grading policy and the ability quantile group, to see how closely student act as if they have full information under different grading policies.

First, the full information benchmark highlights the **GPA-preference** channel. When ability is known, grades matter only because they affect the value students place on GPA. If grading is lenient and grade differences across fields are small, the cost of taking a difficult or mismatched course falls. Students who are relatively weak in STEM, for instance, can now choose it without much risk of harming their GPA. This weakens the link between comparative advantage and major choice: ability still matters, but its influence on decisions declines when GPA differences narrow. In contrast, stricter grading policies that restore meaningful GPA dispersion across fields increase the penalty for mismatch and strengthen sorting by ability. In the model, this appears as a change in the sorting gradient: the relationship between comparative advantage and the probability of majoring in STEM. In Table 6.3, more lenient grading compresses GPA differences and flattens this gradient, indicating that students put relatively more weight on maintaining a high GPA than on aligning with their strongest field.

By adding uncertainty, we can see how the **learning** channel affects students' choices. When ability is uncertain, grades serve as signals that guide belief updating about major-specific ability. Grade inflation makes these signals noisier: a high GPA becomes less informative about true performance. Consequently, students' beliefs update more slowly, and

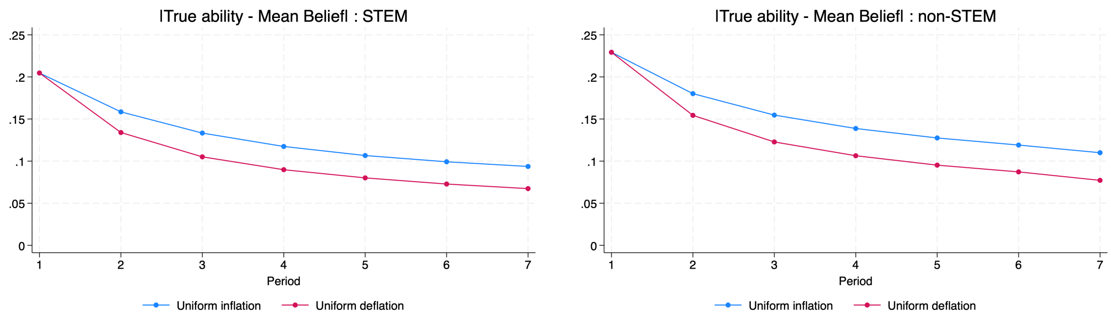


Figure 6.2. Distance Between True Ability and Mean Belief

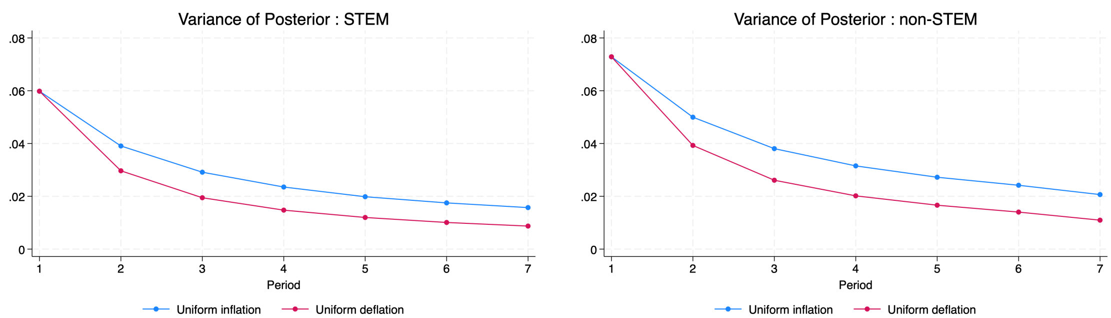


Figure 6.3. Posterior Variance Evolution

the posterior variance of those beliefs remains higher over time, as shown in Figure 6.2-Figure 6.3[26]. Students remain uncertain about where they perform best, and the resulting major choices weakens the sorting compared to the full information benchmark in both grading policy regimes, as well as deviation from the choice one would make under the full information benchmark.

Table 6.5. % Making Different Choice: Full-information vs. Uncertainty

Quantile of Relative Ability (a1/a2)	Q1	Q2	Q3	Q4
Uniform inflation	7.54	4.64	4.06	6.20
Uniform deflation	8.10	5.64	5.18	7.22

However, more informative grading does not necessarily make behavior under uncertainty converge to the full-information benchmark. Table 6.5 reports the percent of students who are making different decision under full information and under uncertainty. Although stu-

[26]The standard deviation of STEM ability is about 0.247-0.272. The standard deviation of non-STEM ability is about 0.274-0.297. Even after taking courses in college there is still 0.25-0.28 SD difference between the true ability and the mean of the posterior under uniform deflation. The gap is larger under uniform inflation which is around 0.34-0.40 SD. The posterior variance is about 0.06-0.08 SD in period 7 under uniform deflation, and about 0.03-0.04 SD in period 7 under uniform inflation.

dents learn more per course under uniform deflation, they also face sharper GPA trade-offs and are less willing to take courses where they might perform poorly. Under uniform inflation, students receive noisier signals but confront weaker incentive to sort by comparative advantage, so knowledge of true ability adds little to their decision. The result is that the choice gap between uncertainty and full information is smaller under inflation, not because students learn more, but because GPA considerations dominate decision-making when grade differences are compressed.

In short, the simulations show that grading policy and uncertainty interact in subtle ways. Lenient grading weakens sorting in general, but it also reduces the difference between behavior under uncertainty and under full information. When grades are inflated, both informed and uninformed students face similar GPA outcomes across fields, so the information advantage from knowing one's true ability matters less. In contrast, when grading is strict and grades differ sharply across fields, uncertainty has a larger effect: students who misjudge their strengths face meaningful GPA penalties and make systematically different choices from those with full information. Thus, lenient grading compresses both performance differences and the behavioral role of information, making choices less tied to ability but also less sensitive to uncertainty.

7 Conclusion

Uneven grade inflation across departments shapes students' educational decisions through two key channels: how grades convey information about academic ability, and how strongly students value maintaining a high GPA. When grading standards differ across fields, students face a tradeoff between exploring uncertain strengths and protecting their GPA, and this tradeoff drives both course-taking behavior and eventual sorting across majors.

The model of this paper highlights these mechanisms. Grade distributions are more inflated in non-STEM fields, female students place greater weight on GPA, and match effect between ability and concentration in course taking is higher in STEM ability rather than non-STEM ability. Time-to-graduation patterns also align with institutional features, with rigid sequencing in STEM extending completion times and more flexible requirements in non-STEM reducing them.

Equalizing grading standards across fields to more inflated non-STEM levels increases STEM graduation rates by 2 to 10 percent and reduces dropout by about 22 percent. However, these policies weaken sorting by comparative advantage. Under inflated grading, as many as 15 percent of students with low relative STEM ability remain in STEM compared with a deflated grading policies to the level where an average student receives B on average.

Gender differences also interact with grading policies. More lenient grading raises female STEM graduation by roughly 10 percent, and the gender gap narrows modestly, by about 4 percentage points. But it remains above 27 percentage points even under the most lenient policies.

Together, the findings show that grade inflation is not unambiguously harmful or beneficial. Uneven inflation disadvantages STEM participation, but inflationary or concealing policies can improve persistence and completion. These benefits, however, come at the cost of weaker signals about ability, less sorting by comparative advantage into majors, with limited progress in closing gender gaps.

The combination of learning and GPA-preference channels also results in the following interesting observation: students' choices are more aligned to the full-information benchmark under more lenient grading policies. This is because under inflated grading, students who know their comparative advantage behave much like those who do not, because GPA outcomes are nearly identical across fields. With stricter grading, grades convey clearer signals about performance, and sorting by comparative advantage becomes more important to maximize the payoff, leading uncertainty about ability plays a greater role in shaping students' decisions.

References

Ahn, T., P. Arcidiacono, A. Hopson, and J. Thomas (2024): "Equilibrium grading policies with implications for female interest in STEM courses," *Econometrica*, 92(3), 849–880. 6, 7, 36, 42

Arcidiacono, P. (2004): "Ability sorting and the returns to college major," *Journal of Econometrics*, 121(1-2), 343–375. 4, 6, 9

Aucejo, E., A. Maurel, and T. Ransom (2024): "College Attrition and the Dynamics of Information Revelation," *Journal of Political Economy*, Forthcoming. 6, 9, 19, 31

Bar, T., V. Kadiyali, and A. Zussman (2009): "Grade information and grade inflation: The Cornell experiment," *Journal of Economic Perspectives*, 23(3), 93–108. 7

Biasi, B., C. Fu, and J. Stromme (2021): "Equilibrium in the market for public school teachers: District wage strategies and teacher comparative advantage," Discussion paper, National Bureau of Economic Research. 34

Bordon, P., and C. Fu (2015): "College-major choice to college-then-major choice," *The Review of economic studies*, 82(4), 1247–1288. 6, 9

Butcher, K. F., P. J. McEwan, and A. Weerapana (2014): "The effects of an anti-grade-inflation policy at Wellesley College," *Journal of Economic Perspectives*, 28(3), 189–204. 7

Conlon, J. J., L. Pilossoph, M. Wiswall, and B. Zafar (2018): "Labor market search with imperfect information and learning," Discussion paper, National Bureau of Economic Research. 6

Crawford, G. S., and M. Shum (2005): "Uncertainty and learning in pharmaceutical demand," *Econometrica*, 73(4), 1137–1173. 6

Dale, S. B., and A. B. Krueger (2002): "Estimating the payoff to attending a more selective college: An application of selection on observables and unobservables," *The Quarterly Journal of Economics*, 117(4), 1491–1527. 10

Denning, J. T., E. R. Eide, K. J. Mumford, R. W. Patterson, and M. Warnick (2022): "Why have college completion rates increased?," *American Economic Journal: Applied Economics*, 14(3), 1–29. 7

Erdem, T., and M. P. Keane (1996): "Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets," *Marketing science*, 15(1), 1–20. 6

Exley, C. L., R. Fisman, J. B. Kessler, L.-P. Lepage, X. Li, C. Low, X. Shan, M. Toma, and B. Zafar (2024): "Information-Optional Policies and the Gender Concealment Gap," Working Paper 32350, National Bureau of Economic Research. 4

Fu, C., N. Grau, and J. Rivera (2022): "Wandering astray: Teenagers' choices of schooling and crime," *Quantitative Economics*, 13(2), 387–424. 9

Guvenen, F., B. Kuruscu, S. Tanaka, and D. Wiczer (2020): "Multidimensional skill mismatch," *American Economic Journal: Macroeconomics*, 12(1), 210–244. 6, 44

Hansen, A. T., U. Hvidman, and H. H. Sievertsen (2024): "Grades and employer learning," *Journal of Labor Economics*, 42(3), 659–682. 4

Hsu, J. (2018): "Learning about college major match: Microfoundations from dynamic course-taking," *Available at SSRN 3274259*. 6

Jaeger, D. A., J. M. Nunley, R. A. Seals Jr, C. L. Shandra, and E. J. Wilbrandt (2023): "The demand for interns," *Journal of Economic Behavior & Organization*, 209, 372–390. 4

Jiang, X., K. Chen, Z. Hansen, and S. Lowe (2021): "A second chance at success? Effects of college grade forgiveness policies on student outcomes," *NBER Working Paper*, (w29493). 13

Keane, M. P., and K. I. Wolpin (1994): "The solution and estimation of discrete choice dynamic programming models by simulation and interpolation: Monte Carlo evidence," *The Review of Economics and Statistics*, pp. 648–672. 29

Kotlarski, I. (1967): "On characterizing the gamma and the normal distribution," *Pacific Journal of Mathematics*, 20(1), 69–76. 29

Lepage, L.-P., X. Li, and B. Zafar (2025): "Anticipated Discrimination and Major Choice," Discussion paper, National Bureau of Economic Research. 4, 37

Main, J. B., and B. Ost (2014): "The impact of letter grades on student effort, course selection, and major choice: A regression-discontinuity analysis," *The Journal of Economic Education*, 45(1), 1–10. 7

Newey, W. K., and D. McFadden (1994): "Large sample estimation and hypothesis testing," *Handbook of econometrics*, 4, 2111–2245. 37

Nieswiadomy, M., and M. Kim (2024): "Grade inflation at 34 public universities in Texas (2012–2019)," *Applied Economics*, pp. 1–13. 2

Nunley, J. M., A. Pugh, N. Romero, and R. A. Seals Jr (2016): "College major, internship experience, and employment opportunities: Estimates from a résumé audit," *Labour Economics*, 38, 37–46. 4

Petersheim, C., J. Lahey, J. Cherian, A. Pina, G. Alexander, and T. Hammond (2022): "Comparing Student and Recruiter Evaluations of Computer Science Resumes," *IEEE Transactions on Education*, 66(2), 130–138. 4

Piopiunik, M., G. Schwerdt, L. Simon, and L. Woessmann (2020): "Skills, signals, and employability: An experimental investigation," *European Economic Review*, 123, 103374. 4

Stinebrickner, R., and T. R. Stinebrickner (2014): "A major in science? Initial beliefs and final outcomes for college major and dropout," *Review of Economic Studies*, 81(1), 426–472. 6

Stinebrickner, T., and R. Stinebrickner (2012): "Learning about academic ability and the college dropout decision," *Journal of Labor Economics*, 30(4), 707–748. 9

Tan, B. J. (2023): "The consequences of letter grades for labor market outcomes and student behavior," *Journal of Labor Economics*, 41(3), 565–588. 7

Thomas, J. (2024): "What do course offerings imply about university preferences?," *Journal of Labor Economics*, 42(1), 53–83. 6

Ugalde, M. P. (2022): "Gender, Grade Sensitivity, and Major Choice," . 6

U.S. Department of Education, National Center for Education Statistics (2024a): "Average Grade Point Average by Gender," National Postsecondary Student Aid Study: 2020 Undergraduate Students (NPSAS:UG), Accessed April 2024. 2

——— (2024b): "Estimated Grade Point Average (Average) Without Zeros," National Postsecondary Student Aid Study: 2020 Undergraduate Students (NPSAS:UG), Accessed March 2024. 2

Wiswall, M., and B. Zafar (2015): "Determinants of college major choice: Identification using an information experiment," *The Review of Economic Studies*, 82(2), 791–824. 6

——— (2018): "Preference for the workplace, investment in human capital, and gender," *The Quarterly Journal of Economics*, 133(1), 457–507. 6, 36

——— (2021): "Human capital investments and expectations about career and family," *Journal of Political Economy*, 129(5), 1361–1424. 6

Zafar, B. (2013): "College major choice and the gender gap," *Journal of Human Resources*, 48(3), 545–595. 6

A Tables and Figures

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B The Effect of Pass/Fail Grading Option Expansion

Placebo Test Table B.2-Table B.11 report the regression results of Equation 3 by university. I choose top 10 public universities in Texas in terms of size for the placebo test.

Long-term effect of pass/fail grading option expansion Below I examine if the pass/fail grading option expansion eventually had any effect on students' major choice through changing their course taking behavior. A positive effect of pass/fail grading option expansion of STEM graduation rate supports that students were able to takin more STEM courses to explore the field, which to some degree led them to eventually graduate in STEM. Notice that there was no change in grading policies in STEM and non-STEM, but the policy still reduced the risk of disclosing a bad grade.

In Equation 25, the outcome Y_i is an indicator for whether student i graduated in STEM within five years. The treatment indicator D_i equals one for students in schools that continued the expanded pass/fail option after Spring 2019. The main parameters of interest are the coefficients β_k, which measure how the probability of graduating in STEM differs between treated and untreated schools, relative to the 2018 entering cohort (where β_{-1} is normalized to zero). School fixed effects, $\alpha_{s(i)}$, absorb time-invariant institutional differences in grading standards or composition, while cohort fixed effects, $\lambda_{t(i)}$, flexibly control for differences across entry cohorts. Finally, X_i includes student-level controls such as SAT subject scores, gender, parental education, and initial intended major, ensuring that results are not driven by observable background differences. The index $t(i)$ denotes the student's entering cohort in the spring academic year, so effects are traced relative to the timing of entry.

$$Y_i = \sum_{k \neq -1} \beta_k \cdot (\mathbf{1}\{t(i) - 2019 = k\} \cdot D_i) + \alpha_{s(i)} + \lambda_{t(i)} + X_i'\Gamma + \varepsilon_{it} \tag{25}$$

The setting slightly differs from a canonical event–study design because all cohorts are eventually exposed to the pass/fail expansion, but the degree and timing of exposure varies. The 2019 cohort encountered the policy at the sophomore stage, when exploration of majors is still relatively open; the 2020 cohort was exposed as freshmen, while pre-2019 cohorts were only treated beginning in their third year or later. Table B.1 column (1) shows that β_{2019} is significantly positive—about 1.58% from the baseline—indicating that the 2019 cohort experienced the largest long-run increase in STEM graduation. Columns (2)-(3) subset the sample by gender. The result suggests that sophomores, facing a reduced risk of disclosing bad grades at the point where they could still adjust their course choices, were the most likely to take additional STEM courses and subsequently graduate in STEM. The absence of strong pre-trends further supports the interpretation that the pass/fail expansion had a causal effect concentrated at a critical stage of academic exploration.

Table B.1. Long-term Effect of Pass/Fail Expansion

	(1) All	(2) Male	(3) Female
β_{2016}	0.010	0.007	0.014
	(0.010)	(0.015)	(0.010)
β_{2017}	0.001	-0.000	0.001
	(0.010)	(0.013)	(0.009)
β_{2019}	0.009***	0.008***	0.011
	(0.003)	(0.002)	(0.007)
β_{2020}	-0.006	-0.012	0.001
	(0.012)	(0.012)	(0.007)
SAT Math	0.063***	0.060***	0.067***
	(0.007)	(0.007)	(0.006)
SAT Reading	-0.015**	-0.015**	-0.015***
	(0.005)	(0.006)	(0.004)
Initial Major = non-STEM	-0.614**	-0.576***	-0.642***
	(0.029)	(0.036)	(0.024)
Female	-0.066***		
	(0.017)		
High Parental Edu.	0.014	0.018	0.011
	(0.010)	(0.013)	(0.008)
Constant	0.810***	0.800***	0.759***
	(0.012)	(0.011)	(0.010)
Mean	0.569	0.686	0.454
SD	0.495	0.464	0.498
R^2	0.457	0.364	0.480
N	93494	46425	47069

Notes: SAT subject scores are standardized by subject. * indicates p-value < 0.1, ** p-value < 0.05, and *** p-value < 0.001.

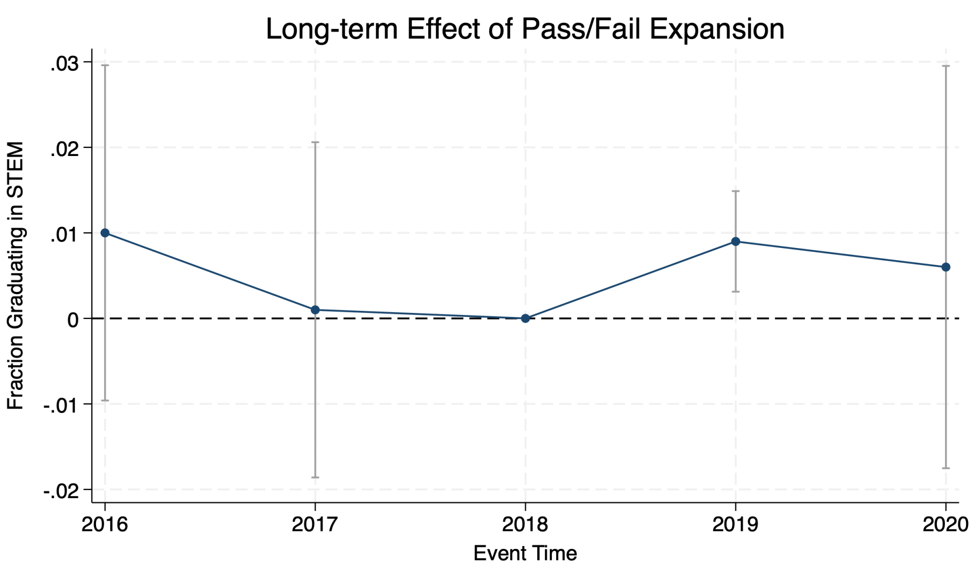

Table B.2. Placebo Test - Extensive Margin (All)

	(1) UT-Austin	(2) UT-Dallas	(3) U of Houston	(4) TAMU	(5) U of North Texas	(6) UT-Arlington	(7) Texas State	(8) UT-El Paso	(9) UT-San Antonio	(10) Texas Tech
Expect	0.017***	0.015***	0.001	0.006**	0.012**	0.004	-0.006	0.006	0.003	-0.002
	(0.003)	(0.004)	(0.004)	(0.003)	(0.006)	(0.007)	(0.006)	(0.007)	(0.005)	(0.006)
PF	0.012***	-0.002	-0.001	0.004	-0.001	-0.008	-0.001	0.009	-0.004	-0.001
	(0.003)	(0.004)	(0.004)	(0.003)	(0.006)	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)
SCH: STEM	0.001***	-0.000	0.002***	-0.003***	-0.002***	-0.003***	-0.003***	-0.001**	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SCH: non-STEM	-0.004***	-0.007***	-0.005***	-0.008***	-0.004***	-0.010***	-0.007***	-0.008***	-0.006***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GPA: STEM	0.035***	0.024***	0.042***	0.003	0.025***	0.053***	0.017***	0.003	0.032***	0.023***
	(0.004)	(0.005)	(0.004)	(0.003)	(0.006)	(0.008)	(0.005)	(0.007)	(0.006)	(0.007)
GPA: non-STEM	0.007	0.019***	0.010*	0.017***	0.014	0.018	0.026***	0.019**	-0.002	0.031***
	(0.005)	(0.006)	(0.005)	(0.003)	(0.009)	(0.012)	(0.009)	(0.009)	(0.009)	(0.010)
2nd semester	0.067**	-0.044	0.009	0.138***	-0.019	0.071	0.215*	0.044	0.049	0.296**
	(0.030)	(0.033)	(0.038)	(0.034)	(0.085)	(0.070)	(0.113)	(0.148)	(0.074)	(0.135)
3rd semester	0.049	-0.021	0.009	0.166***	-0.006	0.128*	0.278**	0.051	0.102	0.242*
	(0.031)	(0.034)	(0.039)	(0.034)	(0.085)	(0.070)	(0.113)	(0.148)	(0.075)	(0.135)
4th semester	0.048	-0.001	-0.010	0.229***	0.034	0.167**	0.346***	0.091	0.128*	0.237*
	(0.031)	(0.035)	(0.039)	(0.035)	(0.086)	(0.071)	(0.114)	(0.148)	(0.075)	(0.135)
5th semester	0.028	0.016	-0.048	0.292***	0.054	0.211***	0.344***	0.082	0.137*	0.217
	(0.032)	(0.036)	(0.041)	(0.035)	(0.086)	(0.072)	(0.114)	(0.148)	(0.076)	(0.135)
6th semester	0.030	0.034	-0.047	0.341***	0.084	0.270***	0.381***	0.104	0.153**	0.221
	(0.033)	(0.037)	(0.042)	(0.036)	(0.087)	(0.073)	(0.115)	(0.149)	(0.077)	(0.136)
7th semester	0.014	0.049	-0.051	0.399***	0.117	0.330***	0.413***	0.121	0.163**	0.271**
	(0.035)	(0.039)	(0.043)	(0.037)	(0.088)	(0.074)	(0.115)	(0.149)	(0.078)	(0.136)
8th semester	-0.013	0.054	-0.064	0.435***	0.141	0.382***	0.440***	0.144	0.173**	0.294**
	(0.036)	(0.041)	(0.045)	(0.038)	(0.089)	(0.076)	(0.116)	(0.150)	(0.079)	(0.137)
Constant	0.716***	0.891***	0.777***	0.790***	0.607***	0.558***	0.423***	0.762***	0.748***	0.489***
	(0.037)	(0.043)	(0.043)	(0.037)	(0.091)	(0.084)	(0.118)	(0.152)	(0.081)	(0.141)
Mean	0.797	0.896	0.828	0.877	0.621	0.654	0.591	0.691	0.752	0.726
SD	0.402	0.305	0.378	0.329	0.485	0.476	0.492	0.462	0.432	0.446
R^2	0.557	0.463	0.522	0.436	0.589	0.576	0.471	0.534	0.524	0.502
N of obs.	194,492	64,743	88,820	240,392	70,696	48,056	101,655	49,437	72,050	81,312

Notes: Standard errors (in parentheses) are clustered at the individual level. Significance levels are indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. SCH means cumulated credit hours earned. GPA means cumulative grade points average.

Table B.3. Placebo Test - Extensive Margin (Female)

	(1) UT-Austin	(2) UT-Dallas	(3) U of Houston	(4) TAMU	(5) U of North Texas	(6) UT-Arlington	(7) Texas State	(8) UT-El Paso	(9) UT-San Antonio	(10) Texas Tech
Expect	0.013***	-0.001	-0.000	-0.004	0.013	-0.009	-0.008	0.002	0.002	-0.014
	(0.004)	(0.007)	(0.007)	(0.004)	(0.008)	(0.010)	(0.007)	(0.010)	(0.008)	(0.010)
PF	0.010**	-0.010	-0.013*	0.008**	0.002	-0.026***	-0.003	0.012	-0.012	-0.001
	(0.005)	(0.007)	(0.007)	(0.004)	(0.008)	(0.010)	(0.007)	(0.010)	(0.008)	(0.010)
SCH: STEM	0.003***	0.003***	0.003***	-0.005***	-0.000	0.002***	-0.001***	0.000	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
SCH: non-STEM	-0.003***	-0.004***	-0.005***	-0.009***	-0.003***	-0.009***	-0.007***	-0.007***	-0.005***	-0.003***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
GPA: STEM	0.030***	0.009	0.032***	-0.010**	0.002	-0.005	-0.021***	-0.017*	0.002	-0.021**
	(0.005)	(0.008)	(0.007)	(0.005)	(0.009)	(0.010)	(0.007)	(0.010)	(0.008)	(0.010)
GPA: non-STEM	-0.011	0.002	-0.006	0.011**	-0.035***	0.069***	0.008	0.037***	-0.018	0.001
	(0.007)	(0.010)	(0.008)	(0.005)	(0.012)	(0.015)	(0.012)	(0.012)	(0.012)	(0.015)
2nd semester	0.076*	-0.013	0.013	0.039	-0.040	0.093*	0.018	0.068	-0.004	0.040*
	(0.046)	(0.048)	(0.064)	(0.052)	(0.060)	(0.051)	(0.067)	(0.283)	(0.029)	(0.023)
3rd semester	0.031	-0.021	0.009	0.094*	-0.015	0.103*	0.099	0.080	0.040	0.011
	(0.046)	(0.050)	(0.064)	(0.053)	(0.061)	(0.053)	(0.067)	(0.284)	(0.030)	(0.027)
4th semester	0.001	-0.052	-0.029	0.165***	-0.016	0.053	0.126*	0.101	0.032	-0.025
	(0.048)	(0.052)	(0.066)	(0.054)	(0.063)	(0.056)	(0.068)	(0.284)	(0.033)	(0.031)
5th semester	-0.054	-0.082	-0.101	0.254***	-0.044	-0.017	0.074	0.070	0.009	-0.095**
	(0.049)	(0.055)	(0.068)	(0.055)	(0.066)	(0.060)	(0.070)	(0.285)	(0.038)	(0.037)
6th semester	-0.079	-0.109*	-0.110	0.324***	-0.050	-0.011	0.090	0.064	-0.002	-0.110***
	(0.051)	(0.059)	(0.070)	(0.056)	(0.069)	(0.064)	(0.072)	(0.285)	(0.042)	(0.043)
7th semester	-0.116**	-0.123*	-0.125*	0.404***	-0.036	0.010	0.111	0.078	-0.004	-0.028
	(0.054)	(0.064)	(0.072)	(0.058)	(0.073)	(0.070)	(0.075)	(0.286)	(0.048)	(0.050)
8th semester	-0.170***	-0.168**	-0.141*	0.447***	-0.033	0.055	0.128	0.092	-0.025	-0.056
	(0.056)	(0.068)	(0.075)	(0.060)	(0.077)	(0.076)	(0.078)	(0.287)	(0.053)	(0.056)
Constant	0.746***	0.946***	0.837***	0.942***	0.856***	0.686***	0.826***	0.754***	0.916***	0.908***
	(0.055)	(0.065)	(0.071)	(0.056)	(0.075)	(0.078)	(0.077)	(0.287)	(0.048)	(0.061)
Mean	0.746	0.886	0.795	0.851	0.592	0.668	0.598	0.674	0.713	0.677
SD	0.435	0.318	0.404	0.356	0.491	0.471	0.490	0.469	0.452	0.467
R^2	0.554	0.508	0.538	0.451	0.540	0.545	0.460	0.532	0.533	0.439
N of obs.	103,431	26,254	43,269	106,620	40,078	26,001	62,669	27,786	33,179	28,421

Notes: Standard errors (in parentheses) are clustered at the individual level. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. SCH means cumulated credit hours earned. GPA means cumulative grade points average.

Table B.4. Placebo Test - Extensive Margin (Male)

	(1) UT-Austin	(2) UT-Dallas	(3) U of Houston	(4) TAMU	(5) U of North Texas	(6) UT-Arlington	(7) Texas State	(8) UT-El Paso	(9) UT-San Antonio	(10) Texas Tech
Expect	0.007**	0.006	-0.008	0.008***	0.010	-0.001	-0.002	0.003	-0.000	-0.001
	(0.004)	(0.004)	(0.005)	(0.003)	(0.008)	(0.007)	(0.008)	(0.009)	(0.006)	(0.011)
PF	0.006	-0.008	-0.003	-0.001	-0.006	-0.014*	-0.002	0.000	-0.007	-0.011
	(0.004)	(0.005)	(0.006)	(0.003)	(0.008)	(0.007)	(0.008)	(0.008)	(0.006)	(0.011)
SCH: STEM	0.001***	0.001***	0.002***	-0.003***	-0.000	0.001**	-0.001	0.000	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SCH: non-STEM	-0.003***	-0.004***	-0.004***	-0.007***	-0.002***	-0.008***	-0.004***	-0.005***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
GPA: STEM	0.018***	0.011**	0.032***	-0.004	0.015*	0.017**	0.010	-0.010	0.018***	0.030**
	(0.005)	(0.005)	(0.005)	(0.003)	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.012)
GPA: non-STEM	0.005	0.011**	0.013*	0.017***	0.009	0.003	0.021*	0.013	0.007	0.028*
	(0.005)	(0.005)	(0.007)	(0.003)	(0.011)	(0.011)	(0.013)	(0.011)	(0.010)	(0.014)
2nd semester	0.038	-0.048**	-0.027	0.161***	-0.113**	0.006	0.034	0.046	0.015	-0.022
	(0.031)	(0.023)	(0.038)	(0.038)	(0.047)	(0.046)	(0.084)	(0.110)	(0.020)	(0.016)
3rd semester	0.024	-0.052**	-0.030	0.194***	-0.093*	0.013	0.106	0.068	0.038*	-0.069***
	(0.032)	(0.024)	(0.039)	(0.038)	(0.048)	(0.048)	(0.085)	(0.110)	(0.022)	(0.019)
4th semester	0.021	-0.057**	-0.057	0.255***	-0.101**	0.022	0.139	0.082	0.027	-0.088***
	(0.033)	(0.026)	(0.040)	(0.039)	(0.049)	(0.050)	(0.086)	(0.110)	(0.025)	(0.023)
5th semester	0.010	-0.067**	-0.082**	0.309***	-0.109**	0.016	0.145*	0.077	0.014	-0.108***
	(0.035)	(0.028)	(0.042)	(0.040)	(0.052)	(0.052)	(0.088)	(0.111)	(0.028)	(0.028)
6th semester	0.006	-0.076**	-0.102**	0.344***	-0.115**	0.017	0.144	0.091	0.006	-0.154***
	(0.037)	(0.031)	(0.044)	(0.041)	(0.054)	(0.055)	(0.090)	(0.112)	(0.032)	(0.033)
7th semester	-0.004	-0.082**	-0.110**	0.405***	-0.109*	0.030	0.136	0.078	-0.012	-0.143***
	(0.039)	(0.034)	(0.047)	(0.042)	(0.058)	(0.058)	(0.092)	(0.113)	(0.036)	(0.039)
8th semester	-0.029	-0.094**	-0.135***	0.452***	-0.109*	0.037	0.136	0.093	-0.026	-0.155***
	(0.042)	(0.037)	(0.049)	(0.043)	(0.061)	(0.061)	(0.095)	(0.115)	(0.040)	(0.045)
Constant	0.823***	0.955***	0.847***	0.805***	0.827***	0.920***	0.679***	0.835***	0.826***	0.728***
	(0.040)	(0.034)	(0.044)	(0.041)	(0.060)	(0.061)	(0.094)	(0.118)	(0.039)	(0.055)
Mean	0.875	0.935	0.880	0.920	0.735	0.845	0.754	0.793	0.849	0.769
SD	0.330	0.247	0.325	0.271	0.441	0.362	0.430	0.405	0.359	0.421
R^2	0.564	0.493	0.508	0.406	0.584	0.571	0.494	0.588	0.546	0.452
N of obs.	90,921	38,608	46,277	134,396	34,704	24,834	39,712	23,488	34,168	20,210

Notes: Standard errors (in parentheses) are clustered at the individual level. Significance levels are indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. SCH means cumulated credit hours earned. GPA means cumulative grade points average.

Table B.5. Placebo Test - Extensive Margin (Non-STEM Majors)

	(1) UT-Austin	(2) UT-Dallas	(3) U of Houston	(4) TAMU	(5) U of North Texas	(6) UT-Arlington	(7) Texas State	(8) UT-El Paso	(9) UT-San Antonio	(10) Texas Tech
Expect	0.025***	0.017	-0.008	0.004	0.019**	-0.008	-0.008	0.006	0.005	-0.013
	(0.007)	(0.014)	(0.010)	(0.006)	(0.010)	(0.013)	(0.008)	(0.012)	(0.010)	(0.011)
PF	0.019***	-0.025*	-0.014	0.011*	-0.003	-0.032***	-0.002	0.017	-0.014	-0.011
	(0.007)	(0.014)	(0.010)	(0.006)	(0.009)	(0.012)	(0.008)	(0.012)	(0.010)	(0.011)
SCH: STEM	-0.006***	0.000	-0.002**	-0.014***	-0.014***	-0.020***	-0.016***	-0.016***	-0.007***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SCH: non-STEM	0.001	-0.004***	-0.003***	-0.010***	-0.002***	-0.004***	-0.006***	-0.004***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
GPA: STEM	0.043***	0.015	0.036***	-0.006	-0.003	-0.027*	-0.015**	-0.019	-0.016	0.000
	(0.007)	(0.015)	(0.008)	(0.006)	(0.011)	(0.014)	(0.007)	(0.013)	(0.011)	(0.011)
GPA: non-STEM	-0.010	0.027	0.016	0.029***	-0.044***	0.096***	0.011	0.043***	-0.017	0.019
	(0.011)	(0.019)	(0.011)	(0.008)	(0.016)	(0.019)	(0.012)	(0.015)	(0.015)	(0.016)
2nd semester	0.119**	-0.029	-0.029	0.189***	0.031	0.079	0.058	0.099	0.035	0.013
	(0.050)	(0.084)	(0.079)	(0.043)	(0.114)	(0.058)	(0.074)	(0.205)	(0.040)	(0.026)
3rd semester	0.070	-0.040	-0.023	0.306***	0.108	0.109*	0.188**	0.123	0.102**	-0.013
	(0.051)	(0.087)	(0.079)	(0.044)	(0.115)	(0.062)	(0.075)	(0.206)	(0.042)	(0.029)
4th semester	0.039	-0.062	-0.076	0.444***	0.123	0.063	0.253***	0.160	0.100**	-0.035
	(0.053)	(0.090)	(0.081)	(0.046)	(0.117)	(0.067)	(0.076)	(0.207)	(0.046)	(0.033)
5th semester	-0.042	-0.103	-0.171**	0.568***	0.102	-0.035	0.240***	0.104	0.073	-0.094**
	(0.057)	(0.095)	(0.083)	(0.048)	(0.119)	(0.072)	(0.078)	(0.209)	(0.050)	(0.039)
6th semester	-0.070	-0.126	-0.183**	0.675***	0.113	-0.044	0.277***	0.105	0.074	-0.105**
	(0.060)	(0.101)	(0.086)	(0.051)	(0.121)	(0.079)	(0.080)	(0.210)	(0.055)	(0.044)
7th semester	-0.130**	-0.133	-0.191**	0.828***	0.153	-0.029	0.317***	0.092	0.070	-0.022
	(0.065)	(0.109)	(0.090)	(0.055)	(0.125)	(0.086)	(0.083)	(0.212)	(0.062)	(0.052)
8th semester	-0.209***	-0.164	-0.205**	0.922***	0.184	0.015	0.357***	0.112	0.049	-0.034
	(0.070)	(0.116)	(0.093)	(0.059)	(0.128)	(0.094)	(0.086)	(0.215)	(0.068)	(0.058)
Constant	0.559***	0.778***	0.762***	0.680***	0.708***	0.718***	0.723***	0.655***	0.818***	0.793***
	(0.067)	(0.116)	(0.087)	(0.052)	(0.128)	(0.091)	(0.083)	(0.213)	(0.063)	(0.062)
Mean	0.552	0.696	0.653	0.714	0.410	0.481	0.514	0.470	0.553	0.594
SD	0.497	0.460	0.476	0.452	0.492	0.500	0.500	0.499	0.497	0.491
R^2	0.440	0.436	0.467	0.392	0.395	0.459	0.395	0.460	0.452	0.386
N of obs.	79,997	16,755	38,871	87,821	41,892	23,255	70,044	24,875	31,551	32,886

Notes: Standard errors (in parentheses) are clustered at the individual level. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. SCH means cumulated credit hours earned. GPA means cumulative grade points average.

Table B.6. Placebo Test - Extensive Margin (STEM Majors)

	(1) UT-Austin	(2) UT-Dallas	(3) U of Houston	(4) TAMU	(5) U of North Texas	(6) UT-Arlington	(7) Texas State	(8) UT-El Paso	(9) UT-San Antonio	(10) Texas Tech
Expect	0.001	-0.001	-0.001	0.003***	0.004	0.005*	0.004	-0.001	0.002	0.010
	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.006)
PF	0.001	-0.004	-0.003	0.001	0.000	-0.001	0.002	0.001	-0.004	0.006
	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.006)
SCH: STEM	0.000	-0.000**	0.001***	-0.001***	-0.000	-0.002***	-0.001***	-0.002***	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SCH: non-STEM	-0.001***	0.000	-0.001***	-0.001***	0.000	-0.000	0.003***	0.003***	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
GPA: STEM	0.004**	0.006***	0.014***	0.001	0.016***	0.015***	0.009**	0.021***	0.010***	0.016***
	(0.002)	(0.002)	(0.003)	(0.001)	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)	(0.006)
GPA: non-STEM	0.007***	0.003	0.000	0.001	0.009	0.002	0.011	0.002	0.007	0.019**
	(0.003)	(0.003)	(0.004)	(0.001)	(0.006)	(0.005)	(0.009)	(0.007)	(0.006)	(0.008)
2nd semester	0.008	0.015	-0.041	-0.004	-0.020	-0.015	0.006	0.001	0.002	0.007
	(0.016)	(0.015)	(0.045)	(0.035)	(0.017)	(0.017)	(0.047)	(0.015)	(0.011)	(0.007)
3rd semester	-0.003	0.016	-0.052	-0.001	-0.028	0.004	0.018	-0.004	0.006	-0.015
	(0.017)	(0.015)	(0.045)	(0.035)	(0.018)	(0.018)	(0.047)	(0.016)	(0.012)	(0.009)
4th semester	-0.003	0.017	-0.064	0.017	-0.032	0.024	0.027	-0.004	0.004	-0.014
	(0.017)	(0.016)	(0.046)	(0.036)	(0.020)	(0.019)	(0.048)	(0.018)	(0.014)	(0.012)
5th semester	-0.001	0.023	-0.073	0.041	-0.026	0.054***	0.037	0.010	0.012	-0.010
	(0.018)	(0.018)	(0.047)	(0.036)	(0.022)	(0.021)	(0.050)	(0.021)	(0.016)	(0.015)
6th semester	-0.005	0.025	-0.082*	0.054	-0.026	0.079***	0.045	0.022	0.017	-0.035*
	(0.020)	(0.019)	(0.048)	(0.036)	(0.024)	(0.022)	(0.051)	(0.023)	(0.018)	(0.019)
7th semester	-0.004	0.032	-0.087*	0.069*	-0.018	0.102***	0.054	0.039	0.021	-0.022
	(0.021)	(0.021)	(0.049)	(0.036)	(0.026)	(0.025)	(0.053)	(0.026)	(0.021)	(0.022)
8th semester	-0.020	0.025	-0.103**	0.083**	-0.026	0.112***	0.056	0.050*	0.025	-0.031
	(0.022)	(0.023)	(0.050)	(0.037)	(0.029)	(0.026)	(0.055)	(0.028)	(0.024)	(0.026)
Constant	0.952***	0.954***	0.993***	1.007***	0.923***	0.959***	0.848***	0.871***	0.917***	0.859***
	(0.020)	(0.019)	(0.047)	(0.036)	(0.027)	(0.024)	(0.059)	(0.030)	(0.022)	(0.035)
Mean	0.984	0.991	0.982	0.990	0.975	0.986	0.972	0.971	0.983	0.969
SD	0.124	0.095	0.134	0.099	0.156	0.119	0.165	0.167	0.128	0.172
R^2	0.308	0.240	0.373	0.286	0.382	0.255	0.369	0.293	0.339	0.344
N of obs.	114,355	48,107	50,675	153,195	32,890	27,580	32,337	26,399	35,796	15,745

Notes: Standard errors (in parentheses) are clustered at the individual level. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. SCH means cumulated credit hours earned. GPA means cumulative grade points average.

Table B.7. Placebo Test - Intensive Margin (All)

	(1) UT-Austin	(2) UT-Dallas	(3) U of Houston	(4) TAMU	(5) U of North Texas	(6) UT-Arlington	(7) Texas State	(8) UT-El Paso	(9) UT-San Antonio	(10) Texas Tech
Expect	0.007***	0.019***	0.005	0.006***	0.008*	0.008	0.000	0.012**	0.006	-0.004
	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.005)	(0.003)	(0.005)	(0.004)	(0.004)
PF	0.006***	0.015***	0.011***	-0.000	-0.004	-0.002	-0.006	0.001	-0.001	0.003
	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.005)	(0.003)	(0.005)	(0.004)	(0.004)
SCH: STEM	-0.000**	-0.002***	0.001**	-0.002***	0.001***	0.000	0.002***	0.002***	0.001***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SCH: non-STEM	-0.001***	-0.003***	-0.003***	-0.002***	-0.003***	-0.006***	-0.004***	-0.004***	-0.004***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GPA: STEM	0.029***	0.049***	0.053***	-0.016***	0.029***	0.053***	0.023***	0.017***	0.044***	0.036***
	(0.003)	(0.005)	(0.004)	(0.003)	(0.005)	(0.006)	(0.004)	(0.006)	(0.005)	(0.005)
GPA: non-STEM	-0.006	-0.016***	-0.011**	0.015***	-0.003	-0.007	0.002	-0.008	-0.017***	0.010
	(0.004)	(0.006)	(0.005)	(0.003)	(0.006)	(0.009)	(0.006)	(0.007)	(0.006)	(0.007)
2nd semester	0.020	-0.026	0.032	0.067***	-0.056	0.022	0.209***	-0.038	0.053	0.158**
	(0.018)	(0.035)	(0.052)	(0.023)	(0.073)	(0.041)	(0.078)	(0.116)	(0.048)	(0.069)
3rd semester	0.048***	0.075**	0.098*	0.106***	-0.022	0.140***	0.290***	-0.003	0.160***	0.183***
	(0.019)	(0.036)	(0.052)	(0.023)	(0.073)	(0.041)	(0.079)	(0.116)	(0.048)	(0.069)
4th semester	0.057***	0.115***	0.108**	0.165***	0.031	0.202***	0.360***	0.061	0.205***	0.194***
	(0.019)	(0.037)	(0.053)	(0.023)	(0.073)	(0.042)	(0.079)	(0.117)	(0.049)	(0.069)
5th semester	0.067***	0.177***	0.130**	0.227***	0.131*	0.287***	0.382***	0.112	0.253***	0.209***
	(0.020)	(0.038)	(0.054)	(0.024)	(0.074)	(0.043)	(0.079)	(0.117)	(0.049)	(0.070)
6th semester	0.071***	0.204***	0.147***	0.261***	0.168**	0.314***	0.405***	0.141	0.274***	0.213***
	(0.021)	(0.040)	(0.054)	(0.025)	(0.074)	(0.044)	(0.080)	(0.117)	(0.050)	(0.070)
7th semester	0.062***	0.239***	0.167***	0.294***	0.196***	0.354***	0.415***	0.166	0.286***	0.247***
	(0.023)	(0.042)	(0.055)	(0.026)	(0.075)	(0.046)	(0.080)	(0.118)	(0.052)	(0.071)
8th semester	0.052**	0.250***	0.158***	0.308***	0.208***	0.376***	0.427***	0.171	0.283***	0.255***
	(0.024)	(0.043)	(0.056)	(0.027)	(0.076)	(0.048)	(0.081)	(0.118)	(0.053)	(0.072)
Constant	0.439***	0.534***	0.376***	0.543***	0.309***	0.230***	0.008	0.428***	0.286***	0.196***
	(0.025)	(0.044)	(0.055)	(0.026)	(0.076)	(0.053)	(0.081)	(0.120)	(0.054)	(0.075)
Mean	0.523	0.653	0.556	0.614	0.385	0.452	0.342	0.462	0.492	0.475
SD	0.357	0.328	0.357	0.340	0.381	0.399	0.366	0.392	0.379	0.386
R^2	0.711	0.582	0.650	0.629	0.710	0.692	0.662	0.627	0.670	0.726
N of obs.	193,597	64,268	88,452	239,230	69,576	47,414	99,754	48,574	71,334	80,369

Notes: Standard errors (in parentheses) are clustered at the individual level. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. SCH means cumulated credit hours earned. GPA means cumulative grade points average.

Table B.8. Placebo Test - Intensive Margin (Female)

	(1) UT-Austin	(2) UT-Dallas	(3) U of Houston	(4) TAMU	(5) U of North Texas	(6) UT-Arlington	(7) Texas State	(8) UT-El Paso	(9) UT-San Antonio	(10) Texas Tech
Expect	0.003	0.013**	0.005	-0.002	0.010**	-0.002	-0.001	0.013*	0.003	-0.004
	(0.003)	(0.006)	(0.005)	(0.003)	(0.005)	(0.007)	(0.004)	(0.007)	(0.006)	(0.006)
PF	0.003	0.005	0.006	0.003	0.003	-0.010*	-0.003	0.003	-0.002	0.003
	(0.003)	(0.006)	(0.005)	(0.003)	(0.005)	(0.006)	(0.004)	(0.007)	(0.005)	(0.005)
SCH: STEM	-0.000	-0.000	0.000	-0.003***	0.003***	0.000	0.002***	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SCH: non-STEM	-0.001***	-0.002***	-0.003***	-0.004***	-0.002***	-0.006***	-0.003***	-0.003***	-0.002***	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GPA: STEM	0.023***	0.036***	0.034***	-0.025***	0.015***	0.038***	0.003	0.002	0.027***	-0.008
	(0.003)	(0.008)	(0.005)	(0.004)	(0.005)	(0.008)	(0.004)	(0.008)	(0.006)	(0.006)
GPA: non-STEM	-0.006	-0.009	-0.011*	0.015***	-0.026***	0.025**	0.011*	0.021**	-0.015*	-0.012
	(0.005)	(0.009)	(0.007)	(0.004)	(0.007)	(0.011)	(0.006)	(0.009)	(0.008)	(0.009)
2nd semester	0.023	-0.008	0.081	-0.025	-0.091	0.093**	-0.003	-0.020	0.017	0.011
	(0.025)	(0.038)	(0.073)	(0.037)	(0.072)	(0.040)	(0.033)	(0.168)	(0.024)	(0.018)
3rd semester	0.036	0.071*	0.143*	0.009	-0.078	0.163***	0.073**	0.015	0.095***	0.012
	(0.026)	(0.040)	(0.073)	(0.037)	(0.073)	(0.042)	(0.034)	(0.169)	(0.026)	(0.020)
4th semester	0.030	0.077*	0.154**	0.063*	-0.064	0.181***	0.112***	0.057	0.105***	-0.006
	(0.027)	(0.042)	(0.074)	(0.038)	(0.074)	(0.044)	(0.035)	(0.169)	(0.028)	(0.023)
5th semester	0.023	0.091**	0.163**	0.141***	-0.022	0.222***	0.101***	0.075	0.119***	-0.031
	(0.029)	(0.046)	(0.075)	(0.039)	(0.075)	(0.048)	(0.036)	(0.170)	(0.031)	(0.027)
6th semester	0.019	0.079	0.178**	0.187***	-0.019	0.246***	0.111***	0.075	0.111***	-0.054*
	(0.030)	(0.050)	(0.076)	(0.041)	(0.076)	(0.051)	(0.038)	(0.171)	(0.034)	(0.031)
7th semester	0.004	0.087	0.202***	0.235***	-0.017	0.281***	0.111***	0.085	0.101***	-0.032
	(0.032)	(0.054)	(0.078)	(0.042)	(0.077)	(0.056)	(0.040)	(0.172)	(0.039)	(0.036)
8th semester	-0.003	0.071	0.202**	0.256***	-0.026	0.313***	0.115***	0.086	0.083*	-0.052
	(0.034)	(0.059)	(0.080)	(0.044)	(0.079)	(0.060)	(0.042)	(0.174)	(0.042)	(0.041)
Constant	0.399***	0.520***	0.358***	0.610***	0.414***	0.173***	0.238***	0.340**	0.341***	0.419***
	(0.033)	(0.057)	(0.077)	(0.041)	(0.077)	(0.059)	(0.039)	(0.172)	(0.037)	(0.040)
Mean	0.438	0.612	0.499	0.541	0.321	0.390	0.299	0.410	0.419	0.335
SD	0.347	0.330	0.357	0.340	0.351	0.362	0.334	0.373	0.364	0.316
R^2	0.732	0.648	0.687	0.655	0.732	0.679	0.667	0.639	0.689	0.620
N of obs.	103,272	26,161	43,138	106,496	39,797	25,865	62,243	27,502	32,919	28,213

Notes: Standard errors (in parentheses) are clustered at the individual level. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. SCH means cumulated credit hours earned. GPA means cumulative grade points average.

Table B.9. Placebo Test - Intensive Margin (Male)

	(1) UT-Austin	(2) UT-Dallas	(3) U of Houston	(4) TAMU	(5) U of North Texas	(6) UT-Arlington	(7) Texas State	(8) UT-El Paso	(9) UT-San Antonio	(10) Texas Tech
Expect	0.005	0.011**	0.003	0.008***	0.009	0.014**	-0.004	0.011	0.006	0.001
	(0.003)	(0.005)	(0.005)	(0.003)	(0.006)	(0.006)	(0.005)	(0.007)	(0.005)	(0.007)
PF	0.006*	0.011**	0.010**	-0.002	-0.005	-0.005	-0.011**	-0.007	-0.006	-0.011
	(0.003)	(0.005)	(0.005)	(0.003)	(0.006)	(0.006)	(0.005)	(0.008)	(0.006)	(0.007)
SCH: STEM	-0.001**	-0.001***	0.001***	-0.002***	0.002***	-0.000	0.001***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SCH: non-STEM	-0.001**	-0.001	-0.002***	-0.003***	-0.002***	-0.004***	-0.003***	-0.003***	-0.002***	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GPA: STEM	0.022***	0.054***	0.055***	-0.026***	0.032***	0.055***	0.024***	0.016**	0.041***	0.039***
	(0.004)	(0.007)	(0.005)	(0.003)	(0.006)	(0.008)	(0.006)	(0.008)	(0.006)	(0.009)
GPA: non-STEM	-0.006	-0.008	-0.008	0.021***	0.013	-0.023**	0.010	0.001	-0.005	0.018
	(0.005)	(0.007)	(0.007)	(0.003)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)	(0.011)
2nd semester	0.015	-0.012	0.056	0.105***	-0.177***	-0.002	0.060	-0.006	0.024	-0.042***
	(0.024)	(0.040)	(0.065)	(0.027)	(0.061)	(0.042)	(0.064)	(0.143)	(0.019)	(0.014)
3rd semester	0.056**	0.052	0.119*	0.165***	-0.134**	0.101**	0.177***	0.024	0.116***	-0.046***
	(0.025)	(0.041)	(0.066)	(0.028)	(0.061)	(0.043)	(0.064)	(0.143)	(0.021)	(0.017)
4th semester	0.076***	0.075*	0.121*	0.228***	-0.098	0.165***	0.257***	0.073	0.148***	-0.054**
	(0.026)	(0.043)	(0.066)	(0.029)	(0.062)	(0.044)	(0.066)	(0.143)	(0.024)	(0.021)
5th semester	0.099***	0.135***	0.149**	0.286***	-0.021	0.243***	0.303***	0.132	0.188***	-0.064**
	(0.028)	(0.045)	(0.068)	(0.030)	(0.063)	(0.047)	(0.067)	(0.144)	(0.027)	(0.026)
6th semester	0.107***	0.154***	0.153**	0.315***	-0.001	0.253***	0.322***	0.168	0.195***	-0.096***
	(0.030)	(0.048)	(0.069)	(0.031)	(0.065)	(0.049)	(0.069)	(0.144)	(0.031)	(0.031)
7th semester	0.106***	0.181***	0.161**	0.348***	0.012	0.285***	0.329***	0.186	0.192***	-0.105***
	(0.032)	(0.051)	(0.071)	(0.033)	(0.067)	(0.053)	(0.071)	(0.145)	(0.036)	(0.037)
8th semester	0.093***	0.180***	0.141*	0.359***	0.007	0.303***	0.334***	0.185	0.174***	-0.112***
	(0.034)	(0.054)	(0.072)	(0.034)	(0.069)	(0.057)	(0.074)	(0.146)	(0.040)	(0.042)
Constant	0.525***	0.513***	0.362***	0.563***	0.429***	0.444***	0.186***	0.424***	0.342***	0.279***
	(0.033)	(0.051)	(0.069)	(0.032)	(0.066)	(0.056)	(0.070)	(0.149)	(0.035)	(0.042)
Mean	0.622	0.701	0.619	0.678	0.475	0.611	0.465	0.553	0.597	0.439
SD	0.337	0.301	0.338	0.315	0.382	0.359	0.372	0.379	0.361	0.346
R^2	0.692	0.575	0.624	0.598	0.730	0.674	0.678	0.649	0.661	0.625
N of obs.	90,662	38,386	46,047	134,157	34,335	24,680	39,307	23,191	33,860	19,893

Notes: Standard errors (in parentheses) are clustered at the individual level. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. SCH means cumulated credit hours earned. GPA means cumulative grade points average.

Table B.10. Placebo Test - Intensive Margin (Non-STEM Majors)

	(1) UT-Austin	(2) UT-Dallas	(3) U of Houston	(4) TAMU	(5) U of North Texas	(6) UT-Arlington	(7) Texas State	(8) UT-El Paso	(9) UT-San Antonio	(10) Texas Tech
Expect	0.004	0.027***	0.008	0.004	0.008**	0.004	-0.002	0.012*	0.008	-0.003
	(0.003)	(0.008)	(0.005)	(0.004)	(0.004)	(0.006)	(0.004)	(0.006)	(0.005)	(0.005)
PF	0.006**	0.006	0.002	0.006*	-0.000	-0.012**	-0.002	-0.000	-0.003	-0.005
	(0.003)	(0.008)	(0.005)	(0.004)	(0.004)	(0.006)	(0.004)	(0.006)	(0.005)	(0.005)
SCH: STEM	-0.006***	-0.004***	-0.005***	-0.008***	-0.007***	-0.012***	-0.010***	-0.009***	-0.006***	-0.005***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
SCH: non-STEM	0.002***	0.000	0.000	-0.002***	-0.001*	-0.001***	-0.002***	-0.001*	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GPA: STEM	0.022***	0.022**	0.022***	0.005	0.004	0.010	0.002	-0.007	0.006	0.010*
	(0.003)	(0.010)	(0.005)	(0.004)	(0.005)	(0.007)	(0.004)	(0.007)	(0.006)	(0.006)
GPA: non-STEM	0.001	-0.014	0.006	0.015***	-0.019***	0.038***	0.011**	0.023***	-0.010	0.003
	(0.005)	(0.012)	(0.007)	(0.005)	(0.006)	(0.010)	(0.006)	(0.008)	(0.007)	(0.008)
2nd semester	0.035	-0.051	0.080	0.124***	0.039	0.051	-0.002	-0.003	0.010	0.018
	(0.023)	(0.052)	(0.052)	(0.027)	(0.039)	(0.037)	(0.032)	(0.080)	(0.023)	(0.017)
3rd semester	0.015	0.004	0.130**	0.167***	0.068*	0.085**	0.088***	0.032	0.067***	0.014
	(0.023)	(0.054)	(0.053)	(0.027)	(0.040)	(0.039)	(0.032)	(0.081)	(0.025)	(0.019)
4th semester	-0.010	0.001	0.108**	0.213***	0.085**	0.076*	0.139***	0.072	0.074***	0.009
	(0.024)	(0.056)	(0.054)	(0.028)	(0.041)	(0.041)	(0.033)	(0.082)	(0.027)	(0.021)
5th semester	-0.052**	-0.035	0.072	0.260***	0.093**	0.061	0.146***	0.048	0.070**	-0.008
	(0.026)	(0.059)	(0.056)	(0.030)	(0.042)	(0.044)	(0.034)	(0.083)	(0.030)	(0.025)
6th semester	-0.078***	-0.051	0.065	0.298***	0.102**	0.059	0.165***	0.042	0.055*	-0.026
	(0.028)	(0.063)	(0.058)	(0.032)	(0.043)	(0.047)	(0.035)	(0.085)	(0.033)	(0.028)
7th semester	-0.117***	-0.075	0.058	0.368***	0.114**	0.068	0.173***	0.027	0.038	-0.005
	(0.030)	(0.068)	(0.060)	(0.035)	(0.045)	(0.052)	(0.037)	(0.087)	(0.036)	(0.033)
8th semester	-0.151***	-0.080	0.058	0.394***	0.128***	0.086	0.194***	0.025	0.017	-0.009
	(0.033)	(0.073)	(0.063)	(0.037)	(0.048)	(0.056)	(0.039)	(0.089)	(0.040)	(0.037)
Constant	0.185***	0.411***	0.209***	0.217***	0.201***	0.198***	0.212***	0.258***	0.274***	0.268***
	(0.031)	(0.072)	(0.058)	(0.033)	(0.046)	(0.052)	(0.036)	(0.085)	(0.034)	(0.034)
Mean	0.212	0.327	0.288	0.322	0.142	0.182	0.192	0.196	0.223	0.235
SD	0.241	0.301	0.285	0.282	0.218	0.238	0.243	0.260	0.260	0.255
R^2	0.559	0.602	0.564	0.494	0.530	0.503	0.470	0.490	0.529	0.463
N of obs.	79,801	16,652	38,710	87,645	41,517	23,124	69,492	24,620	31,299	32,532

Notes: Standard errors (in parentheses) are clustered at the individual level. Significance levels are indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. SCH means cumulated credit hours earned. GPA means cumulative grade points average.

Table B.11. Placebo Test - Intensive Margin (STEM Majors)

	(1) UT-Austin	(2) UT-Dallas	(3) U of Houston	(4) TAMU	(5) U of North Texas	(6) UT-Arlington	(7) Texas State	(8) UT-El Paso	(9) UT-San Antonio	(10) Texas Tech
Expect	0.004	0.003	-0.002	0.001	0.013**	0.013**	0.004	0.009	0.007	0.025***
	(0.003)	(0.004)	(0.004)	(0.002)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.008)
PF	0.003	0.007*	0.008*	-0.003	0.001	0.007	-0.004	-0.000	-0.005	0.017**
	(0.003)	(0.004)	(0.004)	(0.002)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.008)
SCH: STEM	-0.003***	-0.006***	-0.002***	-0.005***	-0.001***	-0.006***	-0.003***	-0.003***	-0.003***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SCH: non-STEM	0.003***	0.011***	0.004***	0.006***	0.010***	0.011***	0.008***	0.017***	0.016***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GPA: STEM	0.021***	0.060***	0.035***	-0.043***	0.043***	0.056***	0.039***	0.045***	0.015***	0.034***
	(0.004)	(0.006)	(0.005)	(0.003)	(0.006)	(0.007)	(0.006)	(0.007)	(0.005)	(0.011)
GPA: non-STEM	-0.007	-0.003	-0.014**	0.018***	0.001	-0.032***	-0.016	-0.016*	0.007	0.022*
	(0.004)	(0.006)	(0.006)	(0.003)	(0.009)	(0.009)	(0.011)	(0.009)	(0.008)	(0.013)
2nd semester	0.027	0.088***	0.023	-0.023	-0.090**	-0.006	0.088**	-0.030	0.066***	-0.022
	(0.024)	(0.030)	(0.057)	(0.038)	(0.044)	(0.036)	(0.041)	(0.103)	(0.017)	(0.015)
3rd semester	0.079***	0.160***	0.065	0.034	-0.106**	0.078**	0.175***	-0.078	0.107***	0.008
	(0.025)	(0.031)	(0.057)	(0.039)	(0.045)	(0.038)	(0.043)	(0.104)	(0.019)	(0.018)
4th semester	0.114***	0.192***	0.083	0.106***	-0.100**	0.149***	0.262***	-0.075	0.125***	0.016
	(0.026)	(0.032)	(0.058)	(0.039)	(0.047)	(0.040)	(0.045)	(0.105)	(0.022)	(0.023)
5th semester	0.159***	0.277***	0.133**	0.189***	0.006	0.268***	0.330***	-0.024	0.176***	0.027
	(0.027)	(0.034)	(0.060)	(0.040)	(0.049)	(0.042)	(0.047)	(0.106)	(0.025)	(0.029)
6th semester	0.185***	0.314***	0.156**	0.235***	0.033	0.313***	0.377***	0.005	0.215***	0.018
	(0.029)	(0.037)	(0.061)	(0.040)	(0.051)	(0.045)	(0.050)	(0.107)	(0.028)	(0.034)
7th semester	0.200***	0.375***	0.193***	0.268***	0.062	0.378***	0.425***	0.039	0.245***	0.026
	(0.031)	(0.040)	(0.063)	(0.041)	(0.054)	(0.048)	(0.054)	(0.109)	(0.033)	(0.041)
8th semester	0.208***	0.391***	0.182***	0.288***	0.050	0.419***	0.447***	0.046	0.255***	0.024
	(0.033)	(0.043)	(0.065)	(0.042)	(0.056)	(0.051)	(0.057)	(0.110)	(0.036)	(0.047)
Constant	0.631***	0.406***	0.586***	0.813***	0.442***	0.477***	0.271***	0.391***	0.313***	0.372***
	(0.032)	(0.040)	(0.062)	(0.041)	(0.053)	(0.049)	(0.057)	(0.109)	(0.031)	(0.054)
Mean	0.743	0.782	0.770	0.786	0.711	0.764	0.735	0.739	0.762	0.676
SD	0.239	0.223	0.237	0.225	0.276	0.243	0.278	0.278	0.256	0.273
R^2	0.439	0.387	0.415	0.446	0.538	0.459	0.574	0.488	0.529	0.512
N of obs.	114,133	47,895	50,475	153,008	32,615	27,421	32,058	26,073	35,480	15,574

Notes: Standard errors (in parentheses) are clustered at the individual level. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. SCH means cumulated credit hours earned. GPA means cumulative grade points average.

C Details About Belief Updating

Since a Beta distribution is not a conjugate prior of the truncated normal likelihood of SAT scores, I assume that the belief always takes a form of Beta distribution and calculate the posterior α_{im0} and β_{im0} that best match the mean and variance implied by the actual posterior described in Equation 26.

$$f_{im}^{Posterior}(p) \quad \propto \quad \overbrace{p^{\alpha_{im}-1} \times (1-p)^{\beta_{im}-1}}^{\text{Contribution from the prior}} \times \overbrace{\frac{\frac{1}{\sigma_m^{SAT}}\phi\left(\frac{SAT_{im}-\mu_{im}^{SAT}}{\sigma_m^{SAT}}\right)}{\Phi\left(\frac{800-\mu_{im}^{SAT}}{\sigma_m^{SAT}}\right)-\Phi\left(\frac{200-\mu_{im}^{SAT}}{\sigma_m^{SAT}}\right)}}^{\text{Contribution from the SAT score likelihood}} \tag{26}$$

D Model with Concealing Choice

I assume that each period, students conceal the lowest grade whenever it's profitable (i.e. continuation value is higher). To be more specific, let $PF_{i,t}$ be the number of concealed grades for i at the beginning of t.

$$\max_{\vec{q}} \; \overbrace{U_t(\vec{q}, \Omega_{it})}^{\text{Flow cost of taking bundle } \vec{q}} + 0.95 \cdot \overbrace{\mathbb{E}_{\Omega'_{i,t+1}|\Omega_{it}}[V_{t+1}(\Omega'_{i,t+1}, PF_{i,t+1}|\Omega_{it}, PF_{it})|\vec{q}]}^{\text{Continuation value}} + \overbrace{\sigma\left(\eta_{idt} + \lambda^q\, \eta_{i\vec{q}t}\right)}^{\text{preference shock}} \tag{27}$$

After drawing grade shocks but before making the next period course choice, individuals decide whether to conceal the lowest grade or not. The trade-off is the benefit coming from increased GPA (β_1) versus the cost of concealing (β_5). The cost of concealing is estimated to match how much fraction of students concealed their grades during the expanded pass/fail grading policy in Spring 2021 at UT-Austin.

$$V_{t+1}(\Omega'_{i,t+1}, PF_{i,t+1}) = \begin{cases} V_{t+1}(\Omega'_{i,t+1}, PF_{it}+1) & \text{if } \; V_{t+1}(\Omega'_{i,t+1}, PF_{it}+1) > V_{t+1}(\Omega'_{i,t+1}, PF_{it}) \\ V_{t+1}(\Omega'_{i,t+1}, PF_{it}) & \text{otherwise} \end{cases} \tag{28}$$

$$\text{where} \quad V_{im} = \beta_{0m} + \; \beta_1 GPA_i + \; \beta_{2m} p_{im} + \; \beta_{3m} S_{im} + \; \beta_{4m}\left(p_{im}\cdot S_{im}\right) - \; \overbrace{\beta_5 PF_{i7}}^{\text{Cost of Concealing}}, \quad V_0 = 0 \tag{29}$$

E Auxiliary Moments

Table E.1. Model Fit (Aux 1)

	Female		Male	
	Data	Model	Data	Model
β_1^M: 1(m = STEM)	-0.4193***	-0.229***	-1.2030***	-0.537***
	(0.1177)	(0.0469)	(0.1804)	(0.0519)
β_2^M: 1(m = non-STEM)	-0.0894	-0.269***	-0.6803***	-0.472***
	(0.1916)	(0.0453)	(0.1394)	(0.0500)
β_3^M: 1(m = dropout) x Cum. GPA	-0.1399***	0.0391***	-0.1502***	-0.0148*
	(0.0299)	(0.00920)	(0.0292)	(0.00884)
β_4^M: 1(m = STEM) x Belief in STEM	-0.2898**	0.188***	1.1389***	1.097***
	(0.1291)	(0.0263)	(0.2438)	(0.0406)
β_5^M: 1(m = non-STEM) x Belief in non-STEM	-0.9487***	0.216***	-0.4430***	-0.0691**
	(0.2445)	(0.0284)	(0.1643)	(0.0269)
β_6^M: 1(m = STEM) x Course share in STEM	1.1542***	1.431***	2.5623***	1.959***
	(0.1954)	(0.0223)	(0.2423)	(0.0298)
β_7^M: 1(m = non-STEM) x Course share in non-STEM	0.4034	1.639***	0.8344***	1.088***
	(0.2881)	(0.0255)	(0.3029)	(0.0329)
β_8^M: 1(m = STEM) x (Belief x Course share) in STEM	0.5407**	0.169***	-1.5956***	-1.236***
	(0.2423)	(0.0472)	(0.3247)	(0.0596)
β_9^M: 1(m = non-STEM) x (Belief x Course share) in non-STEM	1.2981***	-0.112***	0.6390*	0.684***
	(0.3396)	(0.0433)	(0.3704)	(0.0578)
β_10^M: 1(m = STEM) x Total N courses	-0.0053**	0.00223**	-0.0110***	-0.00488***
	(0.0026)	(0.00113)	(0.0033)	(0.00136)
β_11^M: 1(m = non-STEM) x Total N courses	0.0029	-0.00146	0.0081***	0.00470***
	(0.0031)	(0.00113)	(0.0031)	(0.00136)
β_0^M: Constant	0.5141***	-0.129***	0.5427***	0.0718**
	(0.1046)	(0.0321)	(0.1000)	(0.0300)

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.2. Model Fit (Aux 4)

	STEM		non-STEM	
	Data	Moment	Data	Moment
β_1^T: Total N courses in STEM	0.0025	0.0456***	-0.0195***	-0.00702
	(0.0025)	(0.00643)	(0.0047)	(0.0115)
β_2^T: Total N courses in non-STEM	0.0168***	0.0980***	-0.0239***	-0.0651***
	(0.0053)	(0.0156)	(0.0029)	(0.00562)
β_3^T: Total N courses in STEM x Total N courses in non-STEM	-0.0016***	-0.00504***	0.0008***	0.00537***
	(0.0003)	(0.000795)	(0.0003)	(0.000550)
β_0^T: Constant	1.1347***	1.088***	1.5384***	2.234***
	(0.0601)	(0.155)	(0.0697)	(0.153)

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

F Asymptotic Variance of the Second Stage Estimates

Setup

Let the second-stage parameter be $\theta \in \mathbb{R}^p$ with true value θ_0. The first-stage parameter is $\alpha \in \mathbb{R}^r$, estimated by MLE as $\hat{\alpha}$ with

$$\sqrt{n}(\hat{\alpha} - \alpha_0) \xrightarrow{d} \mathcal{N}(0, V_\alpha).$$

The auxiliary estimator on the observed data is $\hat{\beta} \in \mathbb{R}^q$, with

$$\sqrt{n}(\hat{\beta} - \beta_0) \xrightarrow{d} \mathcal{N}(0, S_\beta), \quad \beta_0 := h(\theta_0, \alpha_0).$$

Define $h(\theta, \alpha) = \operatorname{plim} \tilde{\beta}(\theta, \alpha)$. Then Jacobians at the truth:

$$G_\theta := \frac{\partial h(\theta_0, \alpha_0)}{\partial \theta'} \in \mathbb{R}^{q \times p}, \qquad G_\alpha := \frac{\partial h(\theta_0, \alpha_0)}{\partial \alpha'} \in \mathbb{R}^{q \times r}.$$

Simulation noise in $\tilde{\beta}(\theta_0, \alpha_0)$ contributes

$$S_{\text{sim}} := \operatorname{Var}\Big(\sqrt{n}\, \tilde{\beta}(\theta_0, \alpha_0)\Big).$$

Finally, let

$$C := \operatorname{Cov}\Big(\sqrt{n}(\hat{\beta} - \beta_0),\, \sqrt{n}(\hat{\alpha} - \alpha_0)\Big) \in \mathbb{R}^{q \times r}.$$

Derivation of Asymptotic Variance

Define $m_n(\theta, \hat{\alpha}) := \hat{\beta} - \tilde{\beta}(\theta, \hat{\alpha})$. Around (θ_0, α_0),

$$m_n(\theta, \hat{\alpha}) \;\approx\; m_n(\theta_0, \alpha_0) - G_\theta(\theta - \theta_0) - G_\alpha(\hat{\alpha} - \alpha_0).$$

With identity weighting ($W = I$), the first-order condition yields

$$\sqrt{n}(\hat{\theta} - \theta_0) \;\approx\; (G_\theta' G_\theta)^{-1} G_\theta' \Big[\sqrt{n} m_n(\theta_0, \alpha_0) - G_\alpha \sqrt{n}(\hat{\alpha} - \alpha_0)\Big].$$

Define the driving term

$$U_n := \sqrt{n} m_n(\theta_0, \alpha_0) - G_\alpha \sqrt{n}(\hat{\alpha} - \alpha_0).$$

The variance is

$$\begin{aligned}\Omega &= \mathrm{Var}(U_n)\\ &= S_\beta + S_{\mathrm{sim}} + G_\alpha V_\alpha G_\alpha' - CG_\alpha' - G_\alpha C'.\end{aligned}$$

Therefore,

$$\sqrt{n}(\hat{\theta} - \theta_0) \xrightarrow{d} \mathcal{N}\Big(0,\ (G_\theta' G_\theta)^{-1} G_\theta' \, \Omega \, G_\theta (G_\theta' G_\theta)^{-1}\Big).$$

Standard Error Calculation

1. Estimate $\hat{S}_\beta$ using the auxiliary model's robust covariance estimator. Estimate $\hat{S}_{sim} = \frac{n}{n_s}\hat{S}_\beta$ where n is the number of observations in the data and n_{sim} is the number of simulated observations.

2. Estimate $\hat{V}_\alpha$ as the inverted observed information matrix from the first-stage MLE.

3. Estimate $\hat{G}_\theta$ and $\hat{G}_\alpha$ Use finite differences with common random numbers in the model:

$$\widehat{G}_{\theta,\cdot k} \approx \frac{\tilde{\beta}(\hat{\theta} + \eta e_k, \hat{\alpha}) - \tilde{\beta}(\hat{\theta} - \eta e_k, \hat{\alpha})}{2\eta}.$$

$$\widehat{G}_{\alpha,\cdot \ell} \approx \frac{\tilde{\beta}(\hat{\theta}, \hat{\alpha} + \eta e_\ell) - \tilde{\beta}(\hat{\theta}, \hat{\alpha} - \eta e_\ell)}{2\eta}.$$

4. Estimate $\hat{C}$: By joint bootstrap: resample the data B times, recompute $(\hat{\beta}^{*(b)}, \hat{\alpha}^{*(b)})$, and set

$$\hat{C} = \frac{n}{B}\sum_{b=1}^{B}(\hat{\beta}^{*(b)} - \hat{\beta})(\hat{\alpha}^{*(b)} - \hat{\alpha})'.$$

5. Estimate $\hat{\Omega}$:

$$\hat{\Omega} = \hat{S}_\beta + \hat{S}_{\mathrm{sim}} + \hat{G}_\alpha \hat{V}_\alpha \hat{G}_\alpha' - \hat{C}\hat{G}_\alpha' - \hat{G}_\alpha \hat{C}'.$$

6. Compute asymptotic variance of $\hat{\theta}$ and the standard errors are the square root of the diagonal terms:

$$\widehat{\mathrm{Var}}(\hat{\theta}) = \frac{1}{n}\,(\hat{G}_\theta' \hat{G}_\theta)^{-1} \hat{G}_\theta' \, \hat{\Omega} \, \hat{G}_\theta (\hat{G}_\theta' \hat{G}_\theta)^{-1}.$$

G Grouping Majors into STEM and non-STEM

Table G.1. CIP Code - Field Group Mapping

STEM/non-STEM	Group	CIP Code (2-digit)	Specific Major Name
non-STEM	Health/Education/Vocational	1	Agriculture, Agriculture Operations, and Related Sciences
non-STEM	Health/Education/Vocational	2	Agriculture, Agriculture Operations, and Related Sciences
non-STEM	Health/Education/Vocational	3	Natural Resources and Conservation
STEM	Engineering	4	Architecture and Related Services
non-STEM	Liberal Arts	5	Area, Ethnic, Cultural, and Gender Studies
STEM	Business/Economics	8	Business, Management, Marketing, and Related Support Services
non-STEM	Social Sciences	9	Communications, Journalism, and Related Programs
non-STEM	Social Sciences	10	Communications Technologies/Technicians and Support Services
STEM	Engineering	11	Computer and Inofrmation Sciences and Support Services
non-STEM	Health/Education/Vocational	12	Personal and Culinary Services
non-STEM	Health/Education/Vocational	13	Education
STEM	Engineering	14	Engineering
non-STEM	Health/Education/Vocational	15	Engineering Technologies/Technicians
non-STEM	Liberal Arts	16	Foreign Languages, Literatures, and Linguistics
non-STEM	Social Sciences	19	Family and Consumer Sciences/Human Sciences
non-STEM	Health/Education/Vocational	20	Vocational Home Economics
non-STEM	Social Sciences	22	Legal Professions and Studies
non-STEM	Liberal Arts	23	English Language and Literature/Letters
non-STEM	Liberal Arts	24	Liberal Arts and Sciences, General Studies and Humanities
non-STEM	Liberal Arts	25	Library Science
STEM	Science	26	Biological and Biomedical Sciences
STEM	Science	27	Mathmatics and Statistics
non-STEM	Health/Education/Vocational	28	Reserve Office Training Corps
non-STEM	Health/Education/Vocational	29	Military Technologies
non-STEM	Liberal Arts	30	Multi/Interdisciplinary Studies
non-STEM	Health/Education/Vocational	31	Parks, Recreation, Leisure, and Fitness Studies
non-STEM	Health/Education/Vocational	32	Basic Skills
non-STEM	Health/Education/Vocational	33	Citizenship Activities
non-STEM	Health/Education/Vocational	34	Health-Related Knowledge and Skills
non-STEM	Health/Education/Vocational	35	Interpersonal and Social Skills
non-STEM	Health/Education/Vocational	36	Leisure and Recreational Activities
non-STEM	Health/Education/Vocational	37	Personal Awareness and Self-Improvement
non-STEM	Liberal Arts	38	Philosophy and Religious Studies
non-STEM	Liberal Arts	39	Theology and Religious Vocations
STEM	Science	40	Physical Sciencs
non-STEM	Health/Education/Vocational	41	Science Technologies/Technicians
non-STEM	Social Sciences	42	Psychology
non-STEM	Health/Education/Vocational	43	Security and Protective Services
non-STEM	Social Sciences	44	Public Administration and Social Service Professions
non-STEM	Social Sciences	45	Social Sciences, General
non-STEM	Social Sciences	45	Anthropology
non-STEM	Social Sciences	45	Archeology
non-STEM	Social Sciences	45	Criminology
non-STEM	Social Sciences	45	Demography and Population Studies
non-STEM	Social Sciences	45	Geography and Cartography
non-STEM	Social Sciences	45	International Relations and Affairs
non-STEM	Social Sciences	45	Political Science and Government
non-STEM	Social Sciences	45	Sociology
non-STEM	Social Sciences	45	Urban Studies/Affairs
non-STEM	Social Sciences	45	Sociology and Anthropology
non-STEM	Social Sciences	45	Rural Sociology
non-STEM	Social Sciences	45	Social Sciences, Other
STEM	Business/Economics	4506	Economics
non-STEM	Health/Education/Vocational	46	Construction Trades
non-STEM	Health/Education/Vocational	47	Mechanic and Repair Technologies/Technicians
non-STEM	Health/Education/Vocational	48	Precision Production
non-STEM	Health/Education/Vocational	49	Transportation and Materials Moving
non-STEM	Liberal Arts	50	Visual and Performing Arts
non-STEM	Health/Education/Vocational	51	Health Professions and Related Clinical Sciences
STEM	Business/Economics	52	Business, Management, Marketing, and Related Support Services
non-STEM	Liberal Arts	54	History
non-STEM	Health/Education/Vocational	60	Residency Programs