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ABSTRACT

What happens when college students cannot enroll in the courses they want? Using conditional random assignment to oversubscribed courses at a large public university, we find that a course shutout reduces the probability that a student ever takes any course in the corresponding subject by 30%. Course shutouts are particularly disruptive for female students, reducing women's cumulative GPAs, probability of majoring in STEM, on-time graduation, and early-career earnings. In contrast, shutouts do not appear to be disruptive to male students' long-run outcomes, with one exception—shutouts significantly increase the probability that men choose a major from the business school.

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1 Introduction

Across the country, states are reducing spending on higher education. In real terms, state appropriations per student are 40% lower now than they were in 1990.[1] One way many colleges respond to this increasing budgetary pressure is by reducing course offerings which causes more courses to be oversubscribed. This increases the number of students who are not able to enroll in (shut out of) courses they want to take.[2] On average, public institutions have a significantly higher student-faculty ratio than private non-profit institutions (see Figure 1) and one important difference between public and private non-profit institutions is the extent to which a student is able to enroll in desired courses. While researchers have speculated that these course shutouts contribute to negative student outcomes, including increased dropout rates and longer time-to-degree, there is limited and conflicting evidence of the effects of course shutouts.[3]

We contribute to the nascent literature on course shutouts by exploiting random variation in course shutouts at a large public university. In 2018, Purdue University introduced a "batch registration" algorithm to assign first-year student course schedules.[4] The number of first-year students in fall 2018 was about 2,000 more than typical and there was little corresponding increase in course capacity. University administrators were concerned that using the existing course registration system would concentrate course shutouts disproportionately on first-generation and disadvantaged students. An advantage of the batch

[1] See Chakrabarti *et al.* (2020).

[2] See Deming (2017); Mitchell *et al.* (2016); Bahr *et al.* (2015) for discussions of the potential impacts of shutouts. We define a shutout in our setting as a primary course request (i.e., non-contingent request) that is not granted, either because no class is assigned or a secondary/contingent course is assigned in its place. This is comparable to a student in a typical enrollment system failing to enroll in a desired course because the course was full or the course conflicted with their schedule. In a typical enrollment system, we would consider a student to be shut out from a course if they formally requested a desired course and were not assigned (e.g., they were waitlisted and never assigned the course) or they were discouraged from making a formal request (e.g., the class was full at the time a student engaged with the enrollment system or the course was not offered at a time that was compatible with their schedule).

[3] Robles *et al.* (2021) find that course shutouts in community colleges significantly increase the probability that students take zero courses in a semester or transfer to a lower-quality two-year college. In contrast, Kurlaender *et al.* (2014) find that course shutouts only affect time-to-degree when shutouts occur in semesters when students could have otherwise graduated.

[4] We limit our analysis to entering first-year students in Fall 2018 for four reasons: (1) in 2018, the batch registration process only applied to entering first-year students and not continuing students (2) batch registration was suspended for spring and summer terms, and reintroduced for fall 2019, which precludes us from studying second-semester freshman, (3) there were changes to the Batch algorithm process after 2018, and (4) Limiting to the 2018 entering cohort allows us to examine long-run outcomes.

registration system is that students are conditionally randomly assigned to oversubscribed courses, which spreads out course shutouts across students.[5] Among first-year students in their first semester, 49% were assigned their preferred course schedule, while the other 51% were shut out from at least one of their top six requested courses. Using the Borusyak & Hull (2023) simulation approach to account for nonrandom exposure in our estimation, we find that course rationing significantly changes both short- and long-term course-taking behavior. First-year students who are initially shut out from a course are 35 percentage points less likely to ever complete the course and 25 percentage points less likely to take a course in the same subject.

In addition to examining the effects of shutouts on course-taking behavior, we also investigate the impact of shutouts on a number of short- and long-run outcomes including credits earned, GPA, major choice, dropouts, and on-time graduation. We find that each first-term course shutout reduces first-term credits earned by 0.2 credits. We do not find a significant effect on short-run GPA, but first-term course shutouts do have a negative effect on students' senior-year GPA. We also find that each shutout decreases the probability that students major in STEM by 1.6 percentage points and increases the probability that students choose a major from the business school by 1.1 percentage points. To put these results in context, two fewer shutouts have the same impact on majoring in STEM as an $8,000 STEM major choice incentive in Texas (Denning & Turley, 2017).[6] Additionally, a course shutout reduces the probability that students drop out in their first term by 0.5 percentage points but has no long-term effects on dropouts. Finally, we estimate that shutouts have a negative, but statistically insignificant effect on whether students graduate within 4 years.

Overall, these results suggest that shutouts affect student course-taking, but have mixed effects on broader student outcomes. However, these overall results mask important differences by gender. When we look at the effects separately for female and male students, we find that shutouts lead to large negative effects for female students while having little or

[5] The algorithm explicitly randomizes the order in which students are matched to courses after an initial sorting of students by scheduling constraints. See Appendix III for a full description of the algorithm.

[6] Denning & Turley (2017) find that a SMART grant that paid STEM majors $2,000 a semester up to $8,000 in total increased the number of STEM majors in Texas by 3.2 percentage points.

even modestly positive effects for male students. For female students, we find that each first-semester freshman shutout reduces first-semester credits earned by 0.4 credits, cumulative GPA by 0.05 points, the probability of majoring in a STEM field by 2.9 percentage points (or 5.0%), the probability of graduating within 4 years by 5 percentage points (or 7.5%), and starting salary by $2,100. In contrast, for male students, shutouts do not have a significant effect on credits earned, cumulative GPA, choosing a STEM major, or on-time graduation. However, each shutout is estimated to increase the probability that male students choose a major from the business school by 1.9 percentage points (or 24%) and starting salary by $2,000.

Our results contribute to the existing literature in several ways. First, our research contributes directly to the emerging literature on college course shutouts. Shutouts, which are prevalent even at selective private universities,[7] are particularly common at public institutions (Gurantz, 2015). Robles *et al.* (2021) find that shutouts decrease course-taking at community colleges and increase transfers to lower-ranked community colleges. Despite the difference in institutional setting, our estimates of the effects of shutouts on course-taking and leaving the institution are similar. Our paper also pushes the literature forward by identifying the effects of shutouts for a broader range of students and by examining the effects of shutouts on previously unexplored outcomes including course-taking patterns, major choice, GPA, and on-time graduation.[8]

Two important new relationships we explore in this paper are the effects of course shutouts on course-taking patterns and major choice. Because college majors have large effects on

[7] See www.uscannenbergmedia.com/2023/04/12/usc-students-voice-frustration-over-class-web-registration/ and www.columbiaspectator.com/sports/2023/11/28/its-never-been-easy-students-struggle-to-register-for-physical-education-courses/, accessed 4/5/2024

[8] Additionally, Kurlaender *et al.* (2014) examine the effects of shutouts at the University of California-Davis and find shutouts do not impact student outcomes. We do not highlight their study because we believe their null results are due to limitations in their identification strategy and an unusual definition of course shutouts. Kurlaender *et al.* (2014) use randomization in how often students get early access to the course registration site as an instrument for course shutouts, but this instrument leads to an insignificant first stage. When they create a dichotomous variable for "extremely unlucky" or being at the 10th percentile of early registration, they get a statistically significant, but underpowered first stage (F-stat of 7.32). Furthermore, they do not show whether their instrument is balanced across treatment and control groups. Finally, their definition of a course shutout differs from how we define a course shutout. Specifically, Kurlaender *et al.* (2014) define a course shutout as any instance where a student attempts to register for a specific course section and finds that it is full. This means that many of the course "shutouts" in their data could be instances of students who enrolled in a desired course (i.e., not shut out) but had queried the registration site to find which sections of a course have open seats in their enrollment process. This is corroborated by the fact that students average four shutouts per term and that some students average over 40 shutouts per term.

long-term earnings, career trajectories, and lifestyles (Altonji *et al.*, 2012, 2014; Bleemer & Mehta, 2022; Chevalier, 2011; Hastings *et al.*, 2013; Kirkeboen *et al.*, 2016; Patnaik *et al.*, 2020; Webber, 2014), significant policy attention has focused on steering students towards high-returns majors (Bleemer & Mehta, 2021; Denning & Turley, 2017; Sjoquist & Winters, 2015). Furthermore, recent evidence suggests that barriers to accessing high-returns majors can have significant negative consequences for disadvantaged students (Bleemer & Mehta, 2023; Bleemer, 2021). Our paper suggests that course shutouts can significantly influence students' major choices. In particular, we find that shutouts in STEM courses reduce the likelihood that students major in engineering and reduce the likelihood that students choose a major that corresponds to the subject of the shutout course. We also find that shutouts push male students toward the business school and push female students out of STEM majors.

Our finding that shutouts push female students away from STEM majors contributes to research on the "leaky STEM pipeline" (e.g., Buckles, 2019; Griffith, 2010; Price, 2010). Approximately 50% more students initially declare a STEM major than graduate with a STEM degree, with disproportionally larger shifts away from STEM majors for female and under-represented minority students (Speer, 2023). Our finding that first-semester freshman shutouts explain 8.4% of the female-male gap in STEM degrees suggests shutouts are an important factor to consider when addressing the leaky STEM pipeline.

More broadly, our findings contribute to a body of research into the factors that influence college major choice. Student preferences, expected earnings, peer effects, subject ability, and costs have all been shown to affect college major choice (Elsner *et al.*, 2021; Patnaik *et al.*, 2020; Wiswall & Zafar, 2014; Zölitz & Feld, 2021). However, recent research has found that seemingly small changes in student experience, such as the time of day (Haggag *et al.*, 2021; Yim, 2023) or semester (Patterson *et al.*, 2021) a student takes a course, can meaningfully influence major choice as well. Our finding that a course shutout significantly alters students' major demonstrates another way in which seemingly small schedule changes can have large effects.

Our results also relate to research on factors that influence on-time graduation. Fewer than half of graduating low-income students in the United States graduate within four years of college entry (Denning *et al.*, 2022). Delays to graduation increase both the direct costs of college attendance (e.g., tuition, room, and board) and indirect costs (foregone wages). Researchers have investigated how financial incentives affect on-time graduation and have found mixed results.[9] Our finding, that each course shutout during a female student's first semester decreases her on-time graduation likelihood by 5%, suggests that addressing course shutouts may be an important and potentially low-cost way to increase on-time graduation rates.

Finally, our findings that women are disproportionately harmed by course shutouts contribute to a rich literature investigating differences in how female and male students respond to changing educational circumstances. In particular, there is evidence female students may be disproportionately responsive to changes in financial aid (Bartik *et al.*, 2021), learning incentives (Angrist *et al.*, 2009; Kremer *et al.*, 2009), student resources (Angrist *et al.*, 2009; Evans *et al.*, 2020), mentoring programs (Carrell & Sacerdote, 2017), instructor characteristics (Carrell *et al.*, 2010; Fairlie *et al.*, 2014), and course grades (Bleemer & Mehta, 2021; Kugler *et al.*, 2021; Ahn *et al.*, 2024). While most of these studies show that positive circumstances tend to disproportionately benefit women, our study, like Ahn *et al.* (2024), suggests that the converse is also true: negative educational circumstances are likely to disproportionately harm women.

The remainder of the paper is structured as follows. In Section 2 we describe our study environment and data. In Section 3 we describe our empirical approach. In Section 4 we report our primary results and explore the potential mechanisms for our findings. In Section 5 we conclude.

2 Study Environment and Data

Data for this study come from administrative records at Purdue University, a moderately selective public university in Indiana. Compared to all other four-year universities in the

[9]For example, Scott-Clayton (2011) finds that a merit aid program in Georgia increased on-time graduation whereas Angrist *et al.* (2022) find that a merit aid program in Massachusetts decreased on-time graduation. Garibaldi *et al.* (2012) find that a 1000-Euro bump in continuation tuition increased on-time graduation by 5.2%.

United States, Purdue is more selective (58% admitted vs. 67% admitted), has a similar distribution of majors with the exception of more students in engineering (28% at Purdue vs. 4% at all other institutions), and has a smaller fraction of female, Black, and Hispanic students (see Table A.1). Purdue is a land-grant university and is consistently ranked as a top-50 public university in the United States.

Our sample includes 15,112 student-course observations from 241 oversubscribed courses in the 2018 fall semester. Of the 8,566 first-year students in fall 2018, our study follows 7,646 traditional non-athlete students who requested to enroll in one or more of these oversubscribed courses in their first semester. Our analysis sample excludes Division I scholarship athletes (who receive special scheduling treatment) and students over the age of 23 at entry. Table 1 shows that 44% of students in our analysis sample are female, 11% are Asian, 3% are Black, 6% are Hispanic, and 66% are White.[10] Additionally, 17% of our sample are first-generation college students. The average Math SAT score in our sample is 664 and the average Verbal SAT score is 651 (both out of 800).

As part of the enrollment process, students submit their course preferences to the university by completing a course request form (see Figure C.1).[11] After all students submit their preferences, they are assigned a course schedule by Purdue's batch registration algorithm (Müller *et al.*, 2010). The algorithm uses each student's preference ranking for courses as inputs in generating schedules for all students.[12] The algorithm uses the student course preference ranking, along with course availability and student schedule constraints, to assign each student a schedule. While 45% of students in the analysis sample are assigned each of the courses they request, 55% are shut out from at least one requested course with 9% being shut out from two or more courses. Of the 241 oversubscribed courses, the two most common shutout courses are required English writing and communications courses.[13] The remaining

[10] The remaining 15%, categorized as "Other race/ethnicity", are primarily composed of international students. While the data do not designate the race/ethnicity of international students, many of these students come from Asia.

[11] Students can submit up to nine preferences, but in practice only 12% of students submit more than six preferences. Our analysis sample, therefore, includes the first 6 preferences requested by students.

[12] An academic advisor can also indicate whether a course is required for a student, which is typically the result of students being required to take a course with a specific group (e.g., band, sports team, or honors section). We exclude course requests with a "required" designation from our analysis.

[13] Both English and communication requirements can be met with several alternative courses.

239 courses with shutouts come from nearly every subject area offered at the university (See Table A.2 for the distribution of course requests and shutouts by college and Table B.1 for a complete list of oversubscribed courses and shutouts).

In Columns 3 and 4 of Table 1 we explore the characteristics of students that have and have not been shut out of at least one course as a first-semester freshman, respectively. In these raw data, we find that female students and students from a race/ethnicity other than Asian, Black, Hispanic, and White (predominantly international students for whom we do not observe race/ethnicity) are less likely to be shut out of courses. Otherwise, we find similar characteristics for students who are and are not shut out of courses.

3 Empirical Approach

Our empirical approach takes advantage of Purdue's course assignment algorithm that assigns student course schedules based on student preferences and schedule constraints. Whether students with similar course preferences are assigned a slot in an oversubscribed course depends on randomization within the assignment algorithm. However, not all of the variation in course shutouts is exogenous. Nonrandom factors including the student's pre-enrollment major and course priority rankings influence the likelihood of a course shutout. We account for these nonrandom factors by using a control function approach introduced by Borusyak & Hull (2023). By running 1,000 simulations of the exact algorithm used to assign course schedules in Fall 2018, we estimate the probability that each course request will result in a shutout, what Borusyak & Hull (2023) call the "expected treatment" (see Appendix III for a detailed description of the course assignment algorithm). The simulated course shutout probability is a sufficient statistic for the confounding factors (i.e., students with identical preferences will have indistinguishable simulated shutout probabilities). Figure 2, which shows the distribution of shutout probabilities for course requests that resulted in shutout and assignment separately, illustrates overlap in shutout probabilities and the role that randomness plays in whether a student is assigned a course. Once we control for the simulated shutout probability, whether a student is actually shut out of a course is as good as randomly assigned and is uncorrelated with student characteristics, including their potential outcomes (Rosenbaum & Rubin, 1983). Our identification assumption is that, after accounting for the shutout probability, whether a student actually experiences a shutout is random, potential outcomes are uncorrelated with shutout status, and differences between shut-out and non-shut-out students can be causally attributed to course shutouts.[14]

While the course assignment algorithm is not strategy-proof (e.g., a student is more likely to be assigned their entire desired schedule by listing their hard-to-match courses in top priority), our identification strategy is robust to strategic behavior. Strategic behavior by students will be reflected in course preference rankings, captured in our algorithm simulations, and, therefore, accounted for in our identification strategy. Furthermore, because the batch algorithm process was introduced in the observed semester and little information was provided to students about how the batch algorithm process worked, there is likely little scope for strategic behavior in our sample.

Evidence of conditional random assignment of course shutouts can be examined by estimating balance in observable characteristics with the following equation:

$$shutout_{ic} = \boldsymbol{\theta X_i} + \delta ShutoutProbability_{ic} + \gamma_c + \epsilon_{ic} \tag{1}$$

where $shutout_{ic}$ is an indicator for whether student i is shut out of (not assigned to) oversubscribed course c. $\boldsymbol{X_i}$ is a vector of individual characteristics including sex, race/ethnicity, first-generation student status, and SAT math/verbal test scores. $ShutoutProbability_{ic}$ is the estimated probability that student i will be shut out from course c.[15] γ_c is a course fixed effect, which does not affect balance. Finally, ϵ_{ic} is an individual-by-course idiosyncratic

[14] Borusyak & Hull (2023) also propose an alternative instrumental variables approach where the instrument is the realized course shutout minus the simulated shutout probability. This "recentered" course shutout variable takes on high values when a course shutout is unlikely but assigned by chance and low values when a course shutout was likely but, by chance, did not happen. The recentered course shutout is then used as an instrument for the actual course shutout in an instrumental variables regression of an outcome on course shutout. As shown in Appendix Table A.5, this instrumental variables approach produces very similar (nearly identical) results to the control function approach we use in this paper (corresponding results are presented in Table 4). Note that it would not be correct to use the simulated shutout probability directly as an instrument for actual course shutout because both the actual shutouts and the simulated probabilities are correlated with student preferences and potential outcomes.

[15] Shutout probability is calculated as the fraction of our 1,000 simulations where student i is not assigned the requested course. The simulations are obtained from the exact algorithm used to assign students to courses in the Fall of 2018.

error term. In our estimates of Equation 1, we cluster our standard errors at the student level.[16]

In column (1) of Table 2 we show why we need to account for shutout probability when estimating Equation 1. The estimates reported in column (1) do not control for the simulated shutout probability and show that three student characteristics are significantly correlated with course shutout (indicators for Asian, Other Race, and whether the course is in the student's Pre-enrollment Major). Additionally, when all variables are considered jointly, we strongly reject the hypothesis that observable characteristics are the same among shutout and non-shutout students ($p<0.01$). If we do not use the simulated shutout probability, but instead flexibly control for course preference inputs into the assignment algorithm,[17] we still observe some imbalance in observable characteristics. We report this in column (2) of Table 2 where we observe an imbalance in the fraction of Asian and first-generation students shut out after accounting for algorithm inputs. Finally, in column (3) we show that controlling for shutout probability is likely to fully account for differences in potential outcomes between shut-out and non-shut-out students. Controlling for the simulated course shutout probability yields strong evidence of balance: no characteristics vary significantly by whether a student is shut out and the coefficients are jointly insignificant.[18] Note that our simulated shutout probability strongly predicts shutouts—a 1 percentage point increase in simulated shutout probability corresponds to a 0.99 percentage point increase in actual shutout probability.

Our balance over observed student characteristics as reported in column (3) of Table 2 motivates our individual-by-course level analysis of course shutouts. In this analysis, we examine how shutouts affect course-related outcomes, including completing the requested course, taking courses in the subject of the shutout course, and choosing a major that corresponds to the shutout course. We do so by estimating the following equation:

[16] We cluster at the student level, because a student i treatment status in course c is not independent of the other courses student i requests.

[17] these controls include course-by-preference fixed effects, an indicator for whether the student's pre-enrollment major had reserved slots for majors in the course, and a measure of how difficult the student's other courses are to match.

[18] Because we also focus on gender-specific estimates, we also show balance separately for male and female students in Table A.3. The results in Table A.3 show that observable characteristics balance for both female and male students after conditioning on shutout probability.

$$Y_{ic} = \beta Shutout_{ic} + \boldsymbol{\theta X_i} + \delta ShutoutProbability_{ic} + \epsilon_{ic} \quad (2)$$

where Y_{ic} is a course-specific outcome for individual i that has expressed preference for taking course c and all other variables are as previously specified in Equation 1. The parameter of interest is β, which measures the effect of being shutout of a course in a student's first semester on their subsequent academic outcomes. We estimate this equation with ordinary least squares, clustering standard errors at the course-by-preference level.

In addition to examining the effects of a course shutout at the individual-course level, we also investigate the effects of the number of course shutouts at the individual level. We do so by regressing individual-level outcomes onto shutouts, controlling for the probability of each level of treatment, or the generalized propensity score (Imbens, 2000).[19] Specifically, we estimate:

$$Y_i = \beta Shutouts_i + \boldsymbol{\theta X_i} + \delta_1 P[1\,Shutout]_i + \delta_2 P[2\,Shutouts]_i + ... + \delta_5 P[5\,Shutouts]_i + \epsilon_i \quad (3)$$

where Y_i is an individual-level outcome, such as credits earned in each semester and on-time graduation. The variable of interest $Shutouts_i$ is the number of course requests student i was not assigned in their first semester of college. $\boldsymbol{X_i}$ is a vector of individual characteristics. $P[1Shutout]_i$ is the probability of being shutout of exactly one course, which is the fraction of simulated course schedules for i that result in exactly one shutout. Similarly, $P[2\,Shutouts]_i$, $P[3\ Shutouts]_i$, $P[4\ Shutouts]_i$, and $P[5\ Shutouts]_i$ correspond to the probability of being shut out of two, three, four, and five courses, respectively.[20]

To evaluate whether the number of shutouts is likely to be conditionally independent of potential outcomes after accounting for shutout probabilities, we estimate the following

[19] Imbens (2000) defines the generalized propensity score as the conditional probability of receiving a particular level of treatment given pre-treatment variables. He shows that, by making equivalent assumptions to binary propensity score methods, that "one can estimate average outcomes by conditioning solely on the generalized propensity score."

[20] We do not control for $P[6\,Shutouts]_i$ because no students in our simulations had more than 5 shutouts. Additionally, to ensure common support for our estimates, we include fixed effects for the number of potential shutouts, where potential shutouts are the number of courses a student requests that have a positive, non-degenerate, probability of shutouts. Our estimates are robust to the exclusion of these fixed effects.

balance equation:

$$shutouts_i = \boldsymbol{\theta X_i} + \delta_1 P[1\ Shutout]_i + \delta_2 P[2\ Shutouts]_i + ... + \delta_5 P[5\ Shutouts]_i + \epsilon_i \quad (4)$$

where all variables are defined at the student level as in Equation 3. Table 3 reports estimates of Equation 4, which allows us to examine whether the number of shutouts balances across individual characteristics after controlling for the generalized shutout propensity score. While student characteristics do not unconditionally balance in column (1), they do balance conditional on algorithm inputs (Course-by-preference order fixed effects and number of reservation courses) in column (2),[21] and on the conditional shutout probabilities in column (3). While we show balance in both column (2) and column (3),[22] our preferred specification follows column (3), as column (2) requires the inclusion of thousands of fixed effects and drastically reduces the identifying variation in our study. Note that the generalized shutout propensity score strongly predicts the number of shutouts with point estimates on each simulated probability that correspond closely to the number of shutouts. The results of this balance exercise support our assumption that the number of shutouts a student experiences is independent of potential outcomes, after conditioning on generalized shutout probabilities.

4 Results

4.1 Effects of a Course Shutout on Course-taking and Major Choice

We begin by estimating Equation 2 to examine the effects of a first-semester freshman course shutout on course-taking outcomes including course enrollment, course-taking patterns, and major choice. In column (1) of Table 4, we find that a course shutout reduces the probability of attending the course in the semester it is requested by 72 percentage points relative to the non-shutout mean attendance of 85%.[23] Decomposing the imperfect compliance with course

[21] Course-by-preference order fixed effects are fixed effects for specific courses being requested in a specific preference position. For example, one fixed effect would be requesting Introductory Economics in a first preference slot, whereas requesting Introductory Economics in a second-preference slot would be a different and unique fixed effect.

[22] We also show balance separately for male and female students in Table A.4.

[23] We define course attendance as being enrolled in the course immediately after the semester add/drop deadline.

assignment, we find that 8% of students who are shut out of a course end up attending the course with the remaining non-compliance coming from students who are assigned their requested course but drop the course prior to the add/drop deadline. In column (2) we examine the effects of course shutout on course completion and find nearly identical results: students who are shut out of a course in their first semester are 71 percentage points less likely to complete the course that semester. For some students, a course shutout only delays their course completion to the next semester. However, column (3) of Table 4 reports that being shut out of a course in the first semester of freshman year reduces the probability of taking the course as a freshman by 44 percentage points and column (4) reports that a course shutout reduces the probability of ever completing the course by 35 percentage points.[24]

Given that a course shutout reduces the likelihood of ever taking the course, a natural question is: Are students substituting the shutout course with a similar course in the same subject area? Table 5 suggests that this is not usually the case. Panel A of Table 5 reports that a first-semester course shutout decreases the probability that the student completes a course in the shutout course's subject by 61 percentage points in the first semester and 34 percentage points in the first year.[25] If a student does not take a course in the shutout course's subject within a year, it is unlikely that they ever will; a course shutout decreases the probability that a student is ever exposed to the subject by 25 percentage points. In Panel B of Table 5, we find that a course shutout changes the subjects the student is exposed to in college. The number of subjects, outside of the shutout course's subject, a student is exposed to increases by 55 percentage points in the first semester, 32 percentage points by the end of the first year, and 25 percentage points overall. Panel C of Table 5 examines if a course shutout changes the total number of subjects students are exposed to and finds that it reduces the number of subjects in the first semester by 0.061, but has no effects on the long-run total number of subjects a student sees.

That a course shutout affects course-taking behavior suggests that it may also affect

[24]Note that the estimates reported in Table 4 are very similar (nearly identical) to the estimates reported in Table A.5 which were obtained by implementing Borusyak & Hull (2023)'s instrumental variables approach.

[25]The course subject is defined by the subject code that proceeds the course number (e.g., ECON or EDUC) which often corresponds to the department offering the course. However, some departments use several different subject codes and some subject codes correspond to no department.

the major the student chooses. One way a course shutout may impact major choice is by reducing the likelihood a student chooses a major that corresponds to the shut-out course. We investigate this question in Table 6. In column (1), we estimate the effect of a course shutout on choosing a major that corresponds to the course subject and find a negative, but statistically insignificant effect.[26] In columns (2) and (3) we examine the effects separately by STEM and Non-STEM courses. The estimate in column (2) shows that a STEM course shutout has an economically meaningful and marginally significant effect: a STEM course shutout reduces the probability that students choose a major in a corresponding subject by 20% (2.5 percentage points). In contrast, in column (3) we find that non-STEM shutouts have no impact on whether students choose a major in a corresponding subject. In columns (4) and (5) we find similar, and statistically insignificant, effects of shutouts on choosing a corresponding major for both top three and bottom three priority courses, respectively.[27]

4.2 Heterogeneous Effects of a Course Shutout

In results reported in the Appendix, we explore the heterogeneous effects of a course shutout on course-taking behavior in Table A.6 and find that the effects of shutouts on initial course attendance are 4% stronger for female students than male students, 6% stronger for underrepresented minority students than non-underrepresented students, 5% larger for first-generation students than non-first generation students and 6% larger for students with Low SAT scores than those with high SAT scores. This is consistent with evidence that those in privileged positions are more willing to ask for exceptional treatment. For example, male college students are significantly more likely than female students to ask for grade changes (Li & Zafar, 2023). However, these short-term effects disappear and sometimes reverse in the long run. In particular, the effects of shutouts on exposure to courses and subjects are

[26] We define choosing a major that corresponds to the course subject as selecting a major offered by the same department as the course was offered.

[27] In Figure A.1 we find that a shutout in a student's top-priority course significantly decreases the probability that a student majors in a corresponding subject. However, given the effects of 2nd through 6th priority shutouts are all indistinguishable from zero, we are reluctant to draw any strong conclusions from this result. Figure A.2 shows that the effects of a course shutout on course-taking behavior do not systematically differ by priority ranking of courses. For example, the effects of shutouts on whether students ever take a course in a subject area are larger for first- and fourth-priority courses than second- and third-priority courses.

approximately 20% smaller in absolute magnitude for students with low SAT scores relative to students with high SAT scores. One reason for this difference is that students with low SAT scores may be less aware of substitute courses that could replace the shutout required course.

In Table A.7, we explore whether the response to a course shutout differs by course characteristics and find that a course shutout reduces attendance and completion much more for courses that fulfill a general education requirement compared to courses that do not. One reason for this difference could be that many students who requested a particular general education course are doing so only to fulfill a general education requirement and are much more willing to substitute into another course (possibly in a different subject area) that fulfills the same general education requirement. Requested courses that do not fulfill a general education requirement are more likely to relate to the student's interests or desired major and may be why a non-general education course shutout causes less course substitution.[28] We also find that a course shutout in a high-difficulty class is less likely to reduce exposure to the corresponding subject than a low-difficulty class.[29] High-difficulty courses are more likely to be a prerequisite for related upper-division courses and therefore students may be less able to substitute to another course if they wish to remain in their chosen major.

4.3 Effect of Course Shutouts on Student-Level Outcomes

To estimate the effect of the number of shutouts in the first semester on student-level outcomes including credits earned, GPA, on-time graduation, and major choice, we estimate Equation 3 using data at the student level rather than the student-course level. The estimated effects are generally small and insignificant when using the full sample, but there are important gender differences that we describe after presenting the overall effects. Panel

[28] In columns (5) and (6) of Table A.7, we find that a course shutout is much more likely to reduce exposure to subjects in bottom-3 priority requests relative to top-3 preference requests.

[29] We construct the course difficulty measure by (1) regressing course grade onto student observable characteristics (e.g., SAT scores, sex, race), (2) generating average residual GPA by course, and (3) designating a course as high difficulty if it has below median residual average GPA and as low difficulty if it has above median residual average GPA.

A of Figure 3, shows that each shutout during the first semester decreases the number of credits earned in that semester by 0.2 credits, but shutouts have no effect on credits earned in subsequent semesters. When we look at the effects of shutouts on total credits earned in column (1) of Table 7, we find that shutouts have no overall effect. Then, in Panel B of Figure 3, we find that first-semester shutouts slightly decrease the probability that students drop out in their first semester, but have no effect on the likelihood of having dropped out in subsequent semesters. Next, in Panel C of Figure 3, we find that first-semester shutouts have no short-term effects on GPA, though there is a GPA drop in the second semester of students' fourth year. We similarly find no overall effect of first-semester shutouts on cumulative GPA in column (2) of Table 7. We examine the effect of shutouts on graduating within 4 years in column 3 of Table 7 and find that each shutout leads to an economically meaningful, but statistically insignificant 3.0% (1.8 percentage point) decrease in the probability that students graduate within 4 years.

4.4 Gender Differences for Student-Level Outcomes

The results above mask considerable heterogeneity by gender. Shutouts have large negative effects on female students' academic outcomes and somewhat positive effects on male students' outcomes. In Figure 4 we compare the effects of first-semester shutouts over time separately for female and male students. In Panel A we find that, among female students, each shutout reduces the number of credits earned in their first semester by 0.39 and, while not always statistically significant, leads to similar reductions in credits earned in each subsequent semester. In contrast, Panel B shows that shutouts have a generally positive but statistically insignificant effect on credits earned for male students. In Panel C of Figure 4 we find that each shutout increases the probability that female students drop out of the university by the end of their first year by 1.8 percentage points, and while the estimates become less precise over time, the results for later semesters suggest that shutouts cause an increase in female dropouts on the extensive margin and not just in timing. In contrast, Panel D shows that shutouts for male students make them, if anything, less likely to drop out of the university. In Panel E of Figure 4 we find that shutouts have a negative effect on female students' GPA that persists through their first four semesters. In Panel F, we find no short-term effects of shutouts on GPA for male student with evidence suggesting a negative effect on GPA only in the second semester of their fourth year.

In Table 8 we report the effect of shutouts on the same student-level outcomes examined in Table 7, but do so separately by gender. In column (1) we find that female students who have no course shutouts in their first semester tend to complete more cumulative credits than male students with no course shutouts (113 vs 105), but course shutouts may reduce this advantage for women. While statistically imprecise, each shutout decreases cumulative attainment for women by 1.7 credits and increases cumulative attainment by 1.1 credits for male students. Similarly, in column (2) non-shutout female students earn higher GPAs than non-shutout male students (3.33 vs. 3.18), but shutouts reduce this advantage. Specifically, we find that each shutout decreases a female student's cumulative GPA by 0.05 grade points but has no effect on a male student's GPA, meaning each shutout reduces women's GPA advantage over men by 33%.

In column (3) of Table 8 we estimate that each shutout decreases the probability that women graduate within four years by 7% (5 percentage points). In contrast, we find no effects on graduation for men. This difference is economically substantial. Even if we make the conservative assumption that all women affected by shutouts graduate the following semester with a wage equal to what they would have had with seven months of job experience, each course shutout for female students has an expected cost of approximately $1,500 in foregone wages[30] and $800 in additional tuition and housing costs.[31]

In column (4) of Table 8, we show that shutouts have differential effects on majoring in STEM, by gender. Each shutout decreases the probability that female students major in STEM by 5.1% (or 2.9 percentage points). We do not find any effect of shutouts on majoring

[30] We arrive at this value by estimating 7 months of forgone wages due to a December graduation instead of a May graduation at a wage of $50,256. This wage amount is calculated by taking the weighted average first wages by major from Purdue via Purdue's survey of graduates, where the weights are number of (non-shutout) female students from the 2018 entering cohort in each major.

[31] The average 2-semester net price for in-state students, accounting for financial aid and scholarships, is $14,619 (source: https://nces.ed.gov/ipeds/datacenter/ accessed 11/15/2023) and Purdue's estimated net price for one semester for out-of-state and international students is $21,947 and $24,002 respectively (source: https://www.purdue.edu/treasurer/finance/bursar-office/tuition/fee-rates-2023-2024/undergraduate-2023-2024 accessed 11/15/2023. We use IPEDS estimates of 45% in-state, 45% out-of-state, and 10% international students to calculate an average semester cost of attendance of $15,566.

in STEM for male students. To put these results in context, first-semester shutouts alone can explain 8.4% of the female-male STEM major gap at this university.[32] In Appendix Table A.9 we examine the linearity of the effects measured in Table 8 and find no evidence of non-linear effects.

Our finding in Table 8 that each shutout makes female students 5.1% less likely to major in STEM motivates a more detailed examination of the differential effects of shutouts on major choice by gender. In Figure 5 we examine how course shutouts affect major choice (organized by university college) and, while imprecise, these estimates suggest that shutouts are moving female students away from majors in technology and science and into agriculture.[33] Shutouts move male students, but not female students, into business majors. Each shutout increases the probability that a male student majors in business by 1.9 percentage points. This has important implications for gender parity in business majors. At this university, men are 19% more likely than women to major in business and this entire gender gap can be explained by course shutouts.[34]

Finally, in Table 9 we explore whether shutouts have differential effects on post-graduate outcomes as measured in the "first destination" post-graduation survey administered to recent graduates by the university's career center. This survey has several limitations. First, it is only administered to graduates. For the 2018 entering cohort, 83.8% of female students and 78.5% of male students graduated and were invited to take the survey. Second, not all graduates complete the survey with responses from 79.5% of invited female students and 76.9% of invited male students. Third, all post-graduation outcomes including employment, graduate school attendance, and earnings are self-reported. Nonetheless, our results in Table 9 are consistent with our other estimates. In Panel A we show that for female graduates, each shutout decreases estimated earnings by $2,098 or 3.5% ($p<0.05$) and decreases graduate school attendance by a statistically insignificant, but economically meaningful, 3.3 percentage

[32] 57.9% Female students major in STEM compared to 79.6% male students. Female students have 0.63 shutouts on average, meaning that shutouts explain 1.83 percentage points of the 21.7 percentage point gap.

[33] See Panel A of Figure A.3 for the overall effects of shutouts on major sorting.

[34] 8.6% of men major in business. Each shutout decreases the probability that men major in business by 1.9 percentage points and men have an average of 0.7 shutouts in their first semester. This means that 7.2% of men would have majored in business in the absence of shutouts, which is the same fraction of women (7.2%) that major in business.

points or 13%. In contrast, Panel B shows that shutouts do not appear to have any negative effects on male student post-graduation outcomes and are estimated to increase salary by $2,023 or 2.8%.[35]

4.4.1 Can Gender Differences be Explained by Course-Taking Patterns?

Given the large differences in the effects of shutouts for male and female students, a natural question to ask is whether female students request courses where shutouts are disproportionately likely to result in adverse outcomes. To investigate this potential mechanism for our results, we first investigate differences in the types of courses female and male students are shut out from in Table 10. While female students have a smaller share of shutouts coming from STEM and more difficult courses and a greater share of shutouts coming from upper-division and required courses, none of these differences are greater than three percentage points. When we examine gender differences in shutout subject areas, we find small differences in shutouts in the colleges where shutouts are most common (Liberal Arts and Science colleges), but do find a disproportionate share of shutouts come from courses in Agriculture (5% vs. 2%), Education (5% vs. 1%), and Health Science colleges (3% vs. 1%) for female students and a disproportionate share of shutouts come from courses in Engineering (4% vs. 1%) and Polytechnic colleges (11% vs. 4%) for male students.

In Table A.10 we explore to what extent differences in the courses from which male and female students are shut out could explain the differences in the effects of shutouts we observe in Table 8. Table A.10 shows that shutouts in courses where it is women who are disproportionately shut out do not systematically lead to worse outcomes for students. For example, STEM shutouts, which are slightly more common among male students, appear to lead to worse outcomes than non-STEM shutouts, but shutouts in required courses, which are slightly more common among female students appear to lead to somewhat worse outcomes than non-required shutouts. Back-of-the-envelope calculations suggest that there is no difference in the composition of course shutouts that can explain more than 4% of the

[35] We show the effects on post-graduation outcomes for our full sample in Table A.8. We do not find any effects on outcomes for the full sample.

gender gap in the effects of shutouts on any individual outcome examined in Table 8 and a majority of compositional differences in shutouts predict a slightly smaller impact of shutouts for women.[36] Given that differences in the composition of shutouts are unlikely to explain much of why female students are more negatively affected by shutouts than male students, our findings are most consistent with a growing literature that finds that female students are simply more responsive than male students to changes in higher education environments (e.g., Angrist *et al.*, 2009; Bartik *et al.*, 2021; Bleemer & Mehta, 2021; Evans *et al.*, 2020; Kugler *et al.*, 2021; Kremer *et al.*, 2009).

4.5 Additional Effect Heterogeneity for Student-Level Outcomes

While the starkest differences in the effects of shutouts are between female and male students, we explore other potential differences in the Appendix (see Figures A.4 - A.9 and Table A.10). In general, the effects of shutouts do not appear to systematically differ by course or demographic differences other than gender. However, there is one notable exception. In Table A.10, we find that students with high SAT scores are mostly unaffected by course shutouts, while students with low SAT scores experience negative effects on credits earned, GPA, on-time graduation, and the likelihood of STEM major, though the only statistically significant difference is for the STEM major result. This suggests that course shutouts are more disruptive for students with low SAT scores.

[36] Our back-of-the-envelope calculations are constructed as follows: (1) we collect the effects of shutouts in a specific course type (e.g., STEM shutouts) on a specific outcome (e.g., cumulative credits), (2) we collect the effects of shutouts in the reciprocal course type (e.g., Non-STEM shutouts), (3) we take the difference in the effect sizes from step (1) and (2), (4) we multiply the difference from (3) by the difference in gender composition for the course type, and (5) divide our value from (4) by the overall female-male difference in the effects of shutouts for that outcome. For this specific example, (1) the effect of a STEM shutout is a -0.178 reduction in cumulative credits, (2) the effect of a non-STEM shutout is a 0.266 increase in cumulative credits, (3) therefore the difference in STEM vs. Non-STEM is -0.444 credits. (4) 52% of female shutouts are in STEM courses, 54% of male shutouts are in STEM courses, so Female-Male differences in STEM composition can account for -0.444(0.52-0.54)=0.0089 cumulative credits, (5) the estimated Female-Male difference in the effects of shutouts reported in Table 8 is -1.683-1.132=-2.815 credits, so gender differences in STEM shutouts explains -0.3% of the female-male difference in the effect of shutouts on cumulative credits.

5 Conclusion

Private non-profit universities generally offer fewer majors than public universities but students are typically able to enroll in whichever courses they desire. In contrast, students in public universities have a large number of majors to choose from, but frequently find that a course they would like to take is full and are unable to register. In this paper, we examine what happens when college students are not able to enroll in the courses they request. Using data from a large public university where students were conditionally randomly assigned to oversubscribed courses, we find that being shut out from a course in a student's first semester changes the types of courses taken and can even cause a change in the student's major.

Consistent with recent evidence that women are more responsive to changes in educational environments than men (e.g., Angrist *et al.*, 2009; Bartik *et al.*, 2021; Evans *et al.*, 2020), we find that shutouts are particularly disruptive for women. Women who experience course shutouts earn worse grades, take longer to graduate, and are less likely to choose a major in a STEM field. Our findings show that course shutouts can have large effects on student academic outcomes. In an environment where institutions are interested in widening the path to high-return majors, decreasing gender gaps in STEM fields, improving student GPAs, and reducing time to graduation, our estimates suggest that reducing course shutouts, particularly for STEM courses, can be an effective way to improve these student outcomes.

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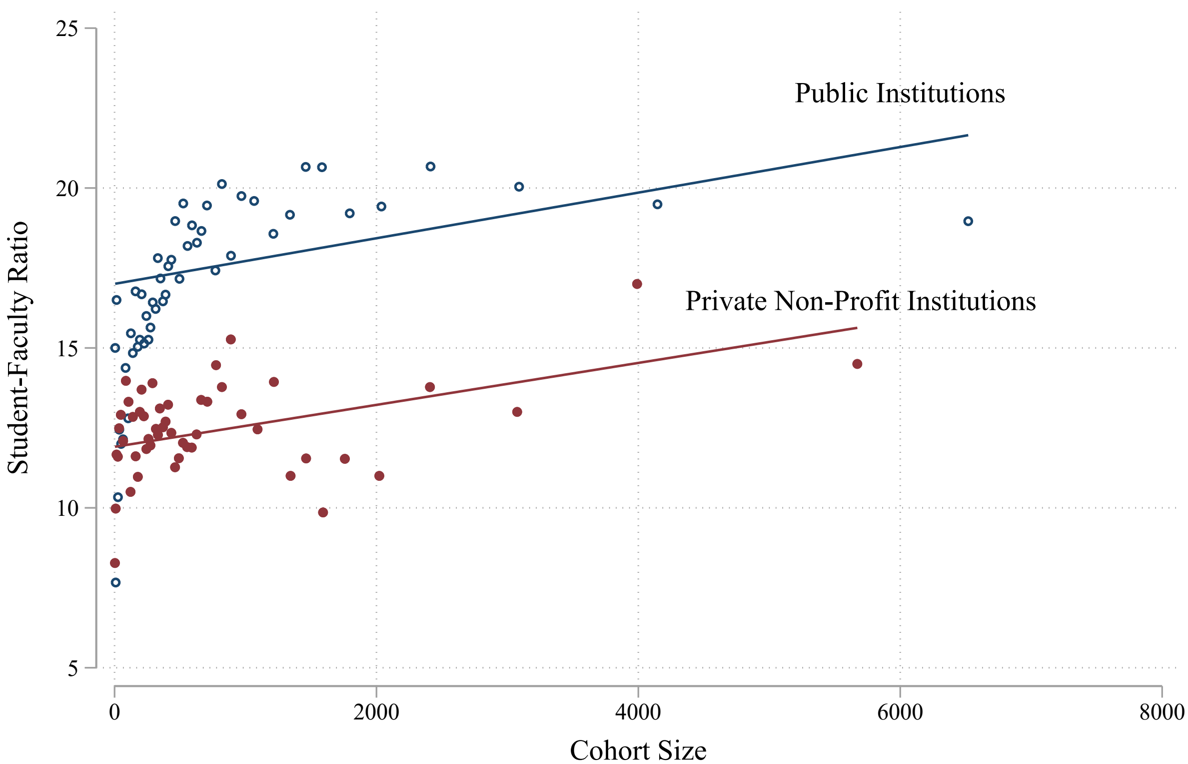
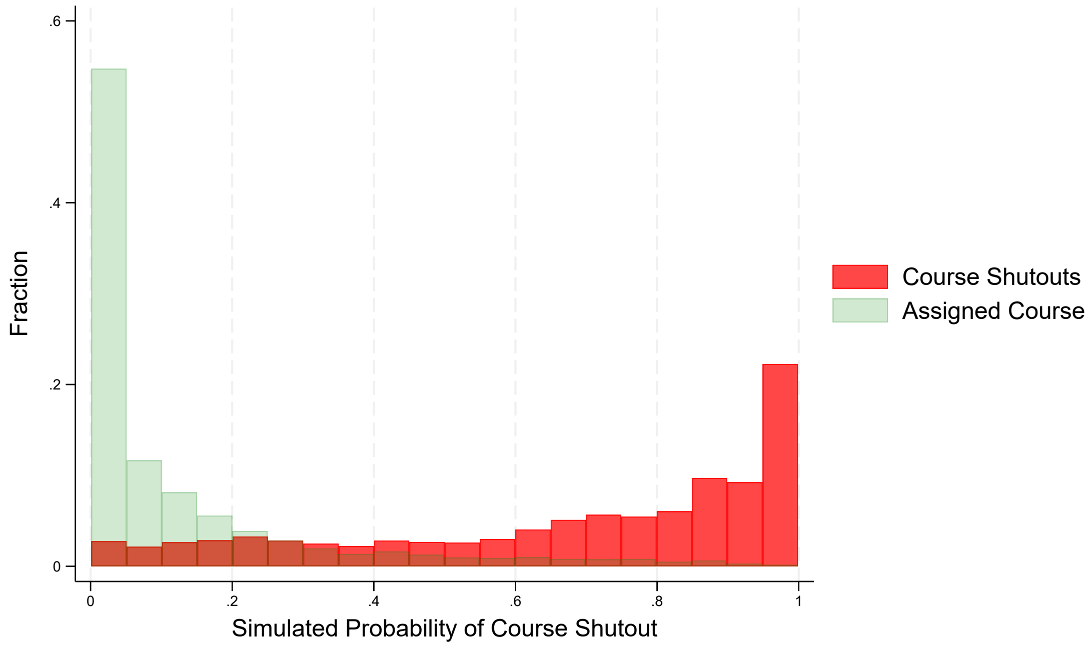
Tables and Figures

Figure 1: Student-Faculty Ratio at Public and Private Institutions



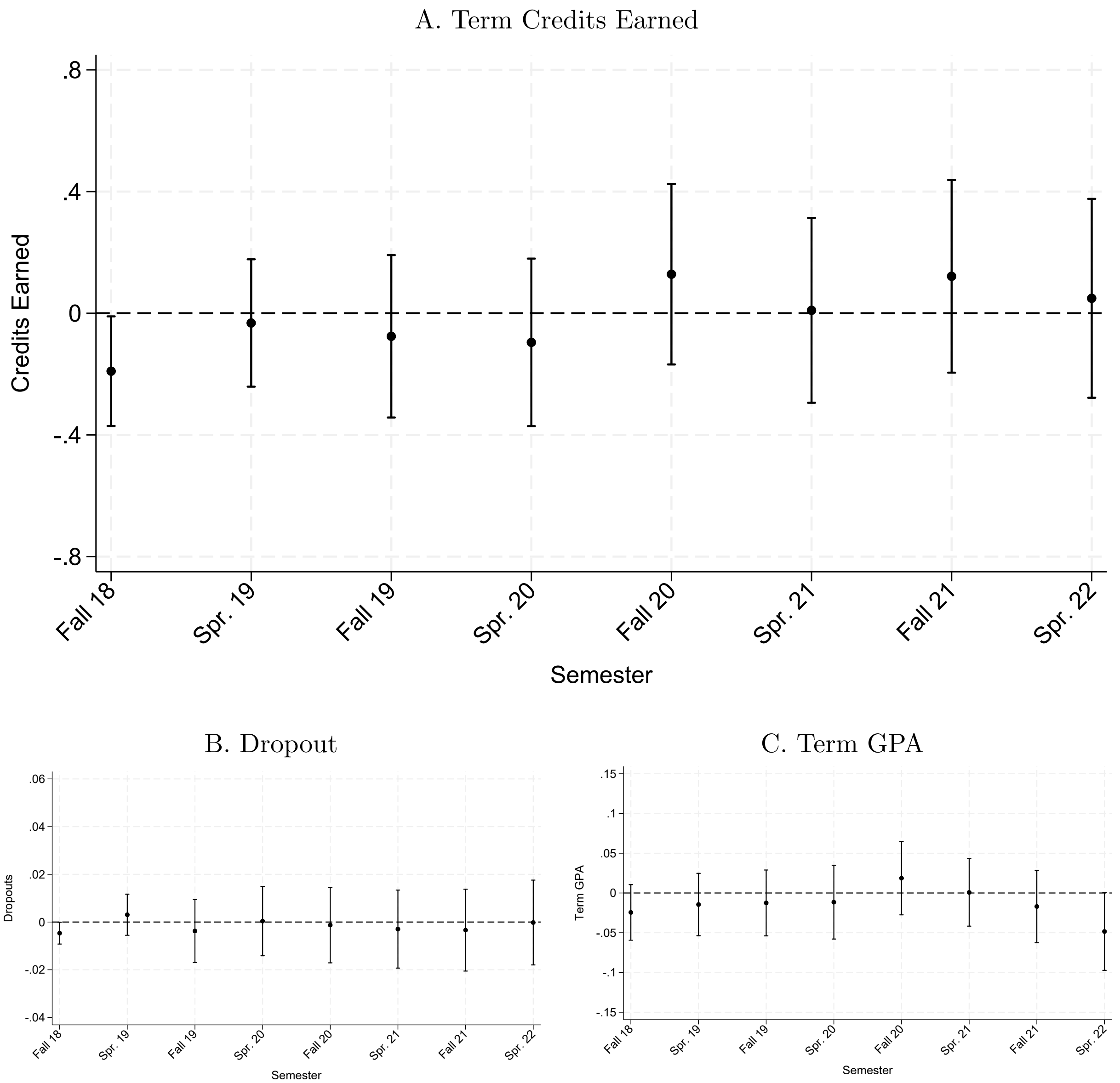
This figure shows the average student-faculty ratio by the size of the incoming class bins as reported in IPEDS for the 2019 academic year separately for public institutions and private non-profit institutions.

Figure 2: Overlapping of Probability Shutout



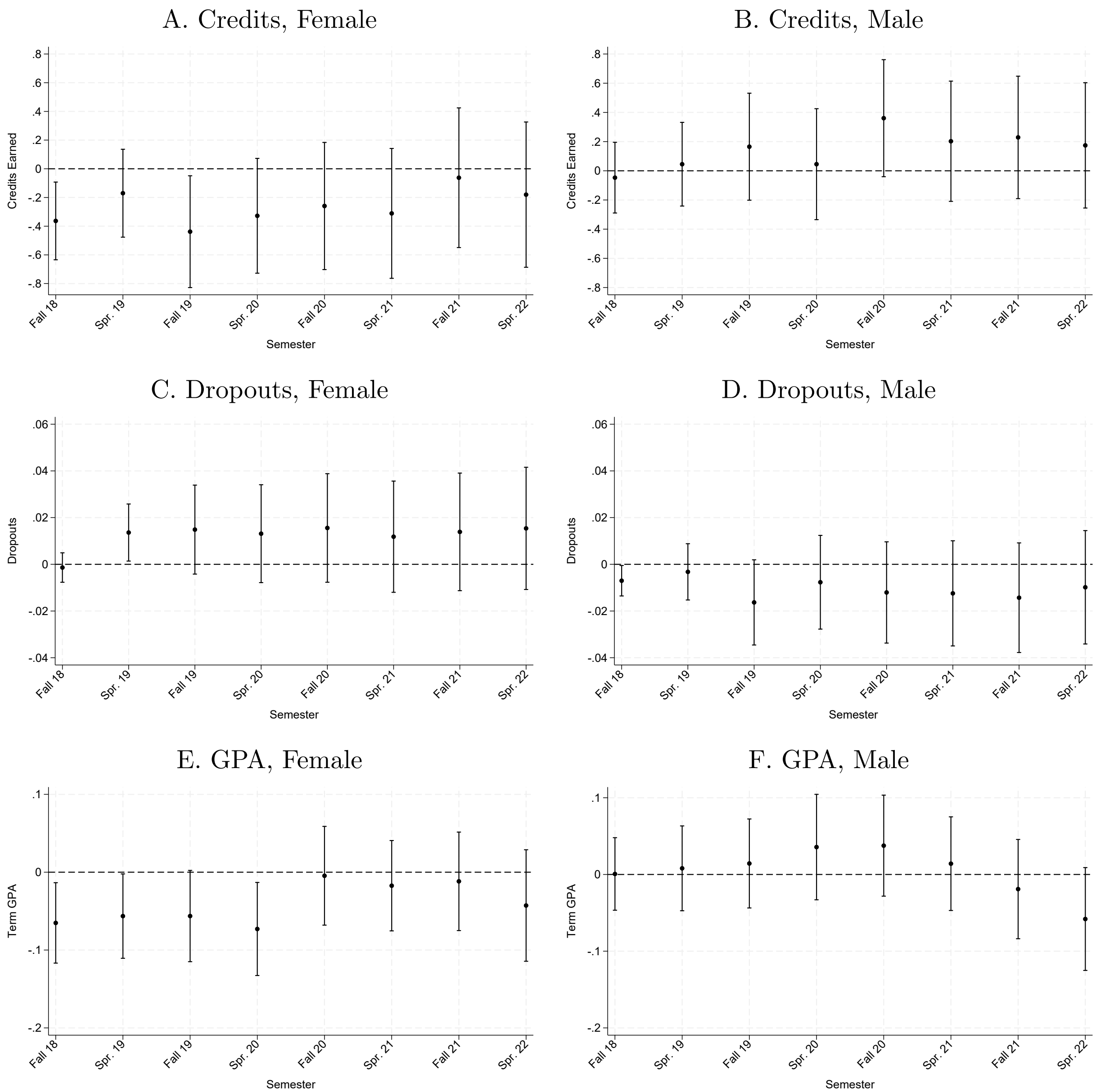
This figure plots the density of course shutout probabilities separately for requests that result in shutouts and course assignments. The probability of course shutouts is defined as the fraction of course requests from 1000 algorithm simulations that result in a shutout.

Figure 3: Effects of First-Semester Total Shutouts by Semester



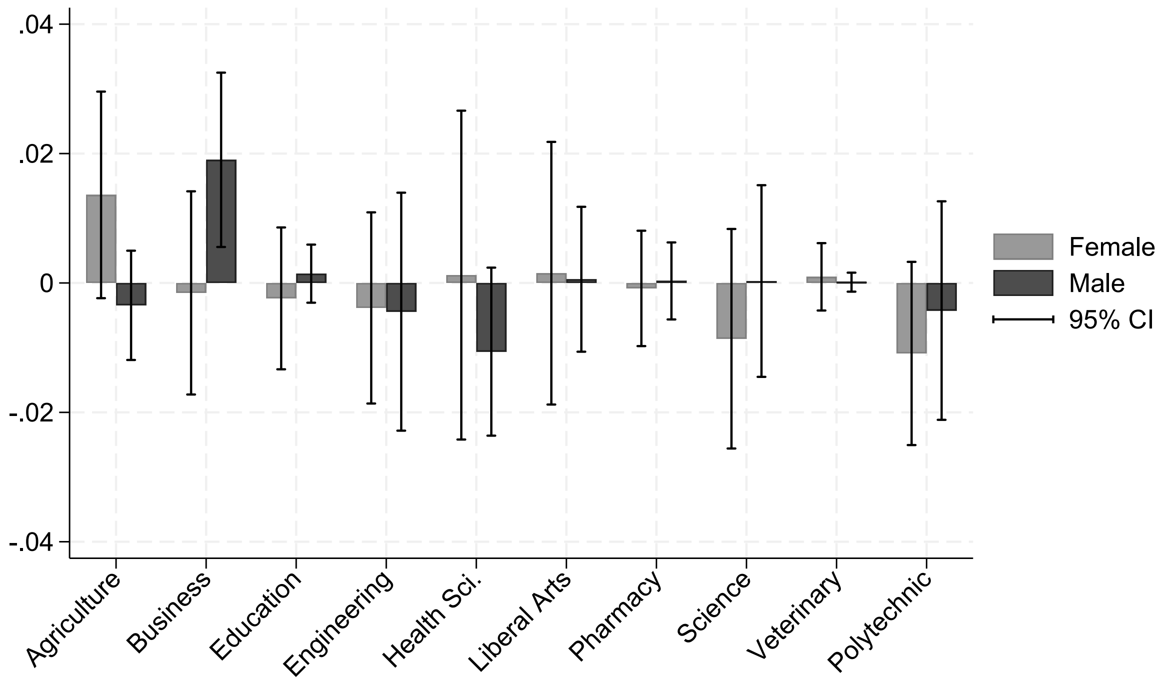
All estimates are at the student level as outlined in Equation 3. Panel A reports the effect of first-semester (Fall 2018) shutouts on credits earned in Fall 2018 and each of the subsequent 7 semesters. Panel B reports the effect of first-term shutouts on whether individuals have dropped out of Purdue by the referenced semester. We define a dropout as having dropped out by a semester if (1) they have not graduated and (2) they do not enroll in any courses in subsequent semesters. Panel C reports the effect of first-term shutouts on GPAs earned in Fall 2018 and each of the subsequent 7 semesters. GPA is omitted if the student is not enrolled in the term. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. 95% intervals from robust standard errors are reported.

Figure 4: Effects of First-Semester Shutouts, by Term and Sex



All estimates are at the student level as outlined in Equation 3. Panels A, C, and E estimate the effects of shutouts on outcomes for female students while Panels B, D, and F estimate the effects of shutouts on outcomes for male students. Panels A and B report the effects of first-term (Fall 2018) shutouts on credits earned in Fall 2018 and each of the subsequent 7 semesters. Panels C and D report the effects of first-term shutouts on whether individuals have dropped out of Purdue by the referenced semester. We define a dropout as having dropped out by a semester if (1) they have not graduated and (2) they do not enroll in any courses in subsequent semesters. Finally, Panels E and F report the effects of first-term shutouts on GPAs earned in Fall 2018 and each of the subsequent 7 semesters. GPA is omitted if the student is not enrolled in the term. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. 95% intervals from robust standard errors are reported.

Figure 5: Effects of Shutouts on Major Choice



This Figure estimates the effect of shutouts on choosing a major from each of the 10 colleges at Purdue University. Engineering, Health Science, Pharmacy, Science, and Polytechnic Colleges are primarily comprised of STEM majors while Agriculture, Business, Education, Liberal Arts, and Veterinary colleges are primarily comprised of Non-STEM majors. Estimates are at the student level, as outlined in Equation 3 and are reported by gender. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. 95% intervals from robust standard errors are reported.

Table 1: Summary Statistics

	All (1)	Analysis Sample (2)	1+ Shutouts (3)	No Shutouts (4)
Any shutouts	0.51	0.55	1.00	0.00
Total shutouts	0.62	0.67	1.20	0.00
Female	0.43	0.44	0.41	0.47
First generation	0.17	0.17	0.17	0.17
Asian	0.11	0.11	0.12	0.10
Black	0.03	0.03	0.02	0.03
Hispanic	0.06	0.06	0.06	0.05
White	0.65	0.66	0.67	0.66
Other race/ethnicity	0.17	0.15	0.13	0.17
Math SAT	662	664	664	663
Verbal SAT	649	651	652	651
Observations	8,566	7,646	4,241	3,405

Summary Statistics are for the 8,566 freshmen from the Fall 2018 entering cohort. Our analysis sample of 7,646 excludes 213 students who are over age 23, 108 Division I athletes (who receive special treatment during scheduling due to unique practice and game restrictions), 588 students who did not request any potentially over-subscribed courses, 5 individuals who have degenerate probabilities of shutout for each of their requested courses, and 6 individuals who do not fulfill the requirement to declare a major prior to enrollment. ($P[Shutout_{ic}] = 1$ or $P[Shutout_{ic}] = 0$). We use 1,000 schedule algorithm simulations to determine the probability of shutout for each course request.

Table 2: Student-by-Course Level Balance Test

	(1)	(2)	(3)
Female	-0.008	-0.002	0.003
	(0.007)	(0.006)	(0.006)
Black	-0.009	-0.014	-0.003
	(0.018)	(0.019)	(0.016)
Hispanic	-0.012	-0.011	-0.003
	(0.012)	(0.012)	(0.011)
Asian	0.024***	0.018**	0.013
	(0.009)	(0.008)	(0.008)
Other Race/Ethnicity	0.022**	0.011	0.011
	(0.009)	(0.008)	(0.008)
First Generation	0.013	0.017*	0.011
	(0.009)	(0.009)	(0.007)
SAT Math	0.009	0.005	0.000
	(0.006)	(0.005)	(0.004)
SAT Verbal	-0.001	-0.006	-0.001
	(0.004)	(0.004)	(0.004)
Course in Pre-enrolled Major	-0.083***	-0.016	-0.003
	(0.023)	(0.031)	(0.018)
Simulated Shutout Probability			0.991***
			(0.012)
F-stat P-Value	0.000	0.077	0.529
Observations	15,121	15,121	15,121
R^2	0.308	0.384	0.559
Course FE	X	–	X
Course-by-Priority FE	–	X	–

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The outcome in this regression is an indicator for being shutout of a potentially oversubscribed course. This sample includes all course-by-individual observations in potentially oversubscribed courses. F-stat p-value comes from a joint test of significance for sex, race/ethnicity, first-generation status, SAT score variables, and whether the course is in the student's pre-enrollment major. Column (3) corresponds to our primary individual-by-course level specification. Columns (2) and (3) additionally control for an indicator for a potential "reservation course". Certain majors reserve slots in classes for at least some students pre-enrolled in a corresponding major. Individuals are in a "reservation course" if they (1) are pre-enrolled in the major offering the course and (2) the major is one of the majors that reserve slots for some students. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Standard errors clustered at the individual level are reported in parentheses.

Table 3: Student-Level Balance Test

	(1)	(2)	(3)
Female	-0.081***	-0.007	0.012
	(0.017)	(0.018)	(0.011)
Black	-0.015	-0.018	-0.009
	(0.050)	(0.049)	(0.032)
Hispanic	-0.004	-0.005	-0.006
	(0.034)	(0.033)	(0.022)
Asian	0.078***	0.031	0.018
	(0.026)	(0.024)	(0.017)
Other Race/Ethnicity	-0.062***	0.045*	0.017
	(0.023)	(0.025)	(0.015)
First Generation	-0.009	0.002	0.021
	(0.021)	(0.020)	(0.014)
SAT Math	-0.029**	-0.003	-0.000
	(0.012)	(0.012)	(0.008)
SAT Verbal	0.006	0.002	0.000
	(0.012)	(0.012)	(0.008)
Simulated Probability of 1 Shutout			0.995***
			(0.016)
Simulated Probability of 2 Shutouts			1.978***
			(0.032)
Simulated Probability of 3 Shutouts			3.095***
			(0.117)
Simulated Probability of 4 Shutouts			4.146***
			(0.424)
Simulated Probability of 5 Shutouts			-0.813
			(3.286)
F-stat P-Value	0	0.75	0.683
Observations	7,646	7,646	7,646
R^2	0.006	0.530	0.610
Course-by-Preference FE	–	X	–
Pre-enrolled Major	–	X	X
Number of Reservation Courses	–	X	X
Possible Shutout FE	–	–	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The outcome in this regression is the number of course shutouts. The sample includes all students who requested one or more potentially oversubscribed course. The reported F-stat p-value is from a joint test of significance for sex, race/ethnicity, first-generation status, and SAT score variables. In Column (2) Course-by-Preference Fixed effects include a fixed effect for each course at every potential priority. Column (3) corresponds to our primary individual-level specification where we control for the simulated probability of 1, 2, 3, 4, and 5 course shutouts. These simulated probabilities are the fraction of simulated schedules for the student that result in exactly the specified number of shutouts. To ensure common support for our estimates, we include fixed effects for the number of courses requested that have a positive and non-degenerate simulated probability of shutouts (possible shutout fixed effects). Our estimates are robust to the exclusion of these fixed effects. Certain majors reserve space in into-level courses for students pre-enrolled in the major (reservation courses). These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Robust standard errors are reported in parentheses

Table 4: Effect of a Course Shutout on Attendance and Completion in Oversubscribed Courses

	Attend First Semester (1)	Complete First Semester (2)	Complete First Year (3)	Ever Complete (4)
Shutout of Course	-0.723***	-0.712***	-0.440***	-0.352***
	(0.009)	(0.009)	(0.011)	(0.010)
Observations	15,121	15,121	15,121	15,121
R^2	0.699	0.667	0.512	0.479
Non-Shutout Mean	0.852	0.836	0.850	0.857
Simulated Shutout Probability	X	X	X	X
Demographic Characteristics	X	X	X	X
Course FE	X	X	X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each outcome in this table relates to the exact course a student was potentially shut out from. Column (1) reports the effects of a shutout on attending a requested course in the semester the request is made. Attendance is defined as being enrolled in the course after the add/drop deadline. Column (2) reports the effects of a shutout on completing a requested course in the semester the request is made. Column (3) reports the effects of a shutout on completing a requested course in Fall, Spring, or Summer semester of the 2018/2019 school year. Column (4) reports the effect of a shutout on completing a requested course by the Fall 2022 semester. Observations are at the student-course level. Each estimate includes controls for simulated shutout probability, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), an indicator for a reservation course, and course-fixed effects. Standard errors that are clustered at the individual level are reported in parentheses. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3.

Table 5: Effect of a Course Shutout on Exposure to Subjects

Panel A: Requested Subject			
	First Semester	First Year	Ever
	(1)	(2)	(3)
Shutout of Course	-0.608***	-0.343***	-0.254***
	(0.010)	(0.010)	(0.010)
Observations	15,121	15,121	15,121
R^2	0.581	0.431	0.398
Non-Shutout Mean	0.879	0.896	0.905
Panel B: Subjects Outside of Requested Subject			
	First Semester	First Year	Ever
	(1)	(2)	(3)
Shutout of Course	0.554***	0.322***	0.255***
	(0.023)	(0.040)	(0.089)
Observations	15,121	15,121	15,121
R^2	0.256	0.154	0.062
Non-Shutout Mean	3.647	6.043	11.790
Panel C: All Subjects			
	First Semester	First Year	Ever
	(1)	(2)	(3)
Shutout of Course	-0.061***	-0.016	0.040
	(0.022)	(0.040)	(0.090)
Observations	15,121	15,121	15,121
R^2	0.197	0.138	0.062
Non-Shutout Mean	4.592	7.001	12.758

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Observations are at the student-course level. In Panel A the outcome is whether students take at least one course from the requested subject. In Panel B the outcome is the number of subjects outside of the requested course in which the student takes at least one course . In Panel C the outcome is the total number of subjects in which a student takes at least one course. Column (1) reports the effects of a shutout on exposure to the relevant subject(s) in the semester the request is made. Column (2) reports the effects of a shutout on exposure to the relevant subject(s) in the Fall, Spring, or Summer semester of the 2018/2019 school year. Column (3) reports the effect of a shutout on exposure to the relevant subject(s) by the Fall 2022 semester. Each estimate includes controls for simulated shutout probability, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), an indicator for a reservation course, and course-fixed effects. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Standard errors that are clustered at the individual level are reported in parentheses.

Table 6: Effect of a Course Shutout on Choosing a Corresponding Major

	All Courses (1)	STEM (2)	Non-STEM (3)	Top 3 (4)	Bottom 3 (5)
Shutout of Course	-0.008	-0.025*	0.002	-0.008	-0.006
	(0.006)	(0.013)	(0.005)	(0.011)	(0.007)
Observations	12,309	6,513	5,796	5,146	7,163
R^2	0.605	0.587	0.629	0.648	0.591
Non-Shutout Mean	0.097	0.128	0.138	0.120	0.142

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The outcome in each column is whether a student chooses a major that corresponds to the course they request. A student's major is defined as their primary graduating major if they have graduated or their most recent primary major if they have not graduated. Majoring in a corresponding subject is defined by choosing a major that shares the same subject code as the course. Observations from courses that do not correspond to a major (e.g. subjects only offered as a minor) or do not fulfill any potential credits in the major (e.g. remedial math courses) are omitted. Column (1) reports results for all potential shutouts. Columns (2) and (3) report results for requested STEM and non-STEM courses, respectively. Columns (4) and (5) report results for top 3 and bottom 3 priority requests, respectively. Observations are at the student-course level. Each estimate includes controls for simulated shutout probability, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), an indicator for a reservation course, and course-fixed effects. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Standard errors that are clustered at the individual level are reported in parentheses.

Table 7: Effect of Shutouts on Student-Level Outcomes

	Cumulative Credits (1)	Cumulative GPA (2)	4-Year Graduation (3)	STEM Major (4)
Total Shutouts	0.067	-0.020	-0.018	-0.016*
	(0.880)	(0.015)	(0.013)	(0.009)
Observations	7,646	7,532	7,646	7,583
R^2	0.133	0.148	0.091	0.516
Non-Shutout Mean	109.000	3.252	0.604	0.694

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column (1) reports the effects of total first-term shutouts on the total credits earned between Fall 2018 and Fall 2022 semesters. Column (2) reports the effects of total first-term shutouts on cumulative GPA between Fall 2018 and Fall 2022 semesters. Students who leave Purdue prior to earning any credits are omitted from this regression. Column (3) reports the effects of total first-term shutouts on graduating from Purdue within 4-years (by the Spring 2022 semester). Column (4) reports the effects of choosing a STEM major. A student's major is defined as their primary graduating major if they have graduated or their most recent primary major if they have not graduated. STEM majors are defined by matching Purdue major CIP codes to the Department of Homeland Security's list of CIP codes that correspond to STEM majors. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Robust standard errors are reported in parentheses.

Table 8: Effect of Shutouts on Student-Level Outcomes, by Gender

Panel A: Female	Cumulative Credits (1)	Cumulative GPA (2)	4-Year Graduation (3)	STEM Major (4)
Total Shutouts	-1.683	-0.046**	-0.050***	-0.029**
	(1.297)	(0.021)	(0.019)	(0.014)
Observations	3,336	3,315	3,336	3,336
R^2	0.079	0.173	0.106	0.529
Non-Shutout Mean	113	3.330	0.669	0.579
Panel B: Male	Cumulative Credits (1)	Cumulative GPA (2)	4-Year Graduation (3)	STEM Major (4)
Total Shutouts	1.132	-0.004	0.004	-0.005
	(1.199)	(0.020)	(0.017)	(0.011)
Observations	4,310	4,217	4,310	4,247
R^2	0.168	0.135	0.086	0.463
Non-Shutout Mean	105	3.180	0.547	0.796
Female vs. Male p-val	0.107	0.148	0.032	0.166

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel A reports results for female students and Panel B reports results for male students. Column (1) reports the effects of total first-term shutouts on the total credits earned between Fall 2018 and Fall 2022 semesters. Column (2) reports the effects of total first-term shutouts on cumulative GPA between Fall 2018 and Fall 2022 semesters. Students who leave Purdue prior to earning any credits are omitted from this regression. Column (3) reports the effects of total first-term shutouts on graduating from Purdue within 4-years (by the Spring 2022 semester). Column (4) reports the effects of choosing a STEM major. A student's major is defined as their primary graduating major if they have graduated or their most recent primary major if they have not graduated. STEM majors are defined by matching Purdue major CIP codes to the Department of Homeland Security's list of CIP codes that correspond to STEM majors. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Robust standard errors are reported in parentheses.

Table 9: Effect of Shutouts on Student-Level Post-Baccalaureate Outcomes by Gender

	Salary	Graduate School	Employed	Job Seeking
Panel A: Female				
	(1)	(2)	(3)	(4)
Total Shutouts	-2098.1**	-0.033	0.012	0.009
	(1006.524)	(0.021)	(0.022)	(0.009)
Observations	2,126	2,239	2,239	2,239
R^2	0.299	0.152	0.141	0.028
Non-Shutout Mean	60393	0.260	0.656	0.031
Panel B: Male				
	Salary	Graduate School	Employed	Job Seeking
	(1)	(2)	(3)	(4)
Total Shutouts	2023.8*	0.007	0.009	-0.013
	(1067.936)	(0.017)	(0.020)	(0.010)
Observations	2,465	2,626	2,626	2,626
R^2	0.245	0.122	0.112	0.059
Non-Shutout Mean	73025	0.220	0.676	0.052
Female vs. Male p-val	0.630	0.126	0.918	0.096

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel A reports results for female students and Panel B reports results for male students. Column (1) reports the effects of total first-term shutouts on salary. Column (2) reports the effects of total first-term shutouts on whether students attended graduate school. Column (3) reports the effects of total first-term shutouts on whether students employed. Column (4) reports the effects on whether students seek employment. All outcomes are self-reported by students to Purdue in the "First Destination" post-graduation survey administered by Purdue University Center for Career Opportunities. We impute salaries for those who are employed, but do not report earnings, by regressing salary on cumulative GPA, graduating college, the interaction term between cumulative GPA and graduating college, employment industry, and student covariates. Similarly, we imputed salary for individuals who were on fellowships, attending graduate school, and participating in internships by regressing salary on cumulative GPA, graduating college, the interaction term between cumulative GPA and graduating college, and student's covariates. We assign $0 earnings if individuals reported their labor market outcomes as "Not seeking an internship", "Other Intentions", "Postponing job search", "Seeking Employment", "Still Seeking Education", "Still Seeking Internship", and "Taking time off (more than 4 months)". This earning variable is going to be the lower-bounded salary. We then run the regressions with the lower-bounded salary as the outcome variable for both female and male students. The result is shown in Column (1). Alternatively, we assign the predicted salary values for individuals who were on fellowships, attending graduate school, and participating in internships to be the upper-bounded salary. We then run the regressions with the upper-bounded salary. The estimates for female and male students are -939.731 with robust standard error of 663.400 and 270.231 with robust standard error of 270.388 respectively. We also assigned a missing value if individuals reported their labor market outcomes as "Fellowship", "Graduate School", and "Internship". In addition, we omitted individuals who stated their labor market outcomes as " Military Service", "Own Venture", "Research", "Service Organization", "Summer classes", and "Volunteering". We exclude individuals who have not graduated from these estimates. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Robust standard errors are reported in parentheses.

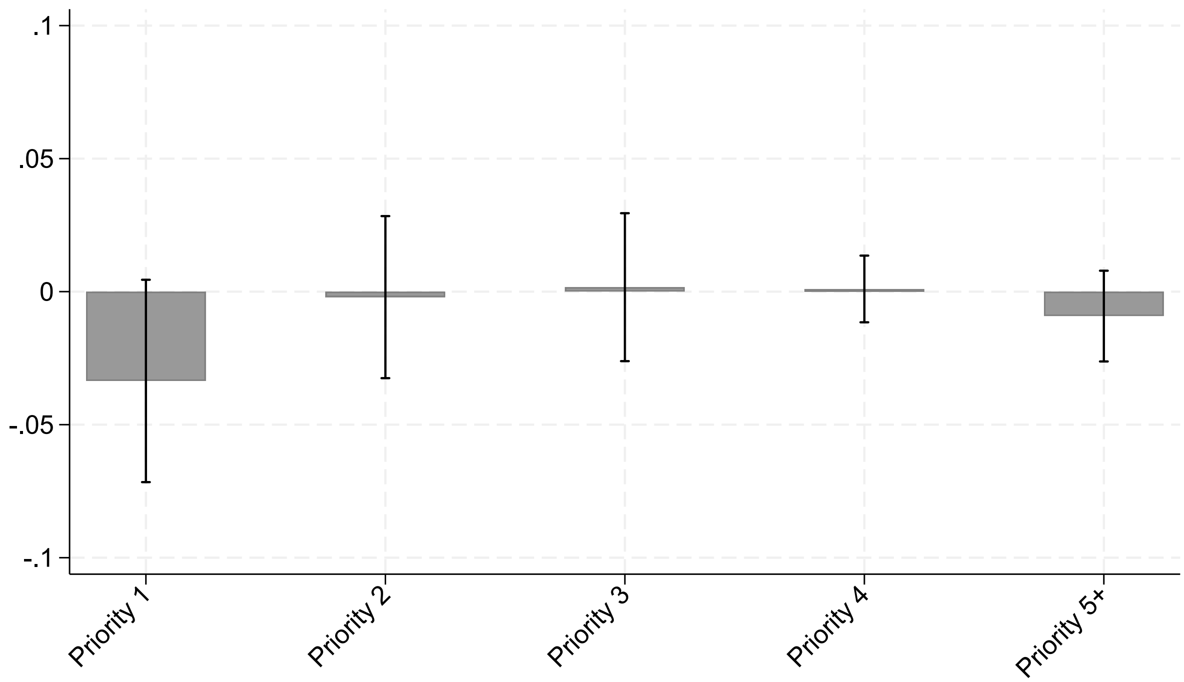
Table 10: Course Characteristics of Shutouts

	Analysis Sample	Female	Male	(2) vs. (3) P-value
	(1)	(2)	(3)	(4)
Course Characteristics				
STEM	0.53	0.52	0.54	0.002
Upper Level	0.04	0.05	0.02	0.000
Required	0.82	0.84	0.81	0.000
Difficult	0.39	0.39	0.40	0.035
Course College				
Agriculture	0.03	0.05	0.02	0.000
Business	0.04	0.03	0.04	0.000
Education	0.03	0.05	0.01	0.000
Engineering	0.03	0.01	0.04	0.000
Health Sci.	0.02	0.03	0.01	0.000
Liberal Arts	0.42	0.43	0.42	0.001
Pharmacy	0.01	0.01	0.01	0.000
Science	0.33	0.34	0.32	0.053
Polytechnic	0.08	0.04	0.11	0.000
Observations	15,184	6,566	8,618	

Observations are in the course-by-individual level. Column (1) reports the share of shutouts by different course characteristics and course colleges from our overall analysis sample. Column (2) reports the share of shutouts by different course characteristics and course colleges from our female student sample while Column (3) reports the share of shutouts by different course characteristics and course colleges from our male student sample. Column (4) reports the p-value of the gender difference by course characteristics and course colleges from Column (2) and Column (3).

Appendix I Supplementary Figures and Tables

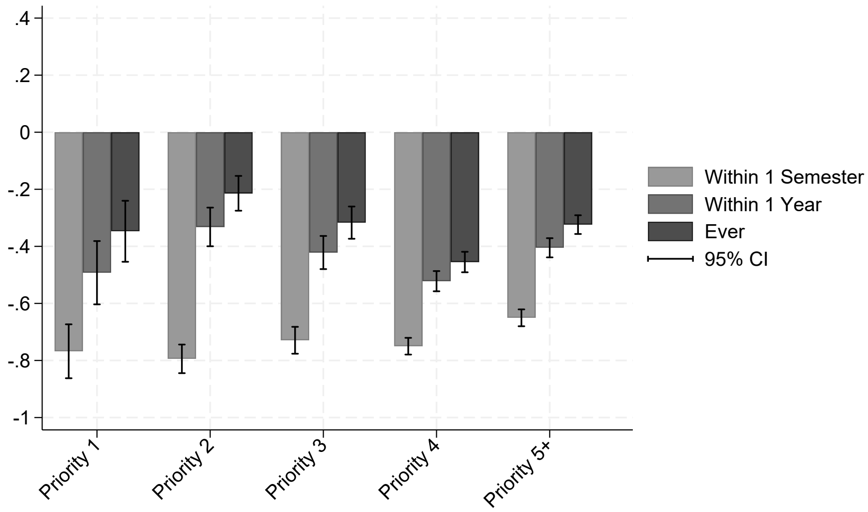
Figure A.1: Effect of Course Shutout on Choosing a Corresponding Major, by Priority



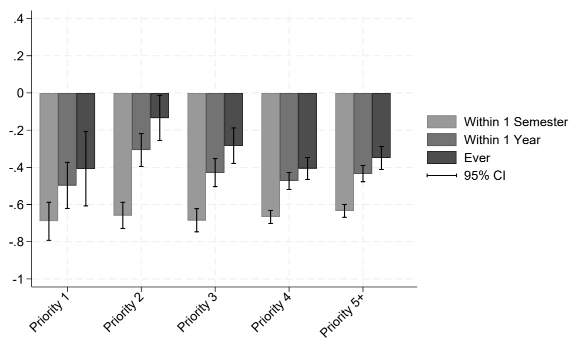
Each bar shows the estimated effect of a shutout on whether a student chooses a major that corresponds to the requested course. A student's major is defined as their primary graduating major if they have graduated or their most recent primary major if they have not graduated. Majoring in a corresponding subject is defined by choosing a major that shares the same subject code as the course. Observations from courses that do not correspond to a major (e.g. subjects only offered as a minor) or do not fulfill any potential credits in the major (e.g. remedial math courses) are omitted. Each estimate includes controls for simulated shutout probability, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), an indicator for a reservation course, and course-fixed effects. 95% confidence intervals come from robust standard errors clustered at the individual level.

Figure A.2: Effect of Course Shutout on Course-Taking, by Priority

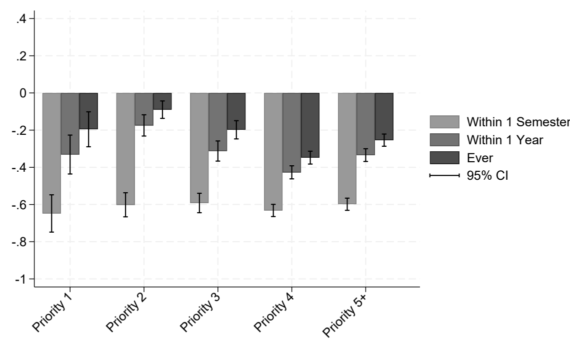
A. Taking Requested Course



B. Number of Courses in Subject

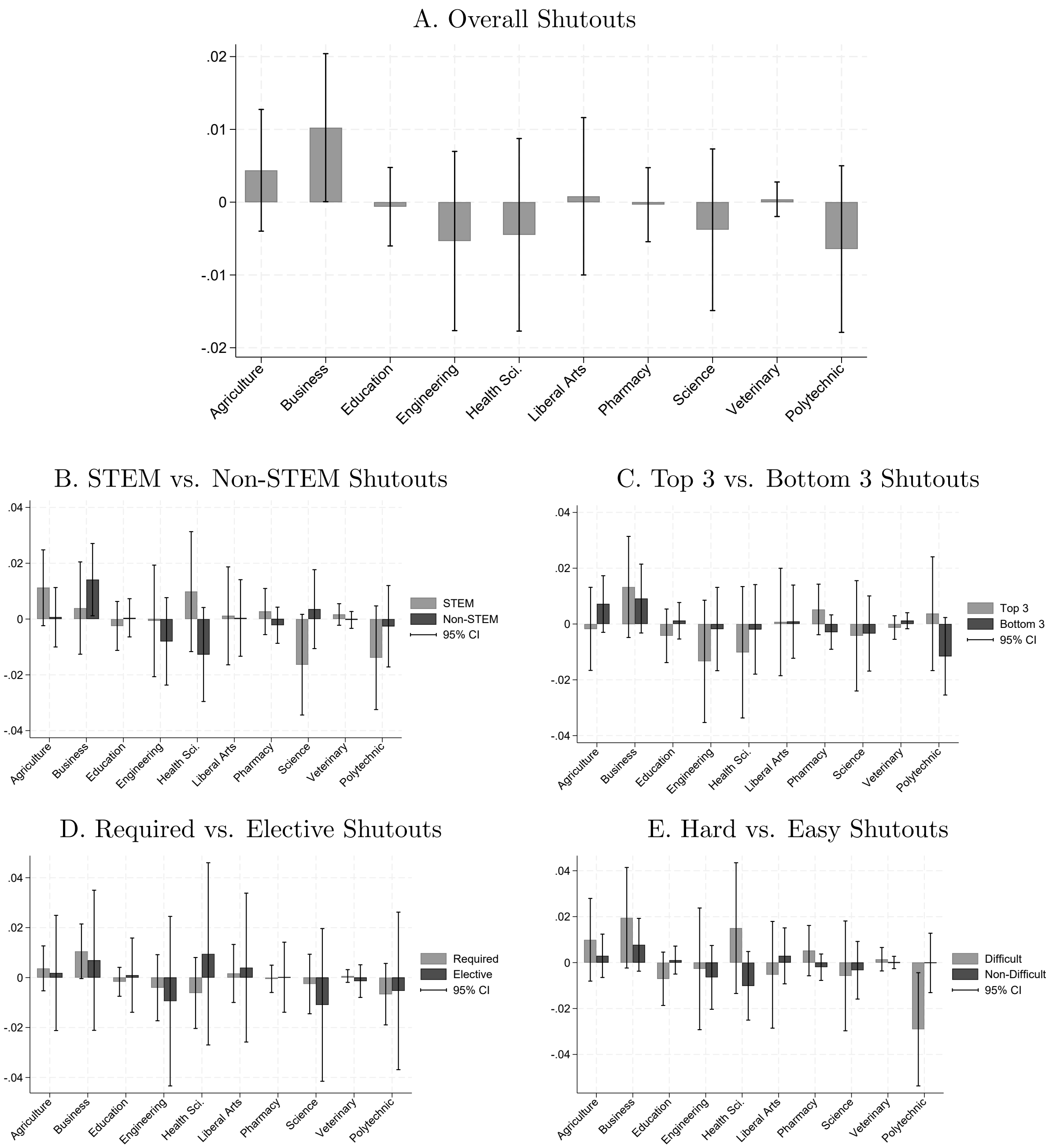


C. Ever Take a Course in Subject



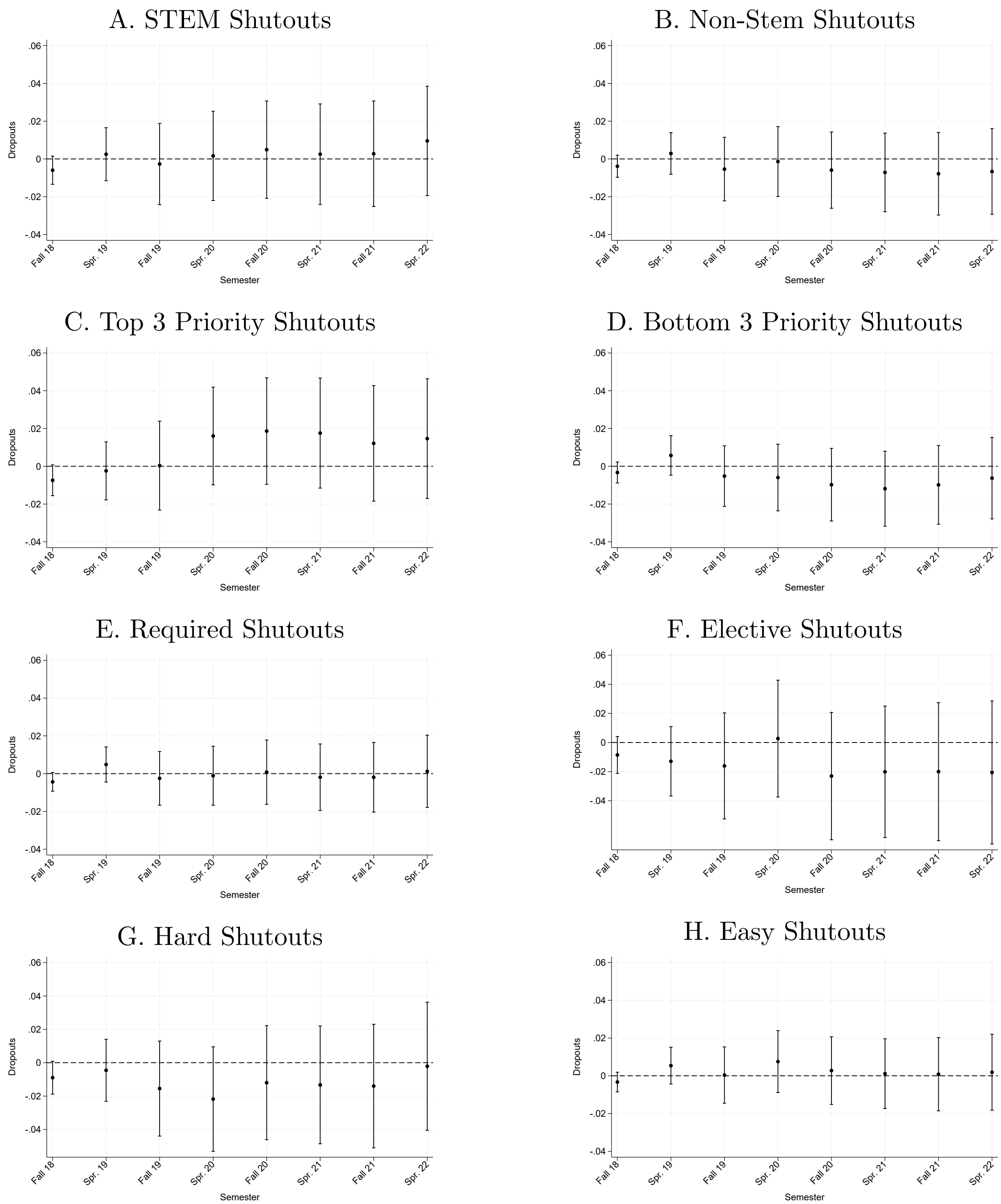
Each bar represents the estimated priority-specific effects of a shutout on an outcome. 95% confidence intervals are reported and derived from robust standard errors. Panel A estimates the effects of shutouts in 1st, 2nd, ..., 5th+ priority-ranked requests on taking the corresponding priority-ranked course. Panel B estimates the effects of shutouts in 1st, 2nd, ..., 5th+ priority-ranked requests on the number of courses taken in the corresponding priority-ranked subject. Panel C estimates the effects of shutouts in 1st, 2nd, ..., 5th+ priority-ranked request on whether a student has taken a course in the corresponding priority-ranked subject.Each estimate includes controls for simulated shutout probability, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), an indicator for a reservation course, and course-fixed effects.

Figure A.3: Effect of Shutouts on Major Choice



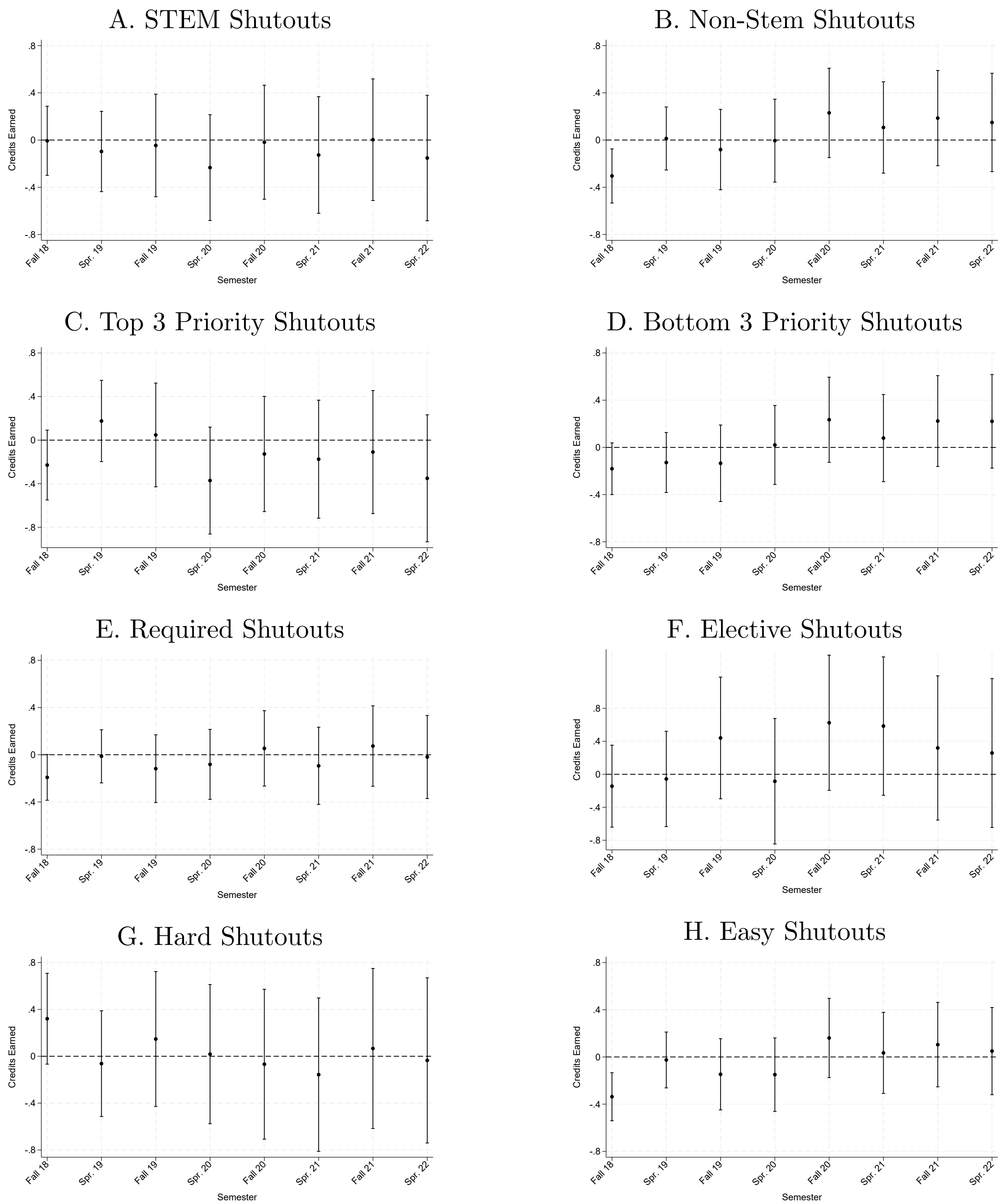
This Figure estimates the effect of shutouts on choosing a major from each of the 10 Purdue Colleges. Panel A shows estimates for all students in our sample, Panel B shows estimates separately for shutouts in STEM and Non-STEM courses, and Panel C shows estimates separately for shutouts in top 3 priority and bottom 3 priority courses. Engineering, Health Science, Pharmacy, Science, and Polytechnic Colleges are primarily comprised of STEM majors while Agriculture, Business, Education, Liberal Arts, and Veterinary colleges offer majors that are not STEM designated. Estimates are at the individual level, as outlined in Equation 3. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. 95% intervals from robust standard errors are reported.

Figure A.4: Effects of First-Semester Shutouts on Dropout



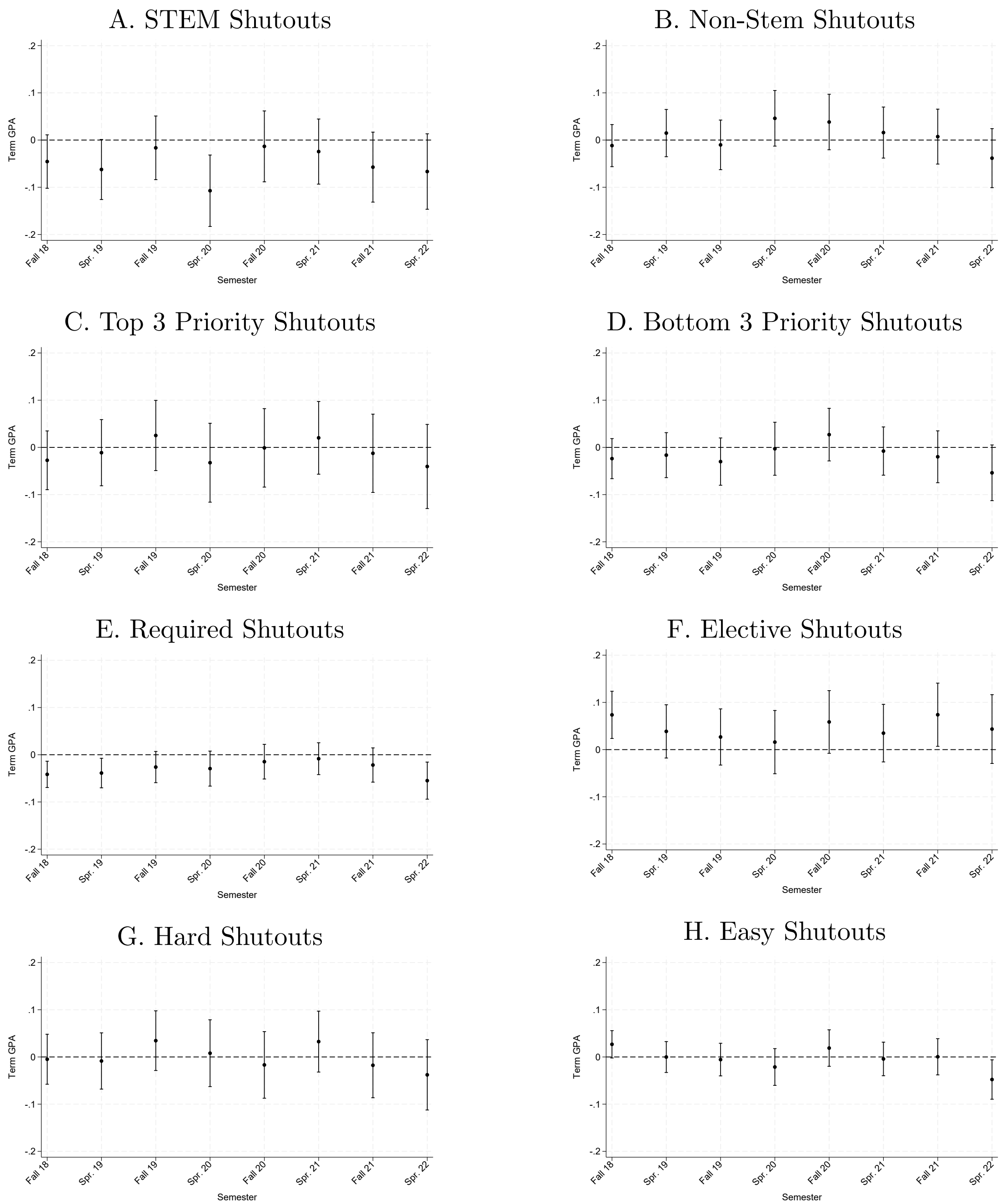
All estimates are at the individual level as outlined in Equation 3. Panels A and B show the effects of STEM and Non-STEM shutouts, respectively. Panels C and D show the effects of shutouts in top 3 priority and bottom three priority courses, respectively. Panels E and F show the effects of shutouts in courses that meet a general education requirement and do not meet a general education requirement, respectively. Finally, Panels G and H show the effects in above-median and below-median difficulty courses, respectively. Difficulty of course is defined as the inverse of residual GPAs in courses, after accounting for student observable characteristics. We define a dropout as having dropped out by a semester if (1) they have not graduated and (2) they do not enroll in any courses in subsequent semesters. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. 95% intervals from robust standard errors are reported.

Figure A.5: Effects of First-Semester Shutouts on Credits Earned



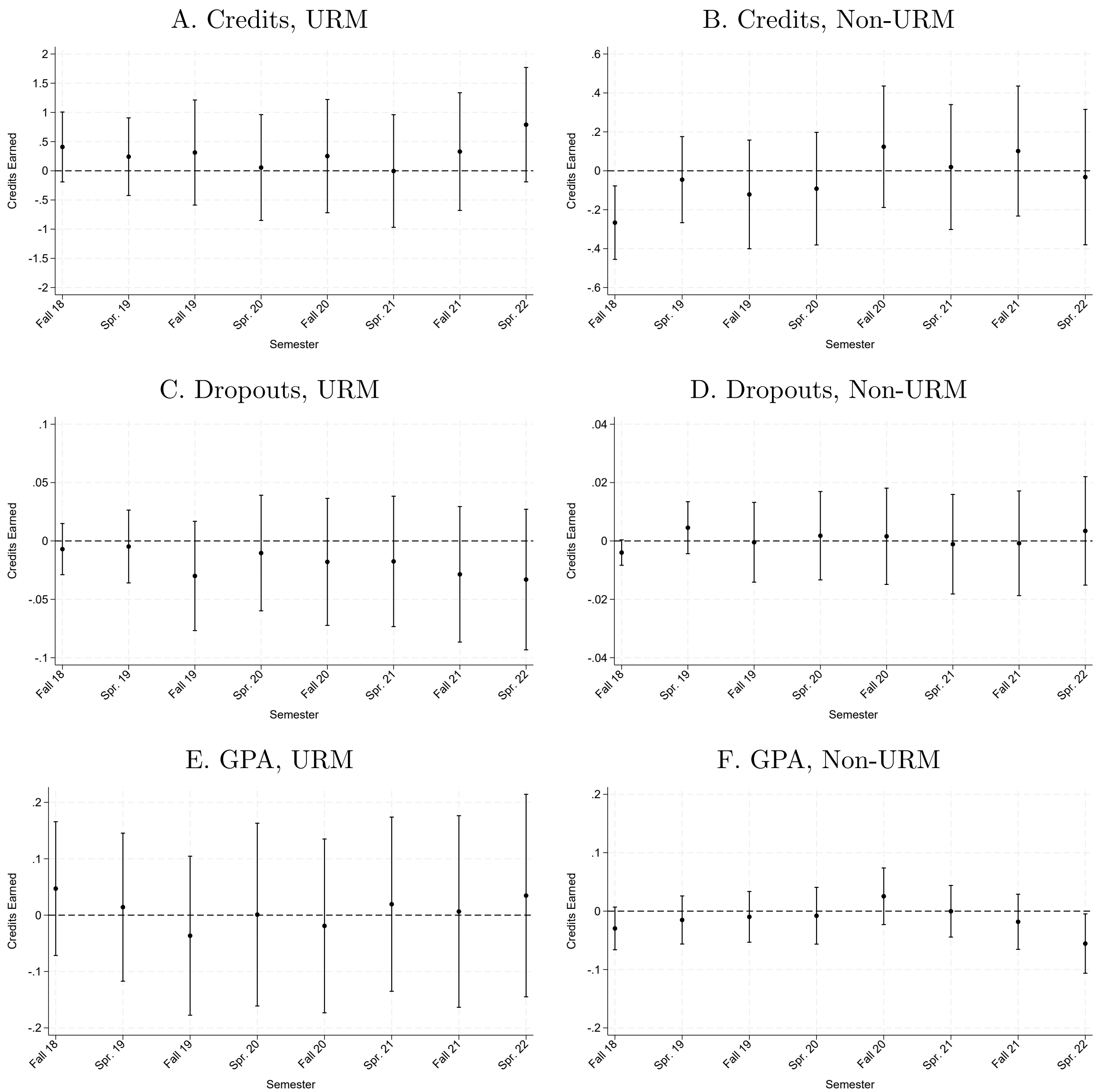
All estimates are at the individual level as outlined in Equation 3. Panels A and B show the effects of STEM and Non-STEM shutouts, respectively. Panels C and D show the effects of shutouts in top 3 priority and bottom three priority courses, respectively. Panels E and F show the effects of shutouts in courses that meet a general education requirement and do not meet a general education requirement, respectively. Finally, Panels G and H show the effects in above-median and below-median difficulty courses, respectively. Difficulty of course is defined as the inverse of residual GPAs in courses, after accounting for student observable characteristics. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. 95% intervals from robust standard errors are reported.

Figure A.6: Effects of First-Semester Shutouts on Term GPA



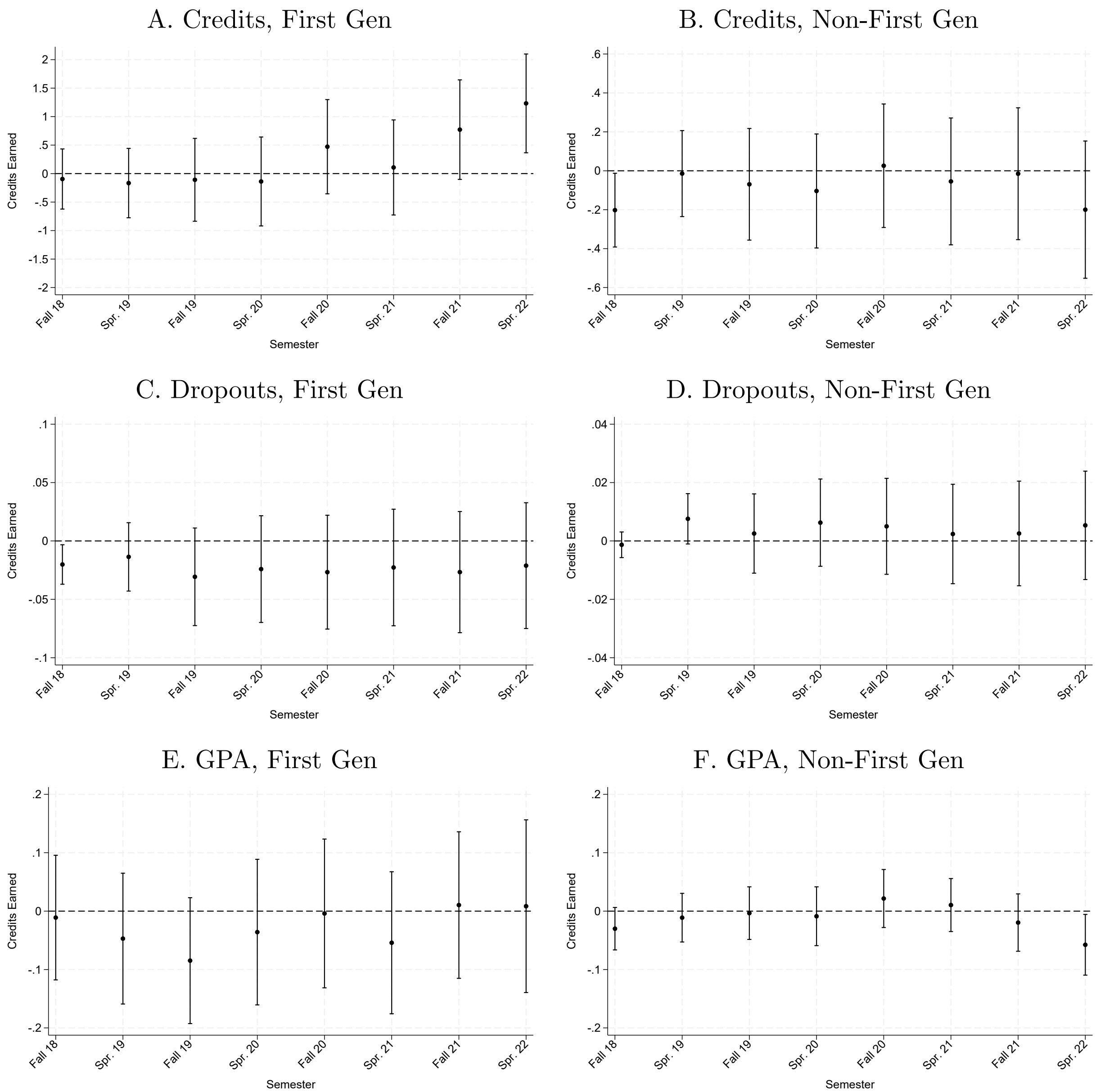
All estimates are at the individual level as outlined in Equation 3. Panels A and B show the effects of STEM and Non-STEM shutouts, respectively. Panels C and D show the effects of shutouts in top 3 priority and bottom three priority courses, respectively. Panels E and F show the effects of shutouts in courses that meet a general education requirement and do not meet a general education requirement, respectively. Finally, Panels G and H show the effects in above-median and below-median difficulty courses, respectively. Difficulty of course is defined as the inverse of residual GPAs in courses, after accounting for student observable characteristics. GPA is omitted if the student is not enrolled in the term. estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. 95% intervals from robust standard errors are reported.

Figure A.7: Effects of First-Semester Shutouts by URM



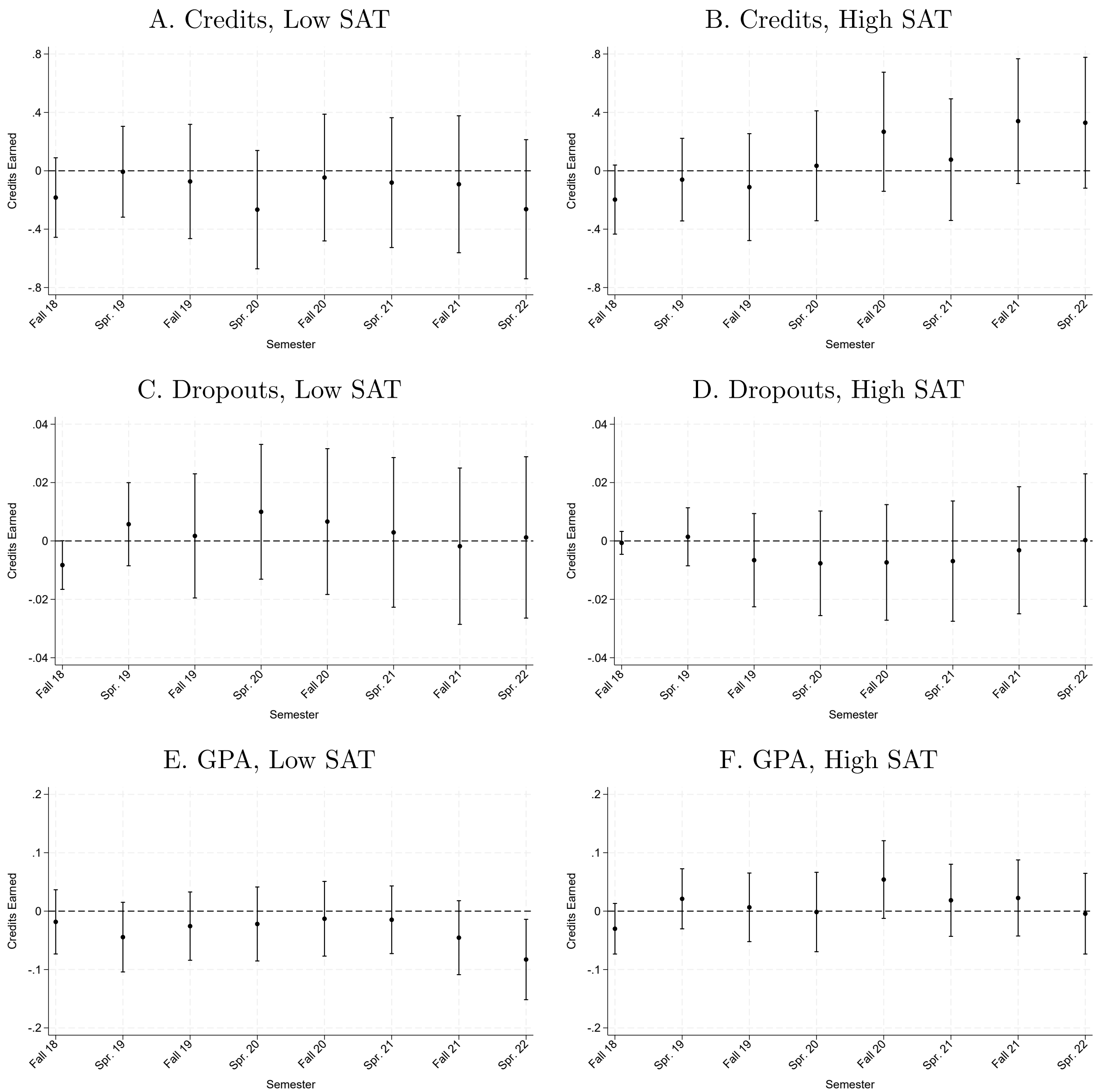
All estimates are at the individual level as outlined in Equation 3. Panels A, C, and E estimate the effects of shutouts on outcomes for under-represented minority students, including Black, Hispanic, and Pacific Islander students while Panels B, D, and F estimate the effects of shutouts on outcomes for Non-Under-respresented minority students including White and Asian students. Panels A and B report the effects of first-term (Fall 2018) shutouts on credits earned in Fall 2018 and each of the subsequent 7 semesters. Panels C and D report the effects of first-term shutouts on whether individuals have dropped out of Purdue by the referenced semester. We define a dropout as having dropped out by a semester if (1) they have not graduated and (2) they do not enroll in any courses in subsequent semesters. Finally, Panels E and F report the effects of first-term shutouts on GPAs earned in Fall 2018 and each of the subsequent 7 semesters. GPA is omitted if the student is not enrolled in the term. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. 95% intervals from robust standard errors are reported.

Figure A.8: Effects of First-Semester Shutouts, by First Gen



All estimates are at the individual level as outlined in Equation 3. Panels A, C, and E estimate the effects of shutouts on outcomes for first generation students while Panels B, D, and F estimate the effects of shutouts on outcomes for Non-first generation students. Panels A and B report the effects of first-term (Fall 2018) shutouts on credits earned in Fall 2018 and each of the subsequent 7 semesters. Panels C and D report the effects of first-term shutouts on whether individuals have dropped out of Purdue by the referenced semester. We define a dropout as having dropped out by a semester if (1) they have not graduated and (2) they do not enroll in any courses in subsequent semesters. Finally, Panels E and F report the effects of first-term shutouts on GPAs earned in Fall 2018 and each of the subsequent 7 semesters. GPA is omitted if the student is not enrolled in the term. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. 95% intervals from robust standard errors are reported.

Figure A.9: Effects of First-Semester Shutouts by SAT



All estimates are at the individual level as outlined in Equation 3. Panels A, C, and E estimate the effects of shutouts on outcomes for below-median SAT students while Panels B, D, and F estimate the effects of shutouts on outcomes for above-median SAT students. Panels A and B report the effects of first-term (Fall 2018) shutouts on credits earned in Fall 2018 and each of the subsequent 7 semesters. Panels C and D report the effects of first-term shutouts on whether individuals have dropped out of Purdue by the referenced semester. We define a dropout as having dropped out by a semester if (1) they have not graduated and (2) they do not enroll in any courses in subsequent semesters. Finally, Panels E and F report the effects of first-term shutouts on GPAs earned in Fall 2018 and each of the subsequent 7 semesters. GPA is omitted if the student is not enrolled in the term. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. 95% intervals from robust standard errors are reported.

Table A.1: Purdue vs. Other University Characteristics

	Purdue	4-Year	4-Year Public	4-Year Less-Selective Public
Demographic Characteristics				
Female	0.424	0.552	0.566	0.550
Asian	0.085	0.043	0.050	0.047
Black	0.029	0.126	0.128	0.129
Hispanic	0.052	0.138	0.156	0.140
White	0.640	0.552	0.535	0.572
Major Composition				
Biology/Life Science	0.039	0.063	0.057	0.066
Business	0.104	0.152	0.136	0.148
Education	0.029	0.061	0.053	0.057
Engineering	0.278	0.038	0.053	0.064
Math	0.011	0.009	0.008	0.009
Physical Sciences	0.021	0.013	0.014	0.016
Selectivity Measures				
Percent Admitted	58	67	71	73
Median English SAT	650	588	569	569
Median Math SAT	680	581	561	560

Source: IPEDS. All variables come from 2018-2019 cohorts to match our sample except for SAT score variables that come from 2021-2022. SAT variables are reported for 2021-2022 because 2018-2019 only report 25th and 75th percentile values. Purdue is excluded from columns 2-4.

Table A.2: Course Shutouts Statistics at Purdue

Course College	Total Course Requests	Total Shutouts	College Shutout Rate	College Fraction of All Shutouts
College of Agriculture	2,471	237	0.096	0.054
College of Education	424	145	0.342	0.033
College of Engineering	2,674	1,023	0.383	0.231
College of Health and Human Sciences	1,247	199	0.160	0.045
College of Liberal Arts	3,212	1,729	0.538	0.390
College of Pharmacy	128	0	0	0
College of Science	2,963	508	0.171	0.115
Polytechnic Institute	1,291	508	0.393	0.115
School of Management	711	81	0.114	0.018

Note: This table summarizes the total course requests, total shutouts, and shutout rate for each college, as well as each college's share of total course shutouts for the Fall 2018 semester at Purdue University. Total course requests is the number of student requests for the oversubscribed courses within the analysis sample. Total shutouts is the number of student course requests that were not assigned to the student's schedule by college. The college shutout rate is the ratio of course shutouts and total course requests by college. Lastly, the college fraction of all shutouts represents each college's contribution to the overall number of course shutouts.

Table A.3: Student-by-Course Level Balance Test, by Gender

	Female Students			Male Students		
	(1)	(2)	(3)	(4)	(5)	(6)
Black	-0.038	-0.052**	-0.023	0.025	0.012	0.021
	(0.023)	(0.026)	(0.021)	(0.024)	(0.021)	(0.025)
Hispanic	-0.021	-0.014	-0.013	-0.003	-0.000	0.004
	(0.022)	(0.021)	(0.017)	(0.016)	(0.017)	(0.015)
Asian	0.026	0.019	0.019	0.025**	0.024**	0.011
	(0.017)	(0.017)	(0.014)	(0.012)	(0.012)	(0.011)
Other Race/Ethnicity	0.028*	0.011	0.019	0.016	0.005	0.003
	(0.016)	(0.014)	(0.012)	(0.012)	(0.012)	(0.010)
First Generation	0.031**	0.043***	0.018*	-0.002	0.002	0.005
	(0.012)	(0.014)	(0.010)	(0.013)	(0.012)	(0.010)
SAT Math	0.014	0.013	-0.002	0.004	0.001	0.000
	(0.010)	(0.009)	(0.006)	(0.006)	(0.006)	(0.005)
SAT Verbal	-0.001	-0.007	-0.000	-0.000	-0.005	-0.001
	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)	(0.006)
Course in Pre-enrolled Major	-0.083***	-0.027	-0.018	-0.101***	-0.014	0.008
	(0.030)	(0.058)	(0.032)	(0.030)	(0.032)	(0.020)
Simulated Shutout Probability			0.992***			0.992***
			(0.017)			(0.016)
F-stat P-Value	0	.004	.238	.033	.633	.967
Observations	6559.000	6559.000	6559.000	8562.000	8562.000	8562.000
R^2	0.289	0.386	0.558	0.333	0.410	0.567
Course FE	X	–	X	X	–	X
Course-by-Priority FE	–	X	–	–	X	–

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The outcome in this regression is an indicator for being shutout of a potentially oversubscribed course. This sample includes all course-by-individual observations in potentially oversubscribed courses. F-stat p-value comes from a joint test of significance for sex, race/ethnicity, first-generation status, SAT score variables, and whether the course is in the student's pre-enrollment major. Columns (3) and (6) correspond to our primary individual-by-course level specification. Columns (2), (3), (5), and (6) additionally control for an indicator for a potential "reservation course". Certain majors reserve slots in classes for at least some students pre-enrolled in a corresponding major. Individuals are in a "reservation course" if they (1) are pre-enrolled in the major offering the course and (2) the major is one of the majors that reserve slots for some students. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Standard errors clustered at the individual level are reported in parentheses.

Table A.4: Student Level Balance Test, by Gender

	Female Students			Male Studuents		
	(1)	(2)	(3)	(4)	(5)	(6)
Black	-0.091	-0.067	-0.058	0.077	0.057	0.057
	(0.068)	(0.075)	(0.043)	(0.075)	(0.078)	(0.048)
Hispanic	-0.022	-0.068	-0.033	0.014	0.012	0.021
	(0.051)	(0.057)	(0.032)	(0.046)	(0.047)	(0.030)
Asian	0.069	-0.009	0.031	0.087***	0.034	0.014
	(0.042)	(0.044)	(0.027)	(0.033)	(0.032)	(0.021)
Other Race/Ethnicity	-0.046	-0.043	0.030	-0.073**	0.056	0.008
	(0.037)	(0.045)	(0.023)	(0.030)	(0.035)	(0.020)
First Generation	0.039	0.077**	0.035*	-0.057*	-0.023	0.003
	(0.031)	(0.034)	(0.019)	(0.030)	(0.031)	(0.019)
SAT Math	-0.024	0.000	-0.004	-0.032**	-0.010	0.001
	(0.018)	(0.022)	(0.012)	(0.016)	(0.017)	(0.010)
SAT Verbal	0.003	0.015	0.004	0.008	0.006	-0.002
	(0.018)	(0.020)	(0.011)	(0.016)	(0.017)	(0.011)
Simulated Probability of 1 Shutout			0.987***			0.999***
			(0.023)			(0.022)
Simulated Probability of 2 Shutouts			1.959***			1.979***
			(0.049)			(0.042)
Simulated Probability of 3 Shutouts			3.207***			3.019***
			(0.193)			(0.152)
Simulated Probability of 4 Shutouts			3.501***			5.001***
			(0.565)			(0.668)
Simulated Probability of 5 Shutouts			1.500			-12.026
			(3.552)			(9.916)
F-stat P-Value	.136	.286	.261	.001	.714	.941
Observations	3341.000	2687.000	3336.000	4311.000	3700.000	4310.000
R^2	0.003	0.638	0.625	0.006	0.546	0.604
Course-by-Preference FE	–	X	–	–	X	–
Pre-enrolled Major	–	X	X	–	X	X
Number of Reservation Courses	–	X	X	–	X	X
Possible Shutout FE	–	–	X	–	–	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The outcome in this regression is the number of courses students being shut out. This sample includes all individual observations in potentially oversubscribed courses. F-stat p-value comes from a joint test of significance for sex, race/ethnicity, first-generation status, and SAT score variables. Columns (3) and (6) correspond to our primary individual-level specification. In Columns (2) and (5), Course-by-Preference Fixed effects include a fixed effect for each course at every potential priority. Columns (2), (3), (5), and (6) control for the number of "reservation courses" a student is enrolled in. Certain majors reserve slots in classes for at least some students pre-enrolled in a corresponding major. Individuals are in a "reservation course" if they (1) are pre-enrolled in the major offering the course and (2) the major is one of the majors that reserve slots for some students. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Simulated probability of 1 shutout is the probability of being shutout of exactly one course, which is the fraction of simulated schedules for a student that result in exactly one shutout. Similarly, simulated probability of 2 shutouts, Simulated probability of 3 shutouts, Simulated probability of 4 shutouts, and Simulated probability of 5 shutouts correspond to the probability of being shut out of two, three, four, and five courses, respectively. To ensure common support for our estimates, we include fixed effects for the number of potential shutouts, where potential shutouts are the number of courses a student requests that have a positive, non-degenerate, probability of shutouts. Our estimates are robust to the exclusion of these fixed effects. Robust standard errors are reported in parentheses

Table A.5: Effect of Course Shutout on Attendance and Completion in Oversubscribed Courses, Borusyak & Hull (2023) re-centered IV strategy

Panel A: Control Function Approach				
	Attend First Semester	Complete First Semester	Complete First Year	Ever Complete
	(1)	(2)	(3)	(4)
Shutout of Course	-0.723***	-0.712***	-0.440***	-0.352***
	(0.009)	(0.009)	(0.011)	(0.010)
Observations	15,121	15,121	15,121	15,121
R^2	0.699	0.667	0.512	0.479
Non-Shutout Mean	0.852	0.836	0.850	0.857
Panel B: Re-centered IV Approach				
	Attend First Semester	Complete First Semester	Complete First Year	Ever Complete
	(1)	(2)	(3)	(4)
Shutout of Course	-0.723***	-0.712***	-0.440***	-0.352***
	(0.009)	(0.009)	(0.011)	(0.011)
Observations	15,121	15,121	15,121	15,121
Non-Shutout Mean	0.852	0.836	0.850	0.857
Simulated Shutout Probability	X	X	X	X
Demographic Characteristics	X	X	X	X
Course FE	X	X	X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each outcome in this table relates to the exact course a student was potentially shut out from. Column (1) reports the effects of a shutout on attending a requested course in the semester the request is made. Attendance is defined as being enrolled in the course after the add/drop deadline. Column (2) reports the effects of a shutout on completing a requested course in the semester the request is made. Column (3) reports the effects of a shutout on completing a requested course in Fall, Spring, or Summer semester of the 2018/2019 school year. Column (4) reports the effect of a shutout on completing a requested course by the Fall 2022 semester. In Panel A, the estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. In panel B, we follow Borusyak & Hull (2023)'s instrumental variables approach where the instrument is the realized course shutout minus the simulated shutout probability and the treatment is the shutout indicator. Observations are at the student-course level. Each estimate includes controls for simulated shutout probability, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), an indicator for a reservation course, and course-fixed effects. Standard errors that are clustered at the individual level are reported in parentheses.

Table A.6: How the Effects of a Course Shutout Differ by Student Characteristics

Panel A: Attendance in the First Semester	Female (1)	URM Minority (2)	First Gen (3)	Low SAT (4)
Shutout of Course	-0.710***	-0.719***	-0.718***	-0.705***
	(0.010)	(0.009)	(0.009)	(0.010)
Interaction	-0.031***	-0.048***	-0.030**	-0.037***
	(0.011)	(0.017)	(0.014)	(0.011)
Demographic	0.019***	0.025**	0.006	0.002
	(0.006)	(0.010)	(0.008)	(0.007)
Observations	15,121	15,121	15,121	15,121
R^2	0.699	0.698	0.699	0.696
Panel B: Ever Complete				
Shutout of Course	-0.353***	-0.353***	-0.354***	-0.384***
	(0.012)	(0.011)	(0.011)	(0.013)
Interaction	0.001	-0.006	0.010	0.063***
	(0.016)	(0.024)	(0.020)	(0.015)
Demographic	0.023***	0.009	-0.005	-0.019***
	(0.006)	(0.010)	(0.008)	(0.007)
Observations	15,121	15,121	15,121	15,121
R^2	0.479	0.477	0.479	0.476
Panel C: Courses Taken in Same Subject Ever				
Shutout of Course	-0.265***	-0.255***	-0.251***	-0.285***
	(0.011)	(0.010)	(0.010)	(0.012)
Interaction	0.026*	-0.000	-0.020	0.062***
	(0.015)	(0.024)	(0.020)	(0.015)
Demographic	0.032***	0.010	-0.003	-0.020***
	(0.006)	(0.009)	(0.007)	(0.006)
Observations	15,121	15,121	15,121	15,121
R^2	0.398	0.396	0.398	0.392

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each outcome in this table relates to completion of courses in the same subject area as a course a student was potentially shutout from. "Shutout" is an indicator for being shutout of a requested course. Each regression controls for shutout probability, which is generated from simulations of the algorithm that generated freshman course assignments in the Fall of 2018. Major in subject There are 10 colleges at Purdue including Agriculture, Education, Engineering, Health and Human Sciences, Liberal Arts, Management, Pharmacy, Polytechnic, Science, and Veterinary Medicine. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Standard errors clustered at the individual level are reported in parentheses.

Table A.7: Heterogeneous Effects of a Course Shutout by Course Characteristics

Panel A: Attend Course in First Term	General Education		High Difficulty		Top 3 Preferences	
	Yes	No	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Shutout of Course	-0.762***	-0.467***	-0.773***	-0.826***	-0.771***	-0.710***
	(0.009)	(0.026)	(0.021)	(0.010)	(0.016)	(0.011)
Observations	12,375	2,746	5,283	8,138	5,812	9,113
R^2	0.689	0.761	0.559	0.711	0.666	0.705
Panel B: Ever Complete Course						
Shutout of Course	-0.380***	-0.181***	-0.276***	-0.433***	-0.285***	-0.385***
	(0.011)	(0.024)	(0.024)	(0.013)	(0.020)	(0.012)
Observations	12,225	2,700	5,283	8,138	5,812	9,113
R^2	0.442	0.681	0.261	0.299	0.414	0.490
Panel C: Ever Take Course in Subject						
Shutout of Course	-0.277***	-0.108***	-0.216***	-0.301***	-0.160***	-0.297***
	(0.011)	(0.023)	(0.022)	(0.012)	(0.017)	(0.012)
Observations	12,225	2,700	5,283	8,138	5,812	9,113
R^2	0.365	0.592	0.206	0.220	0.324	0.410

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each outcome in this table relates to completion of courses in the same subject area as a course a student was potentially shutout from. "Shutout" is an indicator for being shutout of a requested course. Each regression controls for shutout probability, which is generated from simulations of the algorithm that generated freshman course assignments in the Fall of 2018. Major in subject There are 10 colleges at Purdue including Agriculture, Education, Engineering, Health and Human Sciences, Liberal Arts, Management, Pharmacy, Polytechnic, Science, and Veterinary Medicine. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Standard errors clustered at the individual level are reported in parentheses.

Table A.8: Effect of Shutouts on Student-Level Post-Baccalaureate Outcomes

	Salary (1)	Graduate School (2)	Employed (3)	Job Seeking (4)
Total Shutouts	143.837	-0.011	0.012	-0.003
	(734.972)	(0.013)	(0.015)	(0.007)
Observations	4,591	4,865	4,865	4,865
R^2	0.294	0.129	0.113	0.037
Non-Shutout Mean	66,895	0.240	0.665	0.041

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column (1) reports the effects of total first-term shutouts on salary. Column (2) reports the effects of total first-term shutouts on whether students attended graduate school. Column (3) reports the effects of total first-term shutouts on whether students employed. Column (4) reports the effects on whether students seek employment. All outcomes are self-reported by students to Purdue in the "First Destination" post-graduation survey administered by Purdue University Center for Career Opportunities. We impute salaries for those who are employed, but do not report earnings, by regressing salary on cumulative GPA, graduating college, the interaction term between cumulative GPA and graduating college, employment industry, and student covariates. Similarly, we imputed salary for individuals who were on fellowships, attending graduate school, and participating in internships by regressing salary on cumulative GPA, graduating college, the interaction term between cumulative GPA and graduating college, and student's covariates. We assign $0 earnings if individuals reported their labor market outcomes as "Not seeking an internship", "Other Intentions", "Postponing job search", "Seeking Employment", "Still Seeking Education", "Still Seeking Internship", and "Taking time off (more than 4 months)". This earning variable is going to be the lower-bounded salary. We then run the regression with the lower-bounded salary as the outcome variable. The result is shown in Column (1). Alternatively, we assign the predicted salary values for individuals who were on fellowships, attending graduate school, and participating in internships to be the upper-bounded salary. We then run the regression with the upper-bounded salary. The estimate is -324.264 with robust standard error of 489.934. We also assigned a missing value if individuals reported their labor market outcomes as "Fellowship", "Graduate School", and "Internship". In addition, we omitted individuals who stated their labor market outcomes as " Military Service", "Own Venture", "Research", "Service Organization", "Summer classes", and "Volunteering". We exclude individuals who have not graduated from these estimates. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Robust standard errors are reported in parentheses.

Table A.9: Exploring Non-Linear Effects of Shutouts on Cumulative Outcomes by Gender

Panel A: Female	Cumulative Credits	Cumulative GPA	4-Year Graduation	STEM Major
	(1)	(2)	(3)	(4)
One Shutouts	-1.900	-0.024	-0.069***	-0.044**
	(1.690)	(0.027)	(0.025)	(0.018)
Two Plus Shutouts	-2.855	-0.097**	-0.096**	-0.042
	(3.010)	(0.048)	(0.044)	(0.033)
Observations	3,336	3,315	3,336	3,336
R^2	0.079	0.173	0.107	0.530
Non-Shutout Mean	113.169	113.793	113.169	113.169

Panel B: Male	Cumulative Credits	Cumulative GPA	4-Year Graduation	STEM Major
	(1)	(2)	(3)	(4)
One Shutouts	0.627	-0.005	-0.004	0.005
	(1.576)	(0.027)	(0.022)	(0.014)
Two Plus Shutouts	1.461	-0.027	-0.004	-0.014
	(2.699)	(0.046)	(0.038)	(0.024)
Observations	4,310	4,217	4,310	4,247
R^2	0.168	0.135	0.086	0.463
Non-Shutout Mean	104.709	107.135	104.709	106.234

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. A total of 3,478 students experienced a single shutout. Among the 766 students who faced at least two total shutouts, 676 had two shutouts, and 85 experienced three shutouts. Only five students had the experience of encountering four total shutouts. Panel A reports results for female students and Panel B reports results for male students. Column (1) reports the effects of total first-term shutouts on the total credits earned between Fall 2018 and Fall 2022 semesters. Column (2) reports the effects of one first-term shutouts and two plus first-term shutouts on cumulative GPA between Fall 2018 and Fall 2022 semesters. Students who leave Purdue prior to earning any credits are omitted from this regression. Column (3) reports the effects of one first-term shutouts and two plus first-term shutouts on graduating from Purdue within 4-years (by the Spring 2022 semester). Column (4) reports the effects of choosing a STEM major. A student's major is defined as their primary graduating major if they have graduated or their most recent primary major if they have not graduated. STEM majors are defined by matching Purdue major CIP codes to the Department of Homeland Security's list of CIP codes that correspond to STEM majors. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Robust standard errors are reported in parentheses.

Table A.10: Effects of Shutouts on Cumulative Outcomes by Course Characteristics

Panel A: STEM	Cumulative Credits (1)	Cumulative GPA (2)	4-Year Graduation (3)	STEM Major (4)
STEM Shutouts	-0.178	-0.058**	-0.033	-0.017
	(1.432)	(0.024)	(0.020)	(0.014)
Observations	7,646	7,532	7,646	7,583
R^2	0.131	0.148	0.091	0.516
Non-Shutout Mean	108.668	3.252	0.604	0.694
Panel B: Non-STEM	Cumulative Credits (1)	Cumulative GPA (2)	4-Year Graduation (3)	STEM Major (4)
Non-STEM Shutouts	0.266	0.004	-0.007	-0.016
	(1.122)	(0.019)	(0.016)	(0.011)
Observations	7,646	7,532	7,646	7,583
R^2	0.131	0.147	0.091	0.517
Non-Shutout Mean	108.668	3.252	0.604	0.694
STEM vs. Non-STEM p-val	0.806	0.045	0.327	0.995
Panel C: Required	Cumulative Credits (1)	Cumulative GPA (2)	4-Year Graduation (3)	STEM Major (4)
Required Shutouts	-0.314	-0.016	-0.028**	-0.018*
	(0.948)	(0.016)	(0.013)	(0.009)
Observations	7,646	7,532	7,646	7,583
R^2	0.131	0.148	0.093	0.515
Non-Shutout Mean	108.668	3.252	0.604	0.694
Panel D: Non-Required	Cumulative Credits (1)	Cumulative GPA (2)	4-Year Graduation (3)	STEM Major (4)
Non-Required Shutouts	2.426	-0.023	0.043	-0.004
	(2.431)	(0.040)	(0.035)	(0.024)
Observations	7,646	7,532	7,646	7,583
R^2	0.130	0.148	0.090	0.514
Non-Shutout Mean	108.668	3.252	0.604	0.694
Required vs. Non-Required p-val	0.266	0.859	0.054	0.561
Panel E: Upper Courses	Cumulative Credits (1)	Cumulative GPA (2)	4-Year Graduation (3)	STEM Major (4)
Upper Shutouts	4.537	-0.012	0.069	-0.011
	(4.077)	(0.068)	(0.058)	(0.040)
Observations	7,646	7,532	7,646	7,583
R^2	0.130	0.147	0.090	0.514
Non-Shutout Mean	108.668	3.252	0.604	0.694
Panel F: Non-Upper Courses	Cumulative Credits (1)	Cumulative GPA (2)	4-Year Graduation (3)	STEM Major (4)
Non-Upper Shutouts	-0.182	-0.021	-0.022*	-0.016*
	(0.899)	(0.015)	(0.013)	(0.009)
Observations	7,646	7,532	7,646	7,583
R^2	0.132	0.148	0.091	0.515
Non-Shutout Mean	108.668	3.252	0.604	0.694
Upper vs. Non-Upper p-val	0.282	0.895	0.094	0.883

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel A reports results for the effects of total first-term STEM shutouts on cumulative outcomes, and Panel B reports results for the effects of total first-term non-STEM shutouts on cumulative outcomes. Panel C reports results for the effects of total first-term required course shutouts on cumulative outcomes, and Panel D reports results for the effects of total first-term non-required course shutouts on cumulative outcomes. While Panel E reports results for the effects of total first-term upper-level (300 level or above) course shutouts on cumulative outcomes, Panel F reports results for the effects of total first-term lower-level (100 or 200 level) course shutouts on cumulative outcomes. Column (1) reports the effects of the total credits earned between Fall 2018 and Fall 2022 semesters. Column (2) reports the effects of cumulative GPA between Fall 2018 and Fall 2022 semesters. Students who leave Purdue prior to earning any credits are omitted from this regression. Column (3) reports the effects of graduating from Purdue within 4-years (by the Spring 2022 semester). Column (4) reports the effects of choosing a STEM major. A student's major is defined as their primary graduating major if they have graduated or their most recent primary major if they have not graduated. STEM majors are defined by matching Purdue major CIP codes to the Department of Homeland Security's list of CIP codes that correspond to STEM majors. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Robust standard errors are reported in parentheses.

Table A.9: Effects of Shutouts on Cumulative Outcomes by Course Characteristics (Continued)

Panel G: Difficult Courses	Cumulative Credits	Cumulative GPA	4-Year Graduation	STEM Major
	(1)	(2)	(3)	(4)
Difficult Shutouts	1.009	-0.046	-0.060**	0.004
	(1.898)	(0.032)	(0.027)	(0.019)
Observations	7,646	7,532	7,646	7,583
R^2	0.131	0.149	0.092	0.514
Non-Shutout Mean	108.668	3.252	0.604	0.694
Panel H: Non-Difficult Courses	Cumulative Credits	Cumulative GPA	4-Year Graduation	STEM Major
	(1)	(2)	(3)	(4)
Non-Difficult Shutouts	-0.350	-0.015	-0.007	-0.023**
	(0.995)	(0.016)	(0.014)	(0.010)
Observations	7,646	7,532	7,646	7,583
R^2	0.131	0.147	0.091	0.516
Non-Shutout Mean	108.668	3.252	0.604	0.694
Difficult vs. Non-Difficult p-val	0.524	0.406	0.080	0.223
Panel I: Shutouts in Colleges with High Female Enrollment	Cumulative Credits	Cumulative GPA	4-Year Graduation	STEM Major
	(1)	(2)	(3)	(4)
Shutouts in High Female Enroll. Colleges	0.002	-0.013	-0.021	-0.015
	(0.941)	(0.016)	(0.013)	(0.009)
Observations	7,646	7,532	7,646	7,583
R^2	0.132	0.147	0.091	0.514
Non-Shutout Mean	108.668	3.252	0.604	0.694
Panel J: Shutouts in Colleges with Moderate or Low Female Enrollment	Cumulative Credits	Cumulative GPA	4-Year Graduation	STEM Major
	(1)	(2)	(3)	(4)
Shutouts in Med/low Female Enroll. Colleges	0.025	-0.088**	0.001	-0.025
	(2.633)	(0.044)	(0.038)	(0.026)
Observations	7,646	7,532	7,646	7,583
R^2	0.130	0.148	0.090	0.515
Non-Shutout Mean	108.668	3.252	0.604	0.694
High Female Enroll. vs. Med/low Female Enroll. p-val	0.993	0.078	0.559	0.725

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel G reports results for the effects of total first-term difficult course shutouts on cumulative outcomes, and Panel H reports results for the effects of total first-term non-difficult course shutouts on cumulative outcomes. While Panel I reports results for the effects of total first-term shutouts in college with high female enrollment on cumulative outcomes, Panel J reports results for the effects of total first-term shutouts in college with moderate or low female enrollment on cumulative outcomes. The colleges with high female enrollment are the College of Agriculture, the College of Education, and the College of Health and Human Sciences. The colleges with moderate or low female enrollment are the College of Engineering, the College of Liberal Arts, the College of Science, the College of Polytechnic Institute, and the College of Business. Column (1) reports the effects of the total credits earned between Fall 2018 and Fall 2022 semesters. Column (2) reports the effects of cumulative GPA between Fall 2018 and Fall 2022 semesters. Students who leave Purdue prior to earning any credits are omitted from this regression. Column (3) reports the effects of graduating from Purdue within 4-years (by the Spring 2022 semester). Column (4) reports the effects of choosing a STEM major. A student's major is defined as their primary graduating major if they have graduated or their most recent primary major if they have not graduated. STEM majors are defined by matching Purdue major CIP codes to the Department of Homeland Security's list of CIP codes that correspond to STEM majors. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Robust standard errors are reported in parentheses.

Table A.10: Effect of Shutouts on Cumulative Outcomes by Student Characteristics

Panel A: URM	Cumulative Credits	Cumulative GPA	4-Year Graduation	STEM Major
	(1)	(2)	(3)	(4)
Total Shutouts	4.383	0.038	0.034	-0.018
	(2.941)	(0.048)	(0.037)	(0.029)
Observations	888	816	888	825
R^2	0.400	0.226	0.204	0.494
Non-Shutout Mean	98.033	3.097	0.469	0.657
Panel B: Non-URM	Cumulative Credits	Cumulative GPA	4-Year Graduation	STEM Major
	(1)	(2)	(3)	(4)
Total Shutouts	-0.369	-0.025	-0.024*	-0.016*
	(0.921)	(0.015)	(0.013)	(0.009)
Observations	6,758	6,716	6,758	6,758
R^2	0.067	0.139	0.073	0.522
Non-Shutout Mean	110.068	3.270	0.621	0.699
URM vs. Non-URM p-val	0.110	0.224	0.132	0.960
Panel C: First Gen	Cumulative Credits	Cumulative GPA	4-Year Graduation	STEM Major
	(1)	(2)	(3)	(4)
Total Shutouts	2.575	-0.064	-0.010	0.004
	(2.602)	(0.045)	(0.032)	(0.024)
Observations	1,303	1,261	1,303	1,282
R^2	0.167	0.132	0.128	0.500
Non-Shutout Mean	98.538	3.048	0.514	0.636
Panel D: Non-First Gen	Cumulative Credits	Cumulative GPA	4-Year Graduation	STEM Major
	(1)	(2)	(3)	(4)
Total Shutouts	-0.580	-0.013	-0.020	-0.019**
	(0.926)	(0.015)	(0.014)	(0.009)
Observations	6,343	6,271	6,343	6,301
R^2	0.117	0.143	0.089	0.523
Non-Shutout Mean	110.785	3.294	0.623	0.706
1st Gen vs. non-1st Gen p-val	0.248	0.281	0.771	0.960
Panel E: Low SAT	Cumulative Credits	Cumulative GPA	4-Year Graduation	STEM Major
	(1)	(2)	(3)	(4)
Total Shutouts	-0.408	-0.033	-0.027	-0.037***
	(1.339)	(0.022)	(0.018)	(0.014)
Observations	3,761	3,658	3,761	3,698
R^2	0.178	0.145	0.121	0.463
Non-Shutout Mean	102.982	3.125	0.561	0.536
Panel F: High SAT	Cumulative Credits	Cumulative GPA	4-Year Graduation	STEM Major
	(1)	(2)	(3)	(4)
Total Shutouts	0.335	-0.002	-0.005	0.001
	(1.149)	(0.019)	(0.018)	(0.010)
Observations	3,885	3,874	3,885	3,885
R^2	0.056	0.120	0.073	0.462
Non-Shutout Mean	114.411	3.376	0.648	0.850
Female vs. Male p-val	0.617	0.292	0.363	0.022

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column (1) reports the effects of total first-term shutouts on the total credits earned between Fall 2018 and Fall 2022 semesters. Column (2) reports the effects of total first-term shutouts on cumulative GPA between Fall 2018 and Fall 2022 semesters. Students who leave Purdue prior to earning any credits are omitted from this regression. Column (3) reports the effects of total first-term shutouts on graduating from Purdue within 4-years (by the Spring 2022 semester). Column (4) reports the effects of choosing a STEM major. A student's major is defined as their primary graduating major if they have graduated or their most recent primary major if they have not graduated. STEM majors are defined by matching Purdue major CIP codes to the Department of Homeland Security's list of CIP codes that correspond to STEM majors. Each estimate includes controls for summed simulated shutout probabilities, demographic characteristics (sex, race/ethnicity, first-generation status, SAT scores, and pre-enrollment major), and number of reservation courses. These estimates are constructed using a control function approach (Borusyak & Hull, 2023) as outlined in Section 3. Robust standard errors are reported in parentheses.

Appendix II Oversubscribed Courses

Table B.1: Complete List of Oversubscribed Courses

Course Title	Course Requests	Shutouts	Course Title	Course Requests	Shutouts	Course Title	Course Requests	Shutouts
Accel First-Yr Compos	696	488	Environmental Scienc & Conserv	215	60	Intr Pub Pol-Pub Admin	61	43
America In The 1960s	14	11	Essentials Of Nutr	117	95	Intr To Classical Myth	75	39
Analytc Geom & Calc II	878	565	Ethics And Animals	23	9	Intr To Materials Engr	55	16
Ancient Philosophy	5	4	Exploring Teaching	124	42	Intro Acad Prog-Purdue	124	45
Anlytc Geomtry&Calc I	2099	991	First Year Biology Lab	242	117	Intro African American Studies	47	19
Applied Calculus I	1806	107	First-Year Composition	3169	2355	Intro Anthropology	127	71
Art Appreciation	39	21	Forensic Investigation	168	128	Intro Aviation Tech	180	12
Aviation Business	167	101	Foundation Officership	33	3	Intro Behvr Neurosci	24	8
Basic Drawing	178	56	Foundations Of Org Leadership	420	369	Intro Costume Des/Tech	3	2
Bible As Literature	30	22	French Level II	81	40	Intro Creative Writing	14	5
Biol Elem Sch Teach	113	7	French Level V	10	2	Intro Ed Tech	153	48
Biol Freshman Honr Sem	60	4	Freshman Seminar In EAS	49	2	Intro Entr & Innov	107	56
Biol I Divrs Ecol Behv	341	5	Fundament Of Speech	3207	2103	Intro Family Processes	104	52
Biology Resource Sem	220	3	Fundamentals Biol I	1368	379	Intro Health Sciences	232	7
Biotechnology Lab I	4	2	Fundamentals Biol II	66	11	Intro Hosp & Tourism Industry	70	2
Black And White Photography	65	52	Fundamentals Of Music	13	9	Intro Ling St For Lang	5	1
Bowling	16	15	Gen Physics	157	120	Intro Polit Analysis	16	14
Ceramics I	30	29	Gen Social Psychology	30	27	Intro Probability Mdls	21	18
Child Psychology	71	28	General Chemistry	3956	680	Intro Res Meth In Psy	3	1
Chinese Calligraphy	2	1	General Physics	169	110	Intro Sci Fields Psy	122	15
Chinese Level I	20	2	Geosciences Cinema	78	77	Intro Social Psych	76	40
Chinese Level III	3	1	German Level I	49	20	Intro To ANSC Programs	189	24
Classical Wrld Civiliz	38	16	German Level II	34	17	Intro To Animal Agr	157	10
Collab Leader: Interpersonal	854	684	German Level V	12	2	Intro To C Program	123	15
Crit Perspectives Com	22	5	Global Awareness	17	3	Intro To Com Theory	43	27
Crit Think & Com I	1535	996	Global Green Politics	17	11	Intro To Computers	148	95
Crit Think & Com II	995	618	Global History	85	58	Intro To Energy Engr	85	28
Crop Production	43	8	Global Moral Issues	117	103	Intro To Int Design	85	29
Customer Relation Mgmt	42	15	Graphic Communication	19	2	Intro To Linguistics	25	21
Dance Appreciation	33	20	Graphics For CE &Const	83	5	Intro To Medieval Wrld	95	49
Dscr Astr-Solar System	154	92	Great American Books	40	35	Intro To PRMD Programs	63	30
E&M Interactions	20	6	Honors Multivariate Calculus	63	13	Intro To Personal Finance	101	56
Earth Through Time	69	50	Human Antmy & Physiol	23	18	Intro To Philosophy	244	150
Earthquakes Volcanoes	103	75	Human Factors Flight Crew	10	6	Intro To Plant Science	267	139
East Asia & Hist Trad	28	17	Inclusive Classroom	49	24	Intro To Retail Mgmt	26	4
Economics	338	142	Info Tech Architecture	219	157	Intro To Statistics	35	34
Elem Stat Meth	164	102	Interdisc Approach To Writing	83	59	Intro To Tourism Mgmt	53	12
Elementary Psychology	1838	727	Interpreting America	31	17	Introduction To Earth Sciences	30	6
Elements Linguistics	71	19	Intr Actuarial Science	140	45	Introduction To Management	332	11
Engaging English	45	25	Intr Environmental Pol	73	32	Italian Level I	51	18

Course Title	Course Requests	Shutouts	Course Title	Course Requests	Shutouts	Course Title	Course Requests	Shutouts
Italian Renaissance Impact	20	14	Prin Of Persuasion	45	19	The Nuclear Age	31	21
Lab Bio III Cell Strct	17	4	Private Pilot Lectures	64	11	The Planets	187	153
Learning & Motivation	76	41	Prog Appl For Enginrs	773	499	Theatre Appreciation	100	40
Lodging Management	32	23	Progrmng With MM Objs	71	15	Tools	411	9
Macroeconomics	647	477	Quantitative Reasoning	290	142	Trans Ideas To Innovation II	51	3
Magic And Marvels	24	11	Rac & Ethn Diversity	63	42	U S Since 1877	245	134
Materials &Processes I	184	92	Religions Of The West	9	6	Visual Programming	13	9
Materials And Processes II	188	89	Sci & Society In Western Civ I	13	8	Wildlife In America	37	17
Math For Elm Tchrs I	110	4	Science Of Food	54	27	Wind Ensemble I	14	2
Media For Children	56	34	Science Writing & Presentation	121	101	Wom Pol And Publ Pol	27	20
Microecon Food & Agbus	200	63	Screenwriting	22	5	Women Tech:Expl Possib	49	3
Microeconomics	968	391	Second World War	31	27	World's Forest&Society	17	9
Modern Dance Technique I	19	12	Social Problems	321	199			
Money, Trade & Power	10	8	Society & Rock & Roll	12	9			
Multicult Leadrshp Sem	13	2	Spanish Level I	63	26			
Multivariate Calculus	804	76	Spanish Level III	297	16			
Music Theory I	25	24	Spanish Level V	84	24			
Native American Cultures	19	10	Sports & Literature	18	11			
Navigating Gender	51	23	Spreadsht Use Agr Bus	14	7			
New Media Culture	13	6	Statistics & Society	431	196			
Org &Mgt Hosp&Tour Ind	9	5	Std Arabic Level I	15	2			
Phil & The Meaning Of Life	11	4	Strat Success First Yr	24	1			
Philos Of Religion	12	6	Study Skills Seminar	106	27			
Philosophy And Law	71	41	Survey Of Acting	77	41			
Physical Geology	68	48	Symphonic Band	22	9			
Pl Anly Geo Calc I	2007	1075	Technical Graphic Comm	65	44			
Pl Anly Geo Calc II	750	335	Technology And Culture	76	33			
Planet Earth	216	146	Th Minorities In Mgmt	28	1			
Pre-Doctor Of Pharm Orient I	236	2	The Data Mine I	84	16			
Prin Of Economics	333	167	The Italian Cinema	23	16			

Appendix III Algorithm and Simulation Exercises

After students submit their preferences, they are assigned a course schedule through Purdue's batch algorithm system (Müller *et al.*, 2010). The algorithm uses each student's preference ranking of courses and preferred class times as inputs in generating schedules for all students.
The objective of the algorithm is to maximize the use of priority course requests while minimizing the use of alternative course requests provided by students (Müller *et al.*, 2010). The algorithm assigned a single weight to each course request based on the following equation:

$$weight(a \in dom(R)) = 0.9^{prior(R)} \times 0.5^{alt(a)}, \quad (5)$$

where *dom(R)* is the domain of the course request R and *prior(R)* is the ranking of priority requested course, and *alt(a)* is the ordering of the alternate requested courses. In our simulations, we assigned different weights based on the main conditions in Equation (5). Whether students were enrolled or not in those courses based on the available spots for each course.
To use the course request template from Figure C.1 as an example, the algorithm assigns $0.9^1 \times 0.5^0 = 0.9$ as the weight in *CNIT18000* while the weight of *ENGL11000* is $0.9^2 \times 0.5^0 = 0.81$. For the third preference, the algorithm assigns $0.9^3 \times 0.5^0 = 0.729$ in *MA16010* while giving the weights of $0.9^3 \times 0.5^1 = 0.3645$ in *PHYS22000* and $0.9^3 \times 0.5^2 = 0.183$ in *CHM11100*. Based on different weights from each course request provided by students, the algorithm solves the problem by implementing Iterative Forward Search (Müller *et al.*, 2004). Equation (5) implies that the algorithm is more costly to reject a course request with only priority listing and without alternative listings than a course request with both priority and alternative listings.
There are four constraints in which the algorithm has to follow while assigning course assignments to students:

1. Seats limit
   - Each course section has a seat limit for students to enroll. There is an unlimited number of enrollments in some course sections, such as distance learning sections.
2. Overlapping sections
   - Two or more course sections overlapped with each other are not allowed. The algorithm only grants one or none of those courses to students.
3. Distance student conflict
   - A distance conflict occurs when locations of two sections are too far apart with little time (10 minutes or less) for students to arrive the later section on time. No distance conflicts are identified if there are more than 20 minutes gap between two sections.
4. Course reservations by colleges or departments
   - Colleges or departments reserve spots in certain courses for students who have declared majors.

The batch registration process has the following steps:

(i) The algorithm starts by ordering priority students in order of constraints (those with fewest potential of sections for their courses first) and uses a branch and bound technique to evaluate best possible assignments, as defined by their course prioritization

(ii) Students who are not enrolled in their desired number of courses from step 1 are ordered randomly. In this order, the algorithm looks for assignments that do not conflict with existing assignments or schedule constraints.

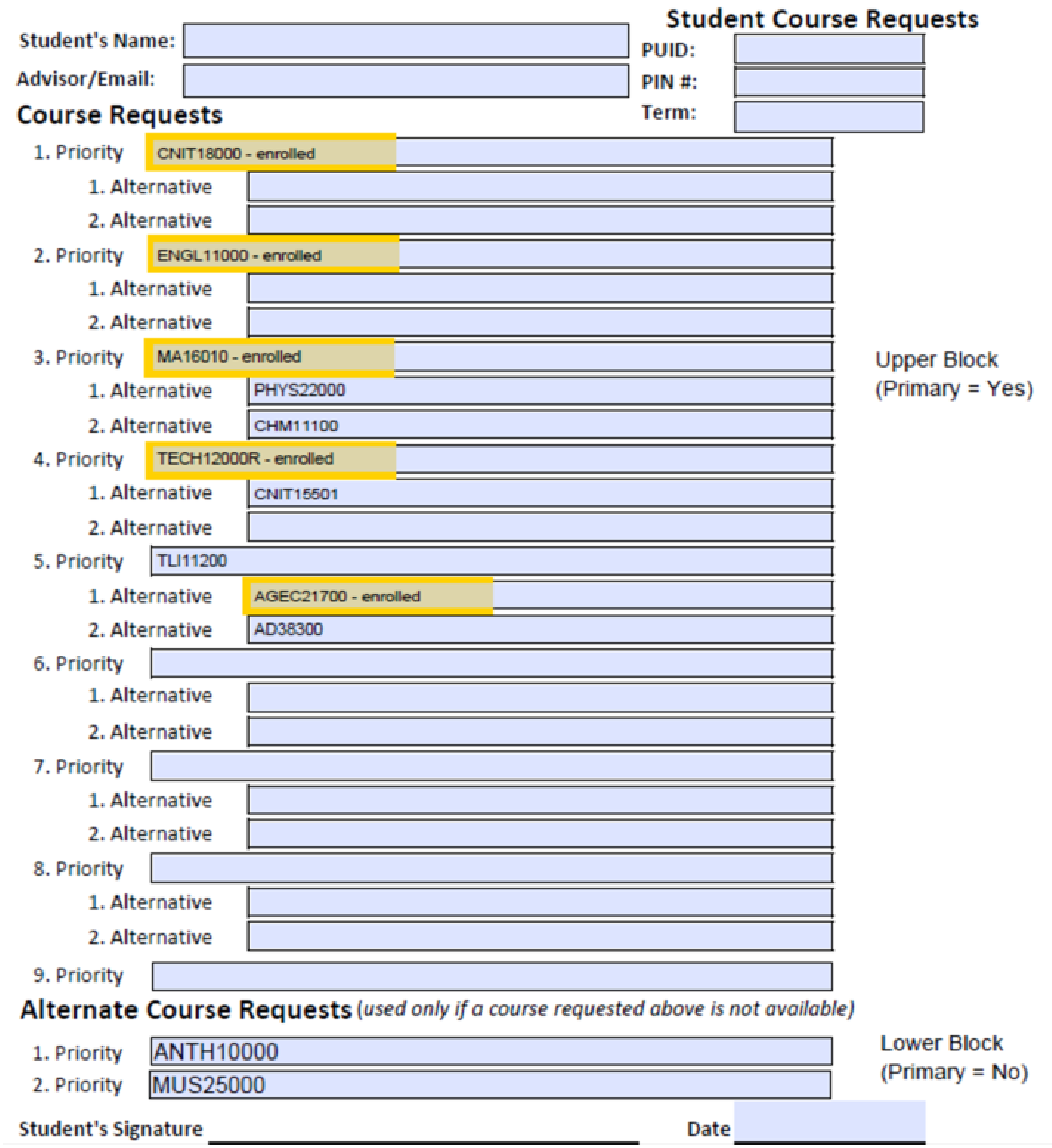
(iii) The algorithm improves the overall schedules by using backtracking technique.

(iv) The algorithm repeats steps $i - iii$ and stores the results.

(v) After a pre-specified run-time (12 hours in the case of Fall 2018 assignments), the batch assignment with the highest weight score is selected

We run 1,000 simulations of the algorithm used in the Fall of 2018 using Java SE 11 to estimate the shutout probability for each assignment request. Interested readers can learn more from (Müller *et al.*, 2010).

Figure C.1: Course Request Form



Student Course Requests

Student's Name:
Advisor/Email:
PUID:
PIN #:
Term:

Course Requests

1. Priority	CNIT18000 - enrolled
1. Alternative	
2. Alternative	
2. Priority	ENGL11000 - enrolled
1. Alternative	
2. Alternative	
3. Priority	MA16010 - enrolled
1. Alternative	PHYS22000
2. Alternative	CHM11100
4. Priority	TECH12000R - enrolled
1. Alternative	CNIT15501
2. Alternative	
5. Priority	TLI11200
1. Alternative	AGEC21700 - enrolled
2. Alternative	AD38300
6. Priority	
1. Alternative	
2. Alternative	
7. Priority	
1. Alternative	
2. Alternative	
8. Priority	
1. Alternative	
2. Alternative	
9. Priority	

Upper Block
(Primary = Yes)

Alternate Course Requests *(used only if a course requested above is not available)*

1. Priority	ANTH10000
2. Priority	MUS25000

Lower Block
(Primary = No)

Student's Signature ______________________ Date ________