"Alone" Students' Academic Outcomes

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Abstract

This paper examines the experiences of college students who are the sole representatives of their race, ethnicity, or nationality in a classroom setting, a situation referred to as being "alone." Assuming that the US Supreme Court ban on Affirmative Action in college admission will reduce representations of underrepresented minority students in selective college campuses, I explore whether being the only student of a particular background in a course section has a causal effect on the academic outcomes of undergraduate students. To answer this, I exploit the random course and section assignment based on freshman students' course preferences at a large public college in the USA. I use actual course assignment data to define an instrument for the treatment of being *alone*. Conditional student's course preferences, the instrument (i.e., being assigned *alone*) is as good as random. The findings show that being the only student in a class by race or ethnicity impacts students' course grades negatively. Being alone in a class by students' racial, ethnic, or national attributes and academic attributes impacts course grades negatively. Being alone in a course by race or ethnicity and college reduces the course grade by 0.054 points for domestic students. Being alone by race or ethnicity and college in the same instructor-taught sections of the course reduces the course grade by 0.076 points for domestic students and 0.30 points for international students. The empirical mechanism reveals that the negative *alone* effects are driven by positive peer effects. Non-linearity in peer effects and comparison of *alone* effect with the average peer effect implies that a part of the *alone* effect can be explained as the loneliness effect.

Keywords: Peer Effects; Racial Peers; Alone Effects; Achievement Gap

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1 Introduction

The issue of how peer groups influence others' outcomes has received a great deal of attention in economics. While a substantial body of literature has documented the significance of peer effects in shaping students' academic trajectories, the nuanced impact of being the sole representative of one's race, ethnicity, or nationality in a classroom—what I term as being "alone"—has not been investigated. This paper seeks to fill this gap by examining the causal effect of being alone in a class affects the academic outcomes of college students. The findings of this research have broader implications beyond education, particularly in understanding how minority individuals navigate in otherwise homogeneous environments in the workplace, political spaces, and social settings.

Associations of self-reported loneliness and academic outcomes have been studied in different fields of social sciences. For example, Rotenberg and Morrison (1993) studied if loneliness predicts dropout from courses. Loneliness has also been associated with academic persistence and retention (Nicpon et al., 2006). These papers provide a mere association between loneliness and academic outcomes without establishing if these are causal or not. In this paper, I study the impacts of course-level loneliness on academic outcomes through the lens of exposure to peer absence. I use data from Purdue University, which is a large public university in the Midwest, to provide causal evidence of the impacts of course-level loneliness on both contemporary course-level outcomes and subsequent student-level outcomes.

In academic settings, students often find themselves "alone" (or, alternately *lone*) in a class when they are the sole representative of their race, ethnicity, or nationality. That means if a student is the only student, in a course, from their background (i.e., race and ethnicity for domestic students, and country of citizenship for international students), then I define them as *lone* students. Then I see if this treatment status impacts their course-level outcomes. Then, I analyze subsequent student-level outcomes that include term-level and graduation-level outcomes. To investigate the effects of numerical solitude or loneliness, this paper uses restrictive administrative data from Purdue, where a course assignment algorithm assigns courses nearly at random, once students' course preferences are accounted for. I discuss the controlling strategy in the empirical strategy section (Section 4).

To deal with this, I use an instrumental variable strategy (IV). I define being a *lone* student in the course assignment data. Then I use being*assigned alone* as the instrument for actually *alone* in the grade file where I see which students completed which courses. Using the actual course request data available in the course assignment formula, one can use the algorithm to generate a simulated assignment (Mumford et al. 2023). Every time the algorithm is fed with the course request data, it generates a file with simulated assignments. Since the algorithm picks students in random order to compile a schedule of courses for students, simulated assignment files can be different from one simulation to another (Mumford et al. 2023). Following that, 1,000 simulated course assignment files were generated. Within each file, I define whether the student was assigned alone or not. The mean of *assigned lone* gives me an estimated measure of the probability of being *alone* for a student in a section of a course. After controlling the probability of being *alone*, I show that the instrument being assigned *alone* is as good as random. A very similar empirical strategy is proposed by Borusyak and Hull (2023) to resolve the endogeneity problem of the instrumental variable. To remove the endogeneity concern, they consider the shock assignment process to generate counterfactuals of the instrument. In my case, the simulated course assignments are the counterfactuals. Borusyak and Hull (2023) consider the mean of the counterfactuals as the expected treatment-which is the probability of being *alone* in this paper.

The population for this study consists of freshman students who began their first term in Fall 2018 at a large public university, totaling over 8,000 students. After excluding students who had a 100% probability of being assigned as "alone" or "not alone," the final sample comprises 5,040 (24,707) student-by-course-by-section (student-by-course-by-section-by-college) observations and 2,065 (2,176) student-level observations. The *grade sample* reveals a strong correlation between the instrument and the treatment in the first stage, with a coefficient exceeding 0.82 across all specifications, indicating both the reliability of the instrument and a high level of compliance with course assignments, ranging between 82% and 88%. Instead of presenting 2SLS estimates, this paper reports reduced form estimates across all regression specifications for each outcome, thus providing intention-to-treat (ITT) estimates.

Being isolated impacts students' course grades negatively, both for domestic and international students at the course-instructor-college level. Finding no other classmates from the same college and race or ethnicity at the section level reduces course grades both for domestic, by 0.076 points, and international students, by 0.30 points. Being the only student from one's race and college in a section also decreases the course grades of domestic students by 0.05 standard deviation. Since the treatment assignment at the section level masks potential endogenous sorting within the course section, treatment defined among academically more homogeneous peers unmasks the heterogeneity of the effect. The problem of endogenous sorting arises when the racial or ethnic peer groups become large, which follows the results Carrell et al. (2013). This paper resolves the masking of treatment effect due to the sorting problem by finding the *alone* effects among academically more homogeneous peers, where the probability of sorting should be low.

The mechanism for this short-run positive effect is the sorting of students by ability within their assigned racial or ethnic groups. Alternatively, the scope to avoid certain peers yields the negative peer effect and positive *alone* effect on course grade. Carrell et al. (2013) explored the effects of peer group assignments at the United States Air Force Academy, discovering that low-ability students, when grouped with higher-ability peers, tended to isolate themselves within subgroups of similarly low-ability peers, leading to worse academic outcomes than anticipated. This phenomenon underscores the complexities of peer effects, where the intended positive influence of mixing students of varying abilities can backfire if students self-segregate. In the current study, a similar concept is explored within a university setting, focusing on "lone" students—those isolated by race, ethnicity, or nationality in their course sections.

The analysis reveals that being *alone* among academically homogeneous peers can have negative effects on course grades, which is explained by positive peer effects irrespective of the group size being large or not. The result is further supported by an alternative definition of being alone among homogenous peers at the course-by-instructor level. This definition allows students to find racial, ethnic, and national peers in any section of the course taught by the same instructor. Being alone among racial, ethnic, and national peers from the same colleges reduces course grades by 0.14 points. For international students, the magnitude of the *alone* effect at this level is larger than for domestic students.

This paper has two major contributions. First, this is the first paper studying how being *alone* in classrooms affects students' academic outcomes shedding light on the relevance of academic loneliness to academic performance. Second, this paper provides evidence that being alone among academically homogenous peers harms academic outcomes. Third, the paper presents policy implications for course assignments while considering the racial, ethnic, and nationality compositions in the class. Options to choose peers from a heterogeneous set of peers make students better off than having a limited number of peers to choose from. As a result, the *not-alone* student group has at least one ability peer effect that positively impacts their course grades when they have options to choose from a large group of racial peers. On the other hand, the difference between large and small peer groups does not alter the ability of peers effects for students who are academically homogeneous. Fourth, this paper relates chronic loneliness to the diverging results at the student level outcomes between domestic and international students. Though being *alone* does not trigger the negative effect of loneliness in academic outcomes in the short run, repeated instances of being *alone*- what I define as chronic loneliness - impact international students negatively, but the domestic students were not impacted in the same direction.

The remaining sections of the paper proceed as follows. In Section 2, I provide a comprehensive review of the relevant literature on peer effects, particularly focusing on the impact of being "alone" in a classroom by race, ethnicity, or citizenship. Section 3 describes the data, including the sample selection and key variables. Section 4 details the empirical strategy, including the identification strategy and the instrumental variable approach used to address the non-random assignment of students to course sections. Section 5 presents the main results, highlighting the differential impacts of being alone on domestic and international students' academic outcomes. In Section 6, I discuss the implications of these findings in the context of educational policy and peer effects literature. Finally, Section 7 concludes with a summary of the key findings and policy implications.

2 Literature

The Peer effects in education literature already have studied peer effects in elementary, high school, and college classroom environments (Sacerdote,2011; Hoxby, 2000). This paper broadly merges with the peer effects literature in higher education. We have varied results on the dormitory-level peer effects in higher education (Sacerdote, 2001; Foster, 2006; Zimmerman, 2003; and Stinebrickner & Stinebrickner,2006). The findings spread from positive to null effects of the dormitory peers on academic outcomes. We do not know much about students who do not find any peers of shared demographic characteristics. Fletcher and Tienda (2008) find that students with larger high school peer networks at college entry outperform those with smaller networks, with marginal increases in same-race peer network size raising GPA by 0.1 points, and minority students benefiting more academically from larger networks than their white counterparts.

Similar to Fletcher and Tienda (2008) that finds positive peer effects, Oliver (2023) uses observational data to understand how racial peers impact the academic outcomes of two-year community college students. The paper finds that minority students exposed to a higher fraction of same-race classmates are likelier to pass their courses and re-enroll in the same subject the following term. While Oliver's (2023) finding is intuitive, I do not find similar results in my paper. I find that overall the racial peer effects are negative or non-existent on course grades both for domestic and international students. My paper is not the first one that finds negative peer effects in higher education and at the classroom level.

To understand negative peer effect results, Carrel et al. (2013) is a notable paper describing when ability mixing can explain such results. Carrel et al. (2013) use the results from Carrel et al. (2009) to design an intervention to improve the course grades of low-ability students while not impacting the high-ability students. Carrel et al. (2009) found that high-ability peers impact the course grades of low-ability students positively and that was a pareto improvement. Based on those results, Carrel et al. (2013) ran a controlled experiment to compare the outcomes of students randomly assigned to peer groups (control) versus those assigned to peer groups designed to maximize peer effects (treatment). The findings reveal that while the experimental design intended to benefit low-ability students by placing them in groups with high-ability peers, the actual outcomes were contrary: low-ability students in the treatment group performed worse than expected, while middle-ability students benefited. They conducted a follow-up survey to understand why the experiment did not replicate Carrel et al. (2009) findings. They conclude that the experiment did not address the endogenous group formation at the micro level within the assigned group. Low-ability students interacted more with low-ability students both for study and social activities purposes.

Similarly to Carrel et al. (2009), Braddy et al. (2017) examine the impact of peer effects on academic performance at the U.S. Naval Academy (USNA) using 17 years of data. The paper found negative peer effects at the broader "company" level, which is the social and residential group that students are randomly assigned to upon entering USNA. Specifically, higher average verbal SAT scores among companymates were associated with lower grades for students in STEM courses. Considering the endogenous group formation at a higher level of assignment found in Carrel et al. (2013), they redefined the treatment at the Course-Company level. All company-mates do not attend in the same section of a course. Hence, the course-company level is a lower level than the company. The size of randomly assigned peer groups at the course-company level is smaller than at the company level. They find positive peer effects at that smaller level. This is because the chance of further sorting within the group is smaller at Course-Company than at the company level.

I use the idea of Carrel et al. (2013) to understand why this paper finds the positive *lone* effect. I discuss this in the empirical mechanism section (Section 5.2).

3 Data

I use data for Fall 2018 freshmen students data from Purdue University. The purpose of using Fall 2018 data is that Purdue assigned courses to all Fall 2018 freshman students using an algorithm called Batch Registration which I leverage to construct a valid instrument. I discuss the algorithm briefly in Appendix 2. There are 8,410 student observations from 79 countries. US, China and India constitute over 93% of the undergraduate student body. However, after dropping those students with 100% or 0% probability of being *alone* at section-by-college peers level, I end up with 25,500 student-by-course-by-section observations, and over 6,305 student-level observations.

I report the summary statistics before dropping any observations and the analysis sample after dropping some observations based on the estimated probability of *alone*. Among all domestic students, 3.83% students were assigned *alone* at the section level whereas 48.09% of all international students were *alone* at that level. The probability of being assigned *alone* reflects the same sharp difference between international and domestic students. I drop all those student-by-course-by-section level observations that have 100% probability of being either *alone* or *not* alone. After dropping those observations, the number of observations drops from 57,520 to 21,820 for domestic students and from 6,474 to 3,729 for international students.

In the analysis sample, 29% domestic student-by-section level observations fall in the assigned *alone* category. As expected the fraction of international student's section-level observations falling in the same category is much larger (i.e., 55.32%). The domestic students sample has a larger proportion of female students and more representation from Black and Hispanic students, while the international students sample includes more Asian[1], particularly Indian and Chinese, students. The average age is slightly higher for international students and these students also have higher SAT math scores but slightly lower SAT verbal scores compared to domestic students.

4 Empirical Strategy

A key challenge in studying the impact of being "alone" in a classroom, like studying the peer effects, is the issue of selection bias. Students do not randomly select their courses or peers, meaning that those who end up "alone" in a class may differ systematically from their counterparts in ways that also affect academic outcomes. For example, students who choose classes where they are likely to be alone could have distinct preferences, abilities, or motivations that influence their performance independently of their peer group. Without addressing this selection problem, it would be difficult to determine whether observed academic outcomes are truly driven by being *alone*. To overcome this, the paper uses an instrumental variable (IV) strategy, exploiting the random nature of course assignment after controlling for students' preferences for courses, which helps isolate the causal impact of being *alone* from selection bias.

To do that, I leverage the course assignment algorithm and students' course preference data from the university to construct the instrument for being alone in a class. As defined previously, a student is defined *alone* when she is the only student from her race or ethnicity (for domestic students) or country of citizenship (for international students) in that course section and the status of being *alone* can be non-random. One possible solution is to use the treatment status

[1] After recoding the race/ethnicity dummy variables, which are supposed to apply only to domestic students but were set to zero for some international students who self-reported within those categories, the course-level results remain qualitatively unchanged. The point estimates and standard errors show little changes, and the effect size remains at 0.11 grade points.

in the course assignment data but not the one in the actual grade sample data. The treatment status in the assignment data is defined as the instrument *assigned alone*. Borusyak & Hull (2023) found an improved solution to resolve the selection problem with the instrumental variable strategy. They develop a method for estimating the effects of treatments where some determinants are generated by exogenous shocks, like railroad construction. The shock assignment process is leveraged to construct counterfactuals by simulating what could have happened under different shock realizations, allowing researchers to adjust for omitted variable bias (OVB) by comparing expected and realized treatments. By centering the treatment on its expected value, the approach isolates the impact of random shocks, addressing bias and ensuring valid causal inference in the presence of endogenous or unobserved determinants.

For assigning a course, it picks a student in a random[2] order. After controlling for the student's course preference, the instrument is arguably random. Using the same algorithm the university used to assign course schedule, I generated 1,000 simulated course assignments with the instrument within it.

Then I constructed a measure of the probability of a student of *being alone* in a class. If a student was 600 times assigned alone in a section, the probability of being *assigned alone* for that student in that section is 0.6. If a student is the only student from her race/ethnicity who requested the course, the probability that the student will be alone in that course is 1.

Being *alone* can be correlated with students' race, ethnicity, and unobserved preferences (reflected in their final course choices), even after controlling for revealed course-request preferences. Ideally, all those observations that have 100% probability of being *alone* or *not-alone* do not drive identifying variations in the instrument. I choose not to use those observations and trim the sample to keep any observations that do not have 100% probability of being *alone* or *not-alone*. Then the identification assumption is- conditional on the estimated probability of being *alone* in a section, actual **assignment** as *alone* is as good as random (this is shown in Column (2) of Table 2). On the course assignment day (i.e., batch day), the variable *assigned_alone* is known. After add/drop deadline, the students can no longer drop a course or modify the registration. At that time, the actual variable *alone* is known. I use *assigned_alone* as the instrument for *alone*.

[2] Some students can get higher importance for some courses. For example, some majors reserve slots in classes for students pre-enrolled in a corresponding major.

First stage regression:

$$alone_{i,sec} = \gamma_0 + \gamma_1 * assigned\_alone_{i,sec} + \Phi X + \gamma_3 * Pr(assigned\_alone_{i,sec}) + \alpha_c + e_{i,sec} \quad (1)$$

Reduced form regression:

$$y_{ic} = \tau * assigned\_alone_{i,sec} + \beta X + \mu * Pr(assigned\_alone_{i,sec}) + \alpha_c + u_{i,sec} \quad (2)$$

The reduced form regression for homogeneous treatment assignment:

$$y_{i,sec} = \tau * assigned\_alone_{i,sec,college} + \beta X + \mu * Pr(assigned\_alone_{i,sec,college}) + \alpha_c + u_{i,sec,college} \quad (3)$$

y is outcome for student i in course-by-section sec. $alone_{i,sec}$ is the dummy variable taking value 1 if the student i is alone, by race/ethnicity, in course section sec and X is a vector student and course specific controls. $pr(Assigned\_alone)$ is the estimated probability of being alone in section sec for student i. I can control for course (α_c) fixed effects. Since the assignment is at the student and course level, I cluster the standard errors at the course level.

For student-level outcomes, the reduced form regression model is:

$$y_i = \tau * assigned\_alone_i + \beta X + \mu * Pr(assigned\_alone_i) + \alpha_c + u_i \quad (4)$$

Here, both the treatment and probability variables are taken as mean at the student level.

4.1 Validity of the instrument

Table 1 shows the check conditional independence four course-level outcomes. The last column is the model under the main identification strategy. It shows that the instrument is not correlated with the demographic characteristics of the students once we control for students' course preferences and the simulated probability. Only being Asian is correlated with the instrument if I add additional observations (who have $pr(alone) = 1$) but I did not use that sample. More important variables like SAT scores are not correlated with the instrument. Table 1 shows the conditional independence check by domestic students' race and ethnicity (column

2) and international students' country of citizenship (column 3). Overall the instrument is not correlated with predetermined demographic characteristics and test scores.

Table 2 shows the first-stage relationship between the treatment and the instrument. The correlation between the treatment and the assignment is 0.87. Across all specifications and the samples, the coefficient is over .82 and the F statistics is very large. This indicates the strong relationship between being *alone* and being *assigned alone*.

5 Results

The paper provides empirical evidence indicating that the absence of academically similar peers—students of the same race/ethnicity and college background—can negatively impact course performance. In Column (1) of Table 3, being the only student from one's race and college in a section decreases course grades of domestic students by 0.054 points and the effect is significant at 1% level. This negative coefficient suggests that being the only student of one's race/ethnicity and college in a course section is associated with a slight decrease in course grades for domestic students, perhaps due to isolation from academically similar peers. With a similar definition of the treatment but assigned at the instructor level instead of the section level, being alone in a course among racial and college peers reduces course grades by 0.076 points for domestic students (Column (4), Table 3).

Now let us come back to Column (2), where I show the effects of being alone at the section level both among peers with the same race and peers with the same college and race. Column (2) shows that the direction of the *alone* effect for same-college racial peers is the same both in Panel A and Panel B: finding no other classmates from the same college and race or ethnicity at the section level reduces course grades both for domestic and international students. For international students, not having any section classmates from the same college and race lowers course grades by 0.30 points, indicating that academic support from familiar peers may be especially critical for international students. However, being *alone* in the section by only race, ethnicity, or nationality tends to increase[3] course grades. At the section level, the negative *alone* effect among racial *and* college peers, but the positive *alone* effect among racial peers supports that the absence of more academically homogeneous peers hurts course grades.

[3]The effect is positive but not significant for domestic students (Column (1) in Table 4).

The idea that lacking more academically homogeneous peers hurts course grades is further supported by another similarly defined treatment. $Assigned\_alone_{c,sec,major} = 1$ if a student is assigned alone at section level among racial peers with the same majors. This variable creates the largest fraction (i.e. 45.6%) of alone students in the analysis sample. The results show that being assigned alone at section level among racial peers with the same majors reduces the course grade by 0.05 points (Column (4), Table 4).

Defining treatment at the professor level rather than the section level is grounded in the idea that students may seek racial or ethnic peers in different sections of a course that are taught by the same instructor. This level of treatment definition highlights notable differences between domestic and international students: only 1.13% of domestic students are assigned alone by race or ethnicity at the professor level, with white domestic students experiencing this in just 0.07% of cases.[4]. Table 3 (Column (3) in Panel A) reports the alone effect for the domestic sample after dropping white domestic students. Being alone at the professor level is negatively associated with the course grade. A similar negative association is reported for the international sample, in Column (4) of Panel B, but it is not statistically significant either. The null[5] *alone* effect.

The paper identifies the racial peer effect as a potential mechanism[6] underlying the observed *alone* effect rules out the shielding mechanism. Specifically, the treatment, defined through the variable *Number of Peers*, enables estimating both peer effects and *alone effect.* $N\_classmates_{c,sec}$ is the number of racial classmates assigned to a student in a class section. A positive *alone* effect is expected to correspond to a negative peer effect coefficient, indicating

[4]Since instructor level definition does not provide a large identifying variation in the treatment for the domestic sample, the paper runs out of options to check robustness for the argument whether treatment assignment among heterogeneous peers yields positive alone effects, as found at section level assignment.

[5]The effect is not significant either for domestic or international student samples. With some specifications, the sign of the effect changes but remains insignificant. With the same specification as Column (3) in Table 3 and including white students, the sign becomes positive and the coefficient remains insignificant.

[6]The previous version of the manuscript identified shield from low-ability racial peers as the mechanism behind positive *lone* effect for domestic students. But the current version finds a null *alone* effect for the domestic sample (see Column (1) in Table 4), leaving me with no option to find the same mechanism at the section level. This is because the analysis sample for the current results is different from the previous one due to sample trimming strategy based on probability of being assigned *alone* at section level among racial and college peers, instead of only racial peers. On the others hand, the treatment defined among academically homogenous peers gives me a negative *alone* effect.

that having more peers improves grades, while having no peers hurts, and vice versa. Table 34 reports the peer effects results. Both number of racial peers from same colleges assigned at course section level, $N\_classmates_{c,sec,college}$ (Column (2)), and number of racial peers from the same colleges assigned at course-instructor level, $N\_classmates_{c,prof,college}$ (Column (4)), increase course grades.

The peer effect estimates follow expected signs for *alone* effects for the domestic student sample in Panel A. On average, having one more peer from one's own race or ethnicity in a course section tends to decrease the course grade. On the contrary, having one more peer from one's own race or ethnicity *and* college in a course section increases the course grade significantly (the coefficient estimate, in the top row, for $N\_classmates_{c,sec,college}$ in Column (1) of Table 34). Students having one more peer from one's own race or ethnicity *and* college in any sections of the course taught by the same instructor increases the course grade significantly (the coefficient estimate for $N\_classmatesc, prof, college$, in the top row, in Column (1) of Table 5). This pattern for domestic students supports the hypothesis that a lack of academically homogeneous peers has a detrimental effect on course grades. Among international students, the peer effect estimates follow the anticipated direction, supporting the positive *alone* effect findings when academically homogeneous peers are absent.

For example, in the case of $N\_classmates_{c,prof,college}$, peer effects increase as the number of racial and college peers rises: 0.0025 for one peer, 0.0023 when increasing from one to two peers, and 0.029 when there are less than five peers (Table 34). This non-linearity implies that the influence of peers varies depending on the group size, with effects averaging out but remaining consistently positive across different peer numbers. These positive peer effect findings reinforce the notion that the absence of racially similar peers negatively impacts grades, as evidenced by the consistently positive estimates.

The result reveals that the *alone* effect can be partly explained by non-linear peer effects. Let us consider the case for $N\_classmatesc, prof, college$. The peer effect estimates are-0.0025 for the domestic student analysis sample, 0.0023 for having two peers instead of one peer, $0 < N\_classmatesc, prof, college < 3$, and 0.029 for $N\_classmatesc, prof, college < 5$ (Table 34). The effect of peers is not linear and it can stay somewhere around the peer effect estimate for the full sample. This non-linearity implies that the influence of peers varies depending on the group size, with effects averaging out but remaining consistently positive across different peer numbers. These positive peer effect findings suggest positive racial peer effects as a mechanism behind the negative *alone* effect in the paper.

A subsequent question evolves when comparing the magnitude of the *alone* effect with peer effects. The non-linear nature of peer effects complicates a straightforward comparison. For instance, adding or removing a peer marginally impacts course grades by 0.023 points; however, when peers decrease from one to zero, course grades drop by 0.076 points—a threefold increase in impact. This larger effect could partly stem from a *loneliness effect* and partly from the non-linearity of peer effects. This nuanced relationship highlights the distinct but interrelated roles of both peer and *alone* effects in academic outcomes.

5.1 Peer Group Size and Homogeneity

In Table 6, I present effects of being alone, both at section level and section-college level, on course grade. The alone effect is positive and significant at section level and negative at and section-college level. If the group size is large, the *alone* effect at section level becomes insignificant. Since being alone by section-by-college means the the absence of academically more homogeneous peers, the results show policy implications about assigning class among heterogeneous and homogeneous classes. Academically more homogeneous peers affects course grades positively due to the nature of the sorting. While heterogeneous peers cannot avoid each other if the group size is small and thus *alone* students can avoid certain negative peer effects that *not-alone* students cannot avoid. Such results are presented in Table 7. Both low verbal and low math ability peer groups impact course grades of *not-alone* students negatively. If the group size is small, the scope for further sorting within the racial and ethnic group is limited. That limited ability of peer choice expose the *not-alone* student group to different (in our case, negative) peer effects. When group size becomes larger, students can endogenously forms peer groups within the assigned racial and ethnic groups. Carrel et al. (2013) found that students sort into smaller groups by ability. Table 7, panel B, shows that students have both positive and negative peer effects coefficients but only positive coefficients are significant.

As a result, the shield-from-low-ability-peers no longer favors *alone* students and *alone* effect becomes insignificant.

On the other hand, peer effects in homogeneous group can be positive irrespective of the option to choose peers. When *not-alone* students are exposed to academically homogeneous peer group, some of them will sort into smaller groups when the assigned racial and ethnic group size is large. However, academic homogeneity characteristics of the peers generates some positive effects. In Table 7, both high verbal and high math peers generate positive peer effects both in small and large peer groups. As a result, the *alone* students do not have the clear advantage of the shield-effect if *not-alone* students are academically homogeneous.

For international students, the same exercise is presented in Table **??** and Table **??**. Column (1) of Table 10 shows that being alone increases the course grades of low-verbal ability international students, while all other coefficient estimates are statistically insignificant. In Table **??**, being assigned to a class with a larger fraction of low-verbal or low-math national peers is negatively associated with course grades, though the estimates in columns (1) and (2) are not statistically significant. Apart from these two coefficients, none of the other estimates suggest significant or noteworthy negative peer effects. Therefore, negative ability peer effects do not appear to be salient in the international student sample and are unlikely to be the driving mechanism behind the positive course-level *lone* effects. Further investigation could explore whether adding a control for representation pressure helps explain these positive effects.

Though a few of the coefficients are positive, those positive peer effects do not lead to the positive *lone* effect. If medium verbal ability is additionally controlled in Column (1), the peer effects mechanism story does not change, and the coefficient of the fraction of peers with medium verbal ability becomes insignificant. For the third mechanism, Tables **??**-**??**, and Table **??** have the assigned number of racial/ethnic peers included as a control variable. If there is any non-linear racial representation pressure on not-alone students, some of those pressures are controlled by the inclusion of the variable.

6 Current and subsequent term outcomes

This section presents a detailed analysis of how being "alone" in a course section affects various student-level outcomes, focusing on both current and subsequent academic terms. The identification strategy used in these regressions relies on the conditional independence assumption, which posits that, given the estimated mean probability of a student being "alone" in Fall 2018, the mean of the course-level instrumental variable is independent of potential student-level outcomes. This analysis is based on 1,420 observations for domestic students and 645 observations for international students, providing a robust sample to explore these effects.

6.1 College Dropout and Graduation Rates

The results have sharp contrasts between domestic and international students. The impacts of being "alone" on dropout rates between domestic and international students go in the opposite direction. Since the instrument variable is now taken as the mean at the term level, the meaning of the point estimate is now different. The independent variable is now a fraction between 0 and 1, and the estimate has to be scaled by the mean of the variable of interest. For domestic students, being "alone" reduces the likelihood of dropping out by approximately 5 percentage points and it is marginally significant. This suggests that despite the potential social isolation, domestic students may exhibit a form of resilience that helps them persist in their studies (Table 9). In stark contrast, international students experience a significant increase in the likelihood of dropping out, with those who are *alone* being 9.9 percentage points more likely to drop out of college compared to their *not-alone* counterparts. This indicates that international students may struggle more acutely with the challenges posed by isolation.

The graduation outcomes further highlight these differences. For domestic students, the likelihood of graduating within five years is positively influenced by being *alone*. This could be due to the reduced distractions or negative peer influences that allow these students to focus more on their academic goals as discussed in the mechanism behind positive *alone* effects in course-level outcomes (Table 10). However, the situation is quite different for international students, where being *alone* reduces their chances of graduating within five years by 12.7 percentage points. The negative effect is even more pronounced when excluding the largest international student groups (Chinese and Indian students), suggesting that students from smaller international communities may face even greater challenges when isolated.

6.2 College and Major Changes in Subsequent Terms

The impact of being "alone" extends beyond the first year, particularly for international students. While domestic students do not exhibit any significant treatment effects related to changing colleges in subsequent terms (Fall 2019, Spring 2020, Fall 2020, and Spring 2021), the picture is different for international students. Those who are *alone* are 11.4 percentage points more likely to change their college in the first semester of their sophomore year (Table 11), and this trend continues through all subsequent terms, with most of the effects being statistically significant (Fig. 6). This indicates that being *alone* may prompt international students to seek out new academic environments in an attempt to find a better fit or to alleviate the isolation they experience.

When it comes to choosing a major, the analysis shows that "alone" international students are more likely to either retain or switch to majors that are popular among students from their own country. This trend is especially strong for majors that are historically the most or second most popular among their peers (Table 12). Among those who started in the College of Engineering, lone domestic students are more likely to retain engineering majors in subsequent terms (Fig. 7). However, the *lone* effect does not exist for this outcome for international students. This behavior suggests that loneliness at both the college and major levels drives international students toward familiar academic environments, potentially as a coping mechanism to counteract the effects of isolation.

Using the first destination survey data, I studied the major choice outcome at graduation and found a stark difference between domestic and international students. The analysis of major choices and subsequent economic outcomes reveals further distinctions between domestic and international students. For domestic students, being *alone* appears to be a motivating factor when it comes to choosing majors that lead to higher-paying careers. Specifically, *alone* domestic White and Asian students are more likely to graduate with a major that historically yields higher salaries compared to majors with median salaries (Table 13). This positive and significant effect is consistent across all subsequent terms from Fall 2019 to Spring 2021, indicating that being *alone* drives domestic students to make strategic academic decisions that enhance their future earning potential. In contrast, international students are not impacted by being *alone* on their choice of high-paying majors. The treatment effects for international students graduating with such a major are consistently negative but insignificant.

In summary, the state of being *alone* in an academic setting manifests divergent outcomes for domestic and international students. While domestic students seem to flourish when they are segregated at the course level. While the treatment impacts domestic student's academic persistence and strategic major selection, international students grapple with the adverse effects of isolation, reflected in higher dropout rates, delayed graduations, and frequent shifts in colleges and majors.

6.3 Discussion on student-level outcomes

The analysis highlights that being *alone* negatively impacts international students for non-contemporaneous outcomes, while the effects are not the same for domestic students. There are several possible explanations for these differences. First, international students are more likely to experience repeated instances of loneliness—what could be termed chronic loneliness. This chronic loneliness may contribute to the adverse effects observed among international students. However, two key issues prevent me from examining this empirically[7]. First, a significant fraction of international students who were alone in their first term dropped out in subsequent terms. Second, after Fall 2018, I was unable to track the instrument, as the batch registration system was only applied to new freshmen. While the algorithm was extended to all undergraduate students starting in Fall 2020, some unknown exceptions were made, and the COVID-19 pandemic disrupted the Spring 2021 semester. I know from the summary statistics of the (Fall 2018) analysis sample that 39% of international students were classified as racially alone in class, compared to only 11% of domestic students in the analysis sample (Table **??**). In the following fall and spring semesters, the difference in the mean of actually being alone remained similar, although both groups were, on average, less alone (Fig. 8). The differential exposure to this type of loneliness is not in the favor of international students. The physical

[7] I propose the following empirical model to show whether the differences in the impacts of loneliness on student-level outcomes are caused by the persistence of loneliness. The treatment occurs at period t and the outcome is measured at a future date, $t+k$.

$$y_{i,t+k} = \sum_{j}^{\bar{t}} \tau_j * assigned\_alone_{i,t-j} + +\beta X + \mu * Pr(assigned\_alone_{i,t}) + \alpha_c + u_{i,t+k}$$

and cultural distance from their home countries exacerbates their loneliness, leading to higher dropout rates, lower graduation rates within five years, and a greater likelihood of switching colleges or majors in search of a more supportive environment.

As being *alone* is associated with college and major changes for international students, this explains their lower five-year graduation rates. In contrast, the treatment effect for domestic students on major and college change outcomes is null. However, there is a marginally significant positive effect on five-year graduation rates among domestic students, which I attribute to the improvement in contemporaneous course grades in Fall 2018. While both domestic and international students benefit in the short term from being alone in class—possibly due to the avoidance of low-ability racial or ethnic peers— it is important to measure whether the contemporary effects can offset the subsequent experience.

Apart from chronic loneliness, the lack of social and cultural connections may hinder international students' integration into the college community, affecting their academic and overall well-being. Unlike domestic students, who may still find some cultural commonality, international students often struggle with the dual challenges of adapting to a new educational system and navigating an unfamiliar cultural landscape. If the effects should diminish over time, then earlier experience in the freshman year may dominate the effects. This discussion suggests the need for educational institutions to recognize and address the unique challenges faced by international students, providing targeted support to foster their sense of belonging and improve long-term outcomes. Addressing chronic loneliness through social integration and support services is crucial for the success and well-being of these students.

7 Tables

Table 1 Conditional Randomness Check for the instrument

	Batch Reg. sample	Analysis sample		
	All	All	Domestic	International
	(1)	(2)	(3)	(4)
Pr(Assigned_alone)		0.8177***	0.6906***	0.8254***
		(0.0261)	(0.0472)	(0.0371)
age	0.0057	-0.0025	-0.0014	-0.0015
	(0.0134)	(0.0104)	(0.0151)	(0.0149)
female	-0.0054	0.0073	0.0021	0.0166
	(0.0173)	(0.0150)	(0.0182)	(0.0277)
black	0.0084	-0.0121	0.1931***	0.0000
	(0.0462)	(0.0355)	(0.0564)	(0.0000)
hispanic	-0.1670***	-0.0477	0.1338**	0.0000
	(0.0401)	(0.0293)	(0.0494)	(0.0000)
other	-0.0758	-0.0833	0.0000	-0.0704
	(0.1157)	(0.0448)	(.)	(0.0501)
asian	-0.3119***	-0.1096***	0.0508	0.0000
	(0.0373)	(0.0262)	(0.0463)	(0.0000)
sat_math	-0.0000	0.0000	0.0000	-0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
sat_verbal	0.0001	0.0001	0.0001	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
domestic	-0.0983**	-0.0013		
	(0.0379)	(0.0257)		
_cons	0.4223	0.0923	-0.0367	0.0832
	(0.3069)	(0.2462)	(0.3491)	(0.3792)
N	5057	5057	3332	1704
R^2	0.175	0.362	0.311	0.364
Demographic Controls	Yes	Yes	Yes	Yes
Course FE	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes
Pre-reg. Major FE	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses are clustered at the course-by-section level. The outcome in this regression is whether students were assigned *alone* or not. Observations come from Fall 2018 freshmen who have $0 < pr(assignedalone) < 1$. Such registration preference has been controlled by taking pre-reg. Major FE indicators.*** p < 0.01, ** p < 0.05, * p < 0.1.

Table 2 First stage relationship

	All	All	Domestic	International
	(1)	(2)	(3)	(4)
Assigned_alone	0.8693***	0.8675***	0.8816***	0.8239***
	(0.0158)	(0.0171)	(0.0221)	(0.0334)
pr(Assigned_alone)	0.0968***	0.0889***	0.0489	0.0865
	(0.0203)	(0.0238)	(0.0357)	(0.0477)
_cons	0.0110	-0.1375	-0.1678	-0.0398
	(0.0060)	(0.2368)	(0.3320)	(0.4111)
N	1713	1679	981	654
R^2	0.831	0.849	0.871	0.797
F Stats.	4832.46	4113.15	2894.04	1004.32
Dmographic Controls		Yes	Yes	Yes
Course FE		Yes	Yes	Yes
Major FE		Yes	Yes	Yes
Pre-reg. Major FE	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses are clustered at the course-by-section level. The outcome in this regression is whether the is *alone* or not. Samples consist of Fall 2018 freshmen students-by-section. Since the grade sample does not include all the sections in the course assignment sample, the regressions in this table are restricted to those observations that have corresponding sections in the grade sample. However, the point estimate of the treatment effect does vary between this sample and the main analysis sample in the following table. Some majors reserve slots in classes for students pre-enrolled in a corresponding major. Such registration preference has been controlled by taking pre-reg. Major FE indicators.$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 3 Effect of being Assigned Alone on Course Grade

	Panel A: Domestic students					
	All				URM	
	(1)	(2)	(3)	(4)	(5)	(6)
$Assigned\_alone_{c,sec,college}$ [0.223]	-0.0540***	-0.0743***				
	(0.0179)	(0.0191)				
$pr(Assigned\_alone_{c,sec,college})$	-0.1445***	-0.1943***				
	(0.0389)	(0.0382)				
$Assigned\_alone_{c,sec}$ [0.056]		0.0745*				
		(0.0396)				
$pr(Assigned\_alone_{c,sec})$		0.0022				
		(0.0500)				
$Assigned\_alone_{c,prof}$ [0.032]			-0.1234		-0.1294	
			(0.1313)		(0.2226)	
$pr(Assigned\_alone_{c,prof})$			0.2266*		0.3004	
			(0.1376)		(0.2385)	
$Assigned\_alone_{c,prof,college}$ [0.081]				-0.0756**		-0.0799
				(0.0727)		(0.0709)
$pr(Assigned\_alone_{c,prof,college})$				-0.0567		0.0446
				(0.0408)		(0.0834)
N	21467	21467	7281	21467	3290	3290
R^2	0.289	0.284	0.258	0.295	0.311	0.337
Control Group Mean	3.141	3.121	3.087	3.125	2.866	2.877
	Panel B: International students					
	All				Chinese/Indian	
$Assigned\_alone_{c,sec,college}$ [0.531]	-0.0239	-0.1061**				
	(0.0338)	(0.0483)				
$pr(Assigned\_alone_{c,sec,college})$	-0.1211*	-0.1237*				
	(0.0723)	(0.0739)				
$Assigned\_alone_{c,sec}$ [0.369]		0.1733***				
		(0.0591)				
$pr(Assigned\_alone_{c,sec})$		-0.0699				
		(0.0622)				
$Assigned\_alone_{c,prof}$ [0.176]			-0.0474		-0.4964***	
			(0.2491)		(0.1547)	
$pr(Assigned\_alone_{c,prof})$			0.0256		0.5671***	
			(0.2519)		(0.1648)	
$Assigned\_alone_{c,prof,college}$ [0.327]				-0.3022***		-0.3776***
				(0.0528)		(0.0600)
$pr(Assigned\_alone_{c,prof,college})$				0.1281**		0.1903***
				(0.0510)		(0.0541)
N	3225	3225	3225	3225	1995	1995
R^2	0.212	0.203	0.199	0.229	0.210	0.264
Control Group Mean	3.423	3.377	3.371	3.418	3.450	3.500

Notes: Robust standard errors in parentheses are clustered at the course-by-section level. The outcome in this regression is the the course grade. The treatment variable is the instrument assigned *alone*. Course fixed effects and college fixed effects are controlled in all the columns. Demographic characteristics include sex, race/ethnicity, SAT scores, and age. Some majors reserve slots in classes for students pre-enrolled in a corresponding major. Such registration preference has been controlled by taking pre-reg. Major FE indicators.$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 4 Effect of being Assigned Alone on Course Grade (combined sample)

	Domestic	All				
	(1)	(2)	(3)	(4)	(5)	(6)
$Assigned\_alone_{c,sec}$ [0.10]	0.0244	0.0671**				
	(0.0382)	(0.0310)				
$pr(Assigned\_alone_{c,sec})$	-0.0473	-0.0184				
	(0.0499)	(0.0378)				
$Assigned\_alone_{c,sec,college}$ [0.266]			-0.0274*			
			(0.0154)			
$pr(Assigned\_alone_{c,sec,college})$			-0.0169			
			(0.0288)			
$Assigned\_alone_{c,sec,major}$ [.456]				-0.0493***		
				(0.0127)		
$Assigned\_alone_{c,prof}$ [0.079]					-0.0911	
					(0.1117)	
$pr(Assigned\_alone_{c,prof})$					0.1590	
					(0.1156)	
$Assigned\_alone_{c,prof,college}$ [0.115]						-0.0847***
						(0.0327)
$pr(Assigned\_alone_{c,prof,college})$						0.0431
Course preference controls				x		
Course FE	x	x	x	x	x	x
College FE	x	x	x	x	x	x
						(0.0351)
N	21467	24707	24707	24707	10522	24707
R^2	0.281	0.262	0.277	0.265	0.229	0.277
Control Group Mean	3.121	3.144	3.165	3.172	3.165	3.154

Notes: Robust standard errors in parentheses are clustered at the course-by-section level. The outcome in this regression is the the course grade. The treatment variable is the instrument assigned *alone*. Course fixed effects and college fixed effects are controlled in all the columns. Demographic characteristics include sex, race/ethnicity, SAT scores, and age. Some majors reserve slots in classes for students pre-enrolled in a corresponding major. Such registration preference has been controlled by taking pre-registered Major FE indicators.$^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 5 Effects of Peers on Course Grade

	(1)	(2)	(3)	(4)
$N\_classmates_{c,sec}$	-0.0001			
	(0.0005)			
Min. 1, Max. 2 peers	-0.0240			
	(0.0443)			
Less than 5 peers	0.0001			
	(0.0141)			
$N\_classmates_{c,sec,college}$		0.0010***		
		(0.0003)		
Min. 1, Max. 2 peers		0.0170		
		(0.0246)		
Less than 5 peers		0.0241***		
		(0.0062)		
$N\_classmates_{c,prof}$			0.0009	
			(0.0020)	
Min. 1, Max. 2 peers			0.0014	
			(0.0026)	
Less than 5 peers			-0.0309	
			(0.0408)	
$N\_classmates_{c,prof,college}$				0.0025***
				(0.0003)
Min. 1, Max. 2 peers				0.0023***
				(0.0006)
Less than 5 peers				0.0293***
				(0.0088)
R^2	0.296	0.331	0.298	
Obs.: full sample	21467	21467	7233	21467
Obs.: $0 < n < 2$	2275	5208	1954	5208
Obs.: $n < 5$	5094	12840	1512	6680
Control Group Mean	3.141	3.121	3.087	3.125
2.866	2.877			
	Panel B: International students			
	All			
$N\_classmates_{c,sec}$	-0.0087			
	(0.0117)			
Min. 1, Max. 2 peers	0.0300			
	(0.0631)			
Less than 5 peers	-0.0107			
	(0.0232)			
$N\_classmates_{c,sec,college}$		0.0088		
		(0.0068)		
Min. 1, Max. 2 peer		-0.0192		
		(0.0561)		
Less than 5 peers		0.0156		
		(0.0177)		
$N\_classmates_{c,prof}$			0.0009	
			(0.0020)	
Min. 1, Max. 2 peers			-0.0594	
			(0.0841)	
Less than 5 peers			-0.0364	
			(0.0268)	
$N\_classmates_{c,prof,college}$ N				0.0510***
				(0.0074)
Min. 1, Max. 2 peers				0.2043***
				(0.0660)
Less than 5 peers				0.0939***
				(0.0207)
R^2	0.212	0.212	0.307	0.222
Obs.: full sample	3225	3225	3172	3225
Obs.: $0 < n < 2$	972	944	762	1080
Obs.: $n < 5$	2472	2899	1731	2512

Notes: Robust standard errors in parentheses are clustered at the course-by-section level. The outcome in this regression is the the course grade. The treatment variable is the instrument assigned number of peers assigned to a setudent. Demographic characteris-

Table 6 Alone effects on Course Grade: homogenous vs heterogeneous *not-alone* group

	Group Size				
	All	Small	Large	Small	Large
	(1)	(2)	(3)	(4)	(5)
$Assigned\_alone_{c,sec}$	0.0749**	0.0656**	0.0470		
	(0.0305)	(0.0311)	(0.0408)		
$pr(Assigned\_alone_{c,sec}$	-0.0313	-0.0474	0.0086		
	(0.0366)	(0.0392)	(0.0517)		
$Assigned\_alone_{c,sec,college}$				-0.0433**	-0.1056***
				(0.0170)	(0.0225)
$ppr(Assigned\_alone_{c,sec,college})$				-0.0419	-0.0284
				(0.0307)	(0.0351)
N	25040	7913	19681	16086	15756
R^2	0.261	0.238	0.271	0.259	0.266
Control Group Mean					

Notes: Robust standard errors in parentheses are clustered at the course-by-section level. The outcome in this regression is the the course grade. The treatment variable is the instrument assigned number of peers assigned to a setudent. Demographic characteristics include sex, race/ethnicity, SAT scores, and age. Some majors reserve slots in classes for students pre-enrolled in a corresponding major. Such registration preference has been controlled by taking pre-reg. Major FE indicators. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

Table 7 Ability Peer Effects on Course Grade

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Peers Assigned at section level						Peers Assigned at section-by-college level					
	Peer group size <= 5: (Small)											
	Fraction of peers assigned											
low_verbal	-0.1159**						-0.1266***					
	(0.0479)						(0.0319)					
medium_verbal		0.0593						0.0253				
		(0.0442)						(0.0282)				
high_verbal			0.0227						0.0604**			
			(0.0442)						(0.0294)			
low_math				-0.1650***						-0.0827**		
				(.0566)						(0.0344)		
medium_math					0.0182						-0.0314	
					(0.0421)						(0.0291)	
high_math						0.0997**						0.1225***
						(0.0465)						(0.0319)
	Peer group size > 5: (Large)											
low_verbal	-0.0767						-0.2776***					
	(0.0696)						(0.0771)					
mid_verbal		-0.0563						-0.0029**				
		(0.0675)						(0.0013)				
high_verbal			0.2227***						0.2746***			
			(0.068)						(0.0807)			
low_math				-0.1084						-0.2694***		
				(0.0795)						(0.0770)		
mid_math					0.0425						0.0111	
					(0.0741)						(0.0808)	
high_math						0.1544**						0.2477***
						(0.0732)						(0.0773)
E(% of respective ability) control	x	x	x	x	x	x	x	x	x	x		
$N\_classmates_{c,sec}$ control							x	x	x	x	x	x
N	4354	4354	4354	4354	4354	4354	7437	7437	7437	7437	7437	7437
R^2	0.265	0.264	0.263	0.265	0.263	0.264	0.282	0.281	0.281	0.282	0.281	0.283
Control Group Mean	3.204	3.204	3.204	3.204	3.204	3.204	3.169	3.169	3.169	3.169	3.169	3.169

Notes: Robust standard errors in parentheses are clustered at the course-by-section level. The outcome in this regression is the the course grade. The treatment variable is the instrument assigned number of peers assigned to a setudent. Demographic characteristics include sex, race/ethnicity, SAT scores, and age. Some majors reserve slots in classes for students pre-enrolled in a corresponding major. Such registration preference has been controlled by taking pre-reg. Major FE indicators.$^{***}p <\ 0.01,^{**}p <\ 0.05,^{*}p <\ 0.1$.

Table 8 *Alone Effects* on *Not-alone* Course Grade

	Domestic	All	Indian/Chinese	International excluding Indian & Chinese
	(1)	(2)	(3)	(4)
Assigned alone	-1.1005	-4.5369*	-0.0556	-0.2089**
	(1.2262)	(2.3382)	(0.0508)	(0.0805)
(simulated) probability of being alone	1.4022	-19.6909***	0.0244	0.2641**
	(2.1865)	(3.5479)	(0.0847)	(0.1292)
Observations	1351	474	337	285
R^2	0.278	0.368	0.259	0.247
Demographic controls	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes

The outcome in this regression is the total points of all the courses in which a student was not *alone*. It is calculated in two steps- first, the course GPA is multiplied by the credit hours of that course, and then sum over all courses in which the student was not *alone*. The treatment variable is *fraction* of sections to which the student was assigned*alone* in Fall 2018. In other words, is the student-level mean of the treatment variable. Demographic characteristics include sex, race/ethnicity, SAT scores, and age. Some majors reserve slots in classes for students pre-enrolled in a corresponding major. Such registration preference has been controlled by taking pre-reg. Major FE indicators.$^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Table 9 *Alone* effects on College Dropouts

	Domestic	All	Indian/Chienese	International excluding Indian & Chinese
	(1)	(2)	(3)	(4)
Assigned alone	-0.0500*	0.0992**	0.0288	0.1796**
	(0.0296)	(0.0390)	(0.0411)	(0.0778)
(simulated) probability of being alone	0.0152	-0.0283	0.0140	-0.2367*
	(0.0557)	(0.0544)	(0.0684)	(0.1207)
Observations	1344	620	323	273
R^2	0.231	0.221	0.271	0.280
Demographic controls	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes

The outcome in this regression is whether a student dropped consecutively two "regular" terms between the current and the next academic years. If a student dropped any two consecutive semesters (Fall or Spring) in the 2018-19 or the 2019-2020 academic years, this regression specifies her as a dropout. The treatment variable is *fraction* of sections to which the student was assigned*alone* in Fall 2018. In other words, is the student-level mean of the treatment variable. Demographic characteristics include sex, race/ethnicity, SAT scores, and age. Some majors reserve slots in classes for students pre-enrolled in a corresponding major. Such registration preference has been controlled by taking pre-reg. Major FE indicators.$^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 10 Alone effects on the probability of graduation

	Domestic	All	Indian/Chienese	International excluding Indian & Chinese
	(1)	(2)	(3)	(4)
Assigned alone	0.0546*	-0.1273***	-0.0556	-0.2089**
	(0.0327)	(0.0418)	(0.0508)	(0.0805)
(simulated) probability of being alone	0.0031	0.0573	0.0244	0.2641**
	(0.0586)	(0.0636)	(0.0847)	(0.1292)
Observations	1420	645	337	285
R^2	0.217	0.202	0.259	0.247
Demographic controls	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes

The outcome in this regression is a dummy indicating whether a student graduated within five years of starting school. The treatment variable is *fraction* of sections to which the student was assigned*alone* in Fall 2018. In other words, is the student-level mean of the treatment variable. The negative coefficient (in column. 2) indicates that, among the international student sample, those who were more frequently assigned alone are less likely to graduate within five years. Demographic characteristics include sex, race/ethnicity, SAT scores, and age. Some majors reserve slots in classes for students pre-enrolled in a corresponding major. Such registration preference has been controlled by taking pre-reg. Major FE indicators.$^{***}p <\ 0.01,^{**}p <\ 0.05,^{*}p <\ 0.1$.

Table 11 The treatment effect on changing college in subsequent terms

	All	Black and Hispanic	International
	(1)	(2)	(3)
Assigned_alone	-0.0142	0.0619	0.1141**
	(0.0461)	(0.0707)	(0.0528)
pr(Assigned_alone)	0.0125	-0.1208	-0.1997**
	(0.0800)	(0.1251)	(0.0804)
Observations	812	302	436
R^2	0.028	0.077	0.127
Demographic controls	Yes	Yes	Yes
Major FE	Yes	Yes	Yes

The outcome in this regression is a dummy indicating whether a student changed her college from the one in the previous semester to another one in the current semester. The treatment variable is *fraction* of sections to which the student was assigned*alone* in Fall 2018. In other words, is the student-level mean of the treatment variable. The positive coefficient (in column. 3) indicates that international students who were more frequently assigned alone are more likely to change their college in the subsequent terms (for more clarification, see Fig. 9). Demographic characteristics include sex, race/ethnicity, SAT scores, and age. Some majors reserve slots in classes for students pre-enrolled in a corresponding major. Such registration preference has been controlled by taking pre-reg. Major FE indicators.$^{***}p <\ 0.01,^{**}p <\ 0.05,^{*}p <\ 0.1$.

Table 12 Treatment effects of keeping or switching a major popular by races/ethnicity

	International	Domestic	Black & Hispanic
	(1)	(2)	(3)
Assigned_alone	0.0898**	0.0355	0.0009
	(0.0375)	(0.0273)	(0.0320)
Pr(Assigned_alone)	-0.1403***	-0.0258	-0.0279
	(0.0527)	(0.0504)	(0.0646)
Observations	515	1110	420
R^2	0.735	0.531	0.705
Demographic controls	Yes	Yes	Yes
Major FE	Yes	Yes	Yes

The outcome in this regression is a dummy indicating whether a student either retained or switched to a major that is one of the top two most popularly chosen majors among the contemporary racial/ethnic population at Purdue. This regression is in reference to all the enrolled students in Spring 2021. The treatment variable is *fraction* of sections to which the student was assigned*alone* in Fall 2018. In other words, is the student-level mean of the treatment variable. The positive coefficient (in column. 1) indicates that international students who were more frequently assigned alone are more likely to either retain or switch to a major that was popular among Spring 2021 enrolled peers with the same nationality (for more clarification, see Fig. 10). Demographic characteristics include sex, race/ethnicity, SAT scores, and age. Some majors reserve slots in classes for students pre-enrolled in a corresponding major. Such registration preference has been controlled by taking pre-reg. Major FE indicators.$^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

Table 13 Treatment effects of graduating with a high-paying engineering major (College of Engineering sample)

	International	Black	Hispanic	Asian	White
	(1)	(2)	(3)	(4)	(5)
Assigned alone	-0.0453	-0.1042	-0.0238	0.1849*	0.6217**
	(0.1111)	(0.2261)	(0.1416)	(0.0951)	(0.2349)
pr(Assigned alone)	0.0714	0.1350	-0.1504	0.1798	0.0621
	(0.1802)	(0.4020)	(0.2723)	(0.1500)	(0.2509)
Observations	235	52	123	269	21
R^2	0.178	0.184	0.067	0.035	0.344
Demographic controls	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes

The outcome in this regression is a dummy indicating whether a student graduates with an engineering major that pays above the median salary. This comes from the Career Center Opportunity survey of the graduates. The treatment variable is *fraction* of sections to which the student was assigned*alone* in Fall 2018. In other words, is the student-level mean of the treatment variable. Demographic characteristics include sex, race/ethnicity, SAT scores, and age. Some majors reserve slots in classes for students pre-enrolled in a corresponding major. Such registration preference has been controlled by taking pre-reg. Major FE indicators.$^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

Figures

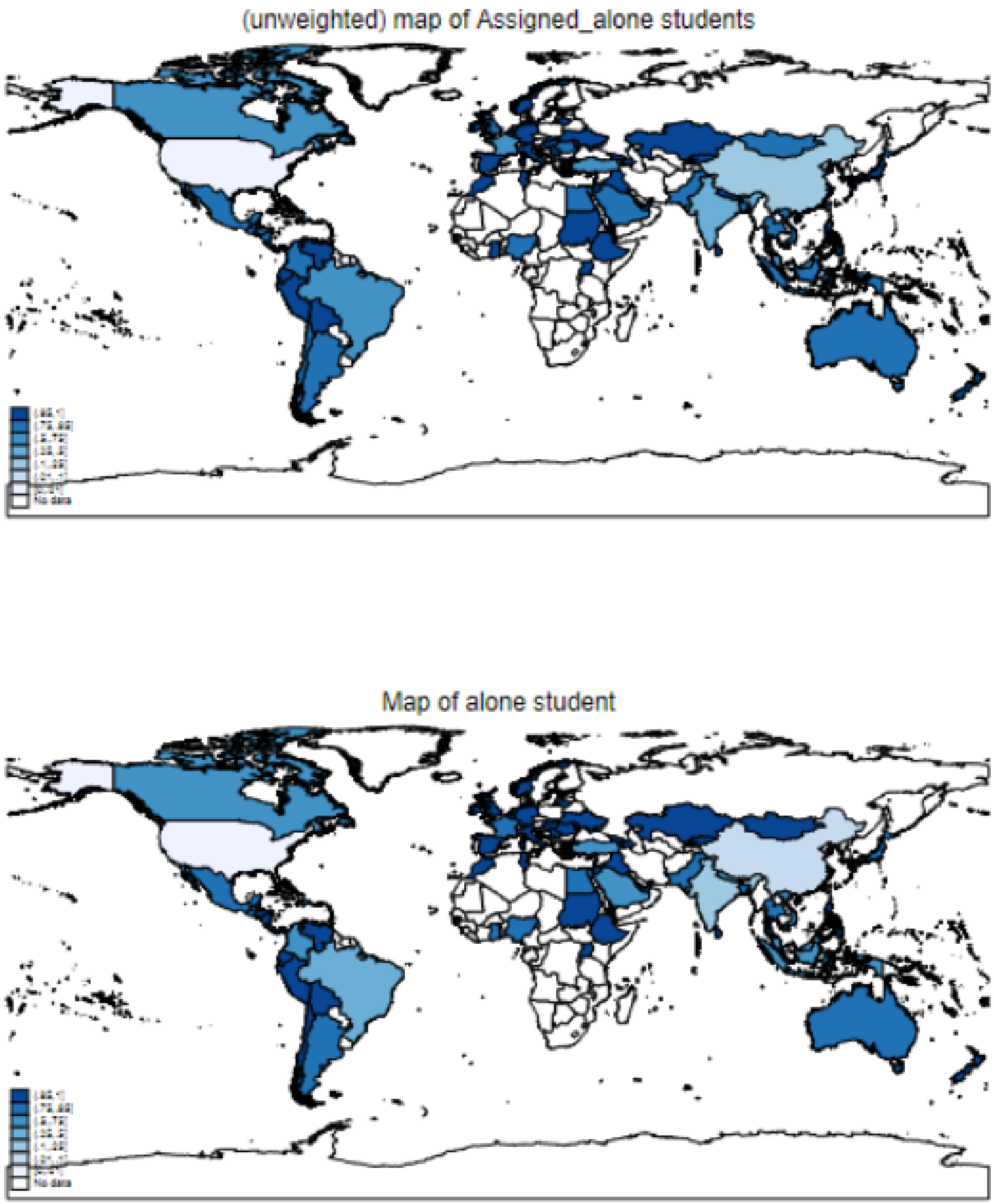

Figure 1: Distribution of races and ethnicity of domestic US students

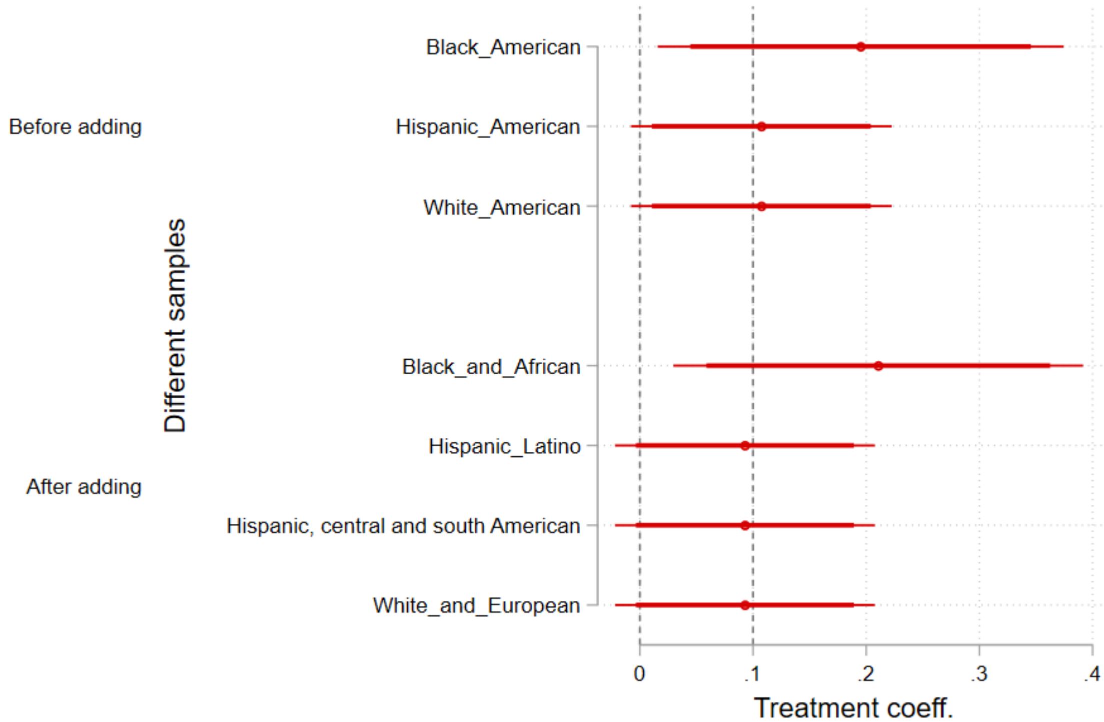

Figure 2: Alternative definition of domestic races (after adding similar looking international peers)

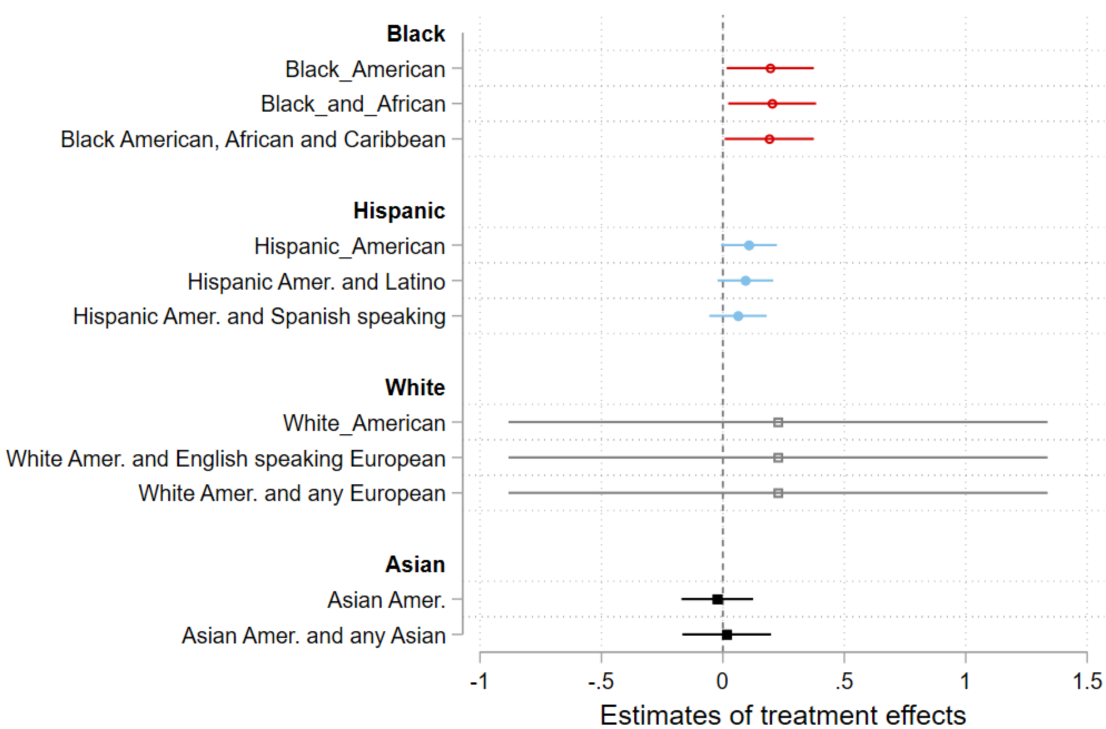

Figure 3: Alternative definition of domestic race and ethnicity

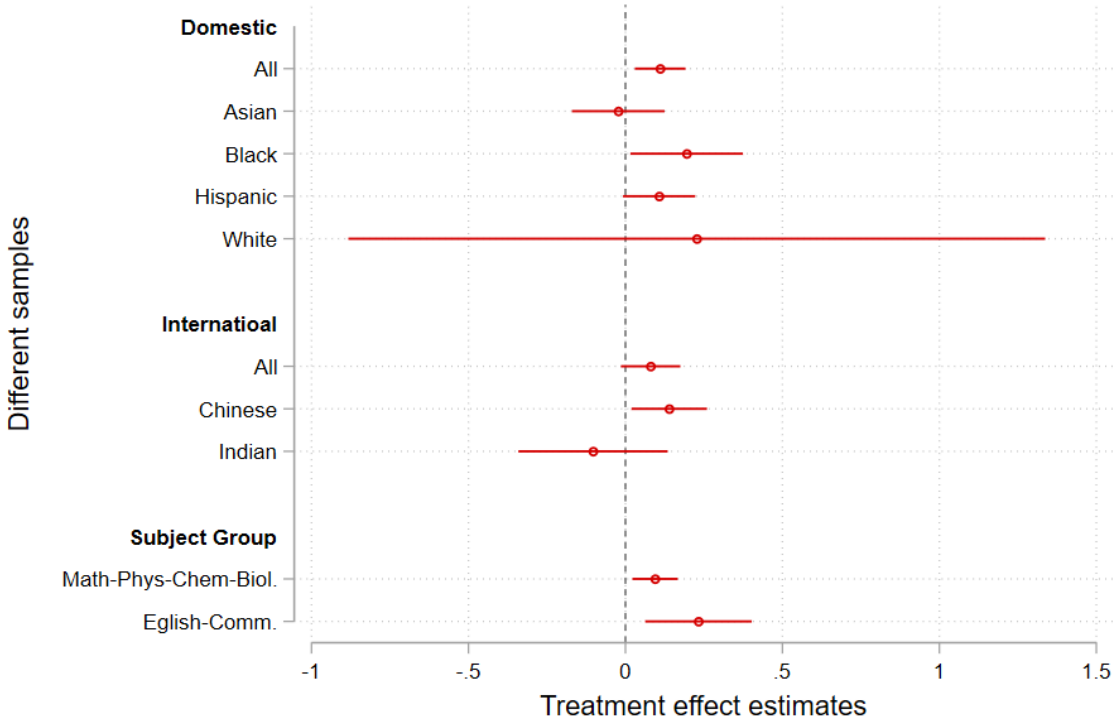

Figure 4: Treatment effects on course grades

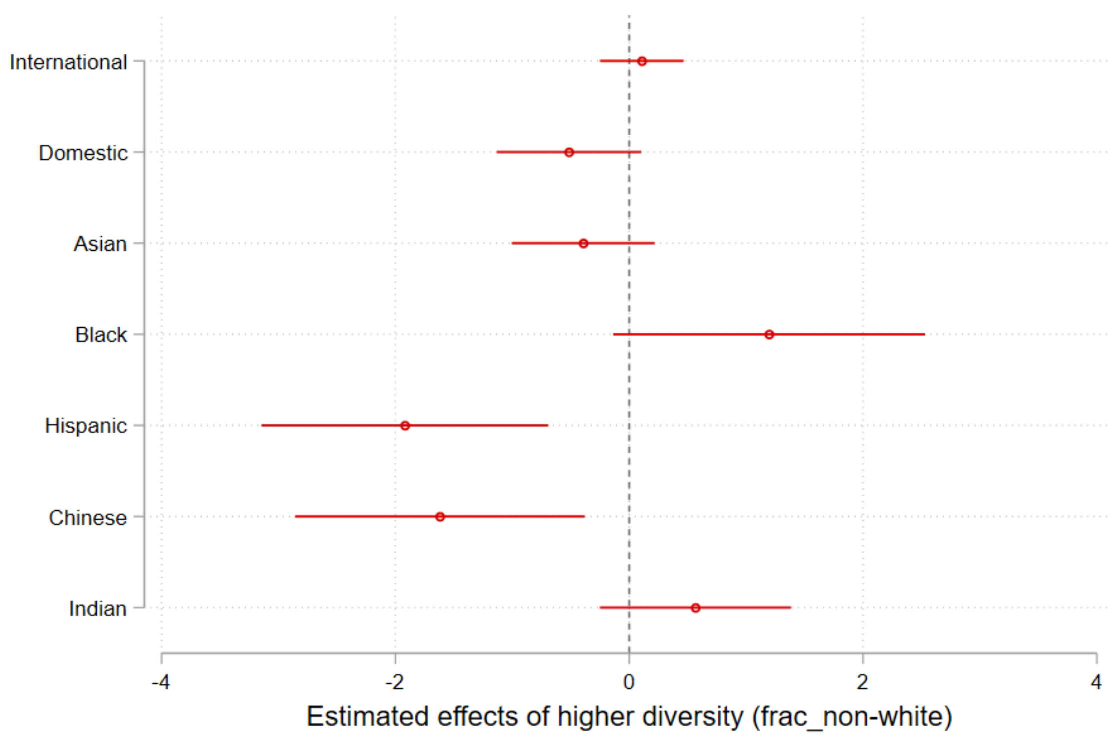

Figure 5: Testing for diversity effect on course grades

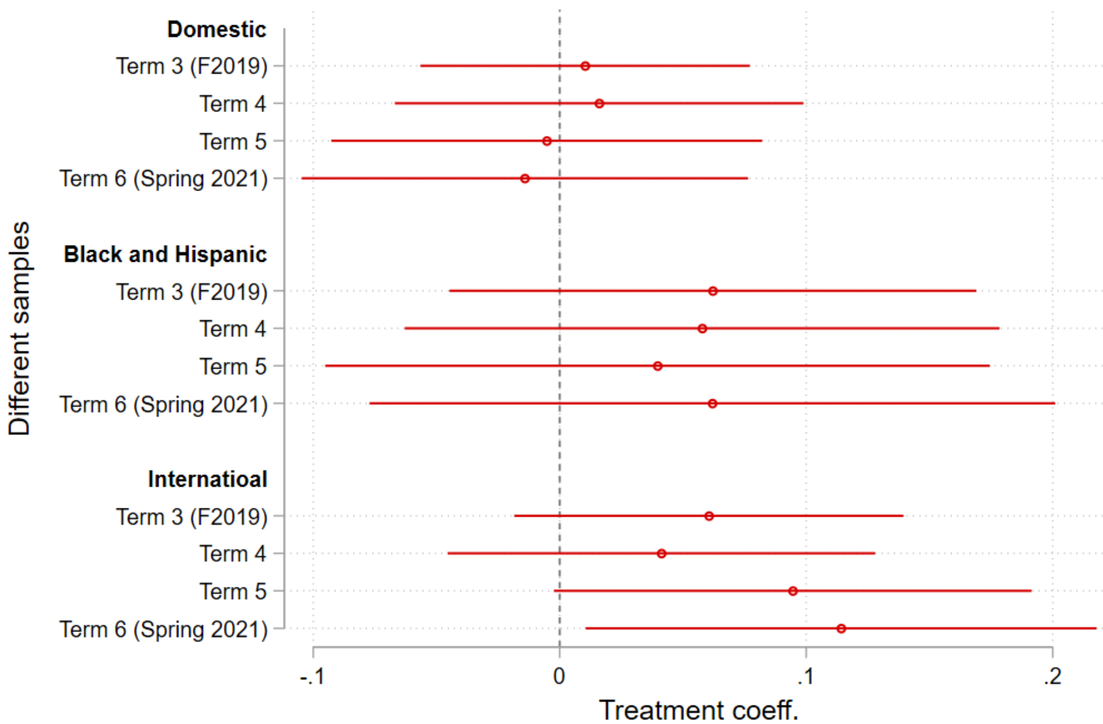

Figure 6: How being *alone* affects students to change college in subsequent terms

Each line represents a point estimate with 95% confidence interval. Sample sizes can be different as follow-up samples differ after the Fall 2018 (i.e., Term 1). Spring 2019 outcome is not regressed and is not shown on the plot as it is too close to Fall 2018. Term 4 is Spring 2020 and Term 5 is Fall 2020.

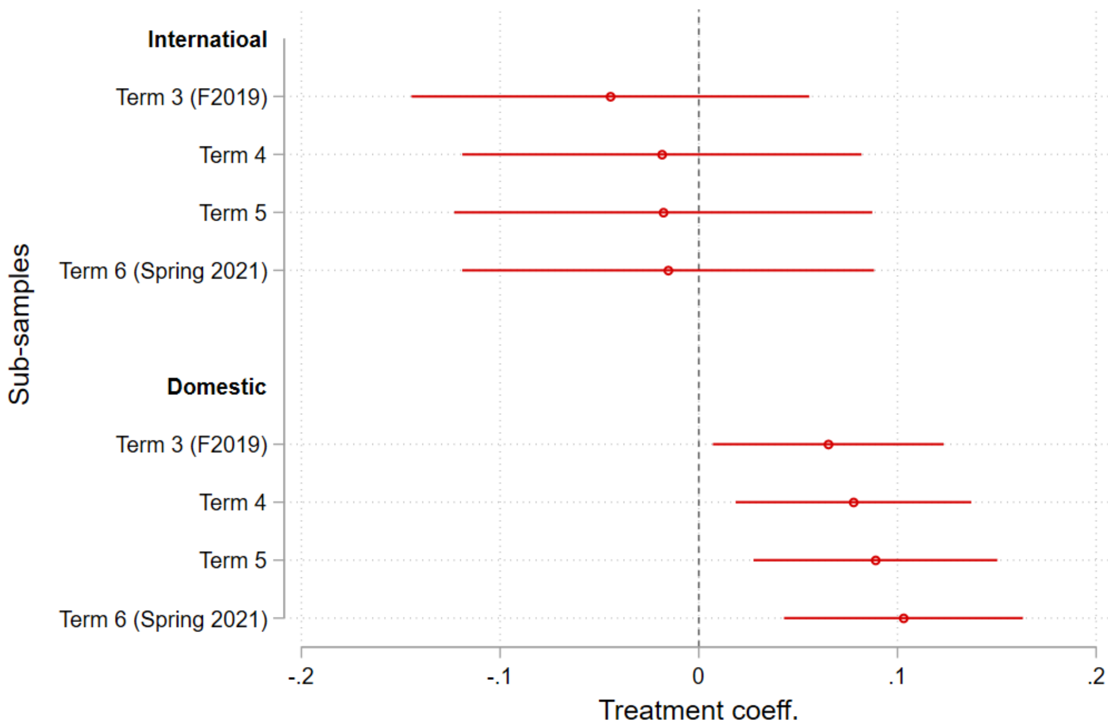

Figure 7: Probability of retaining or switching to a major paying median or above salary

Each line represents a point estimate with 95% confidence interval. Sample sizes can be different as follow-up samples differ after the Fall 2018 (i.e., Term 1). Spring 2019 outcome is not regressed and is not shown on the plot as it is too close to Fall 2018. Term 4 is Spring 2020 and Term 5 is Fall 2020.

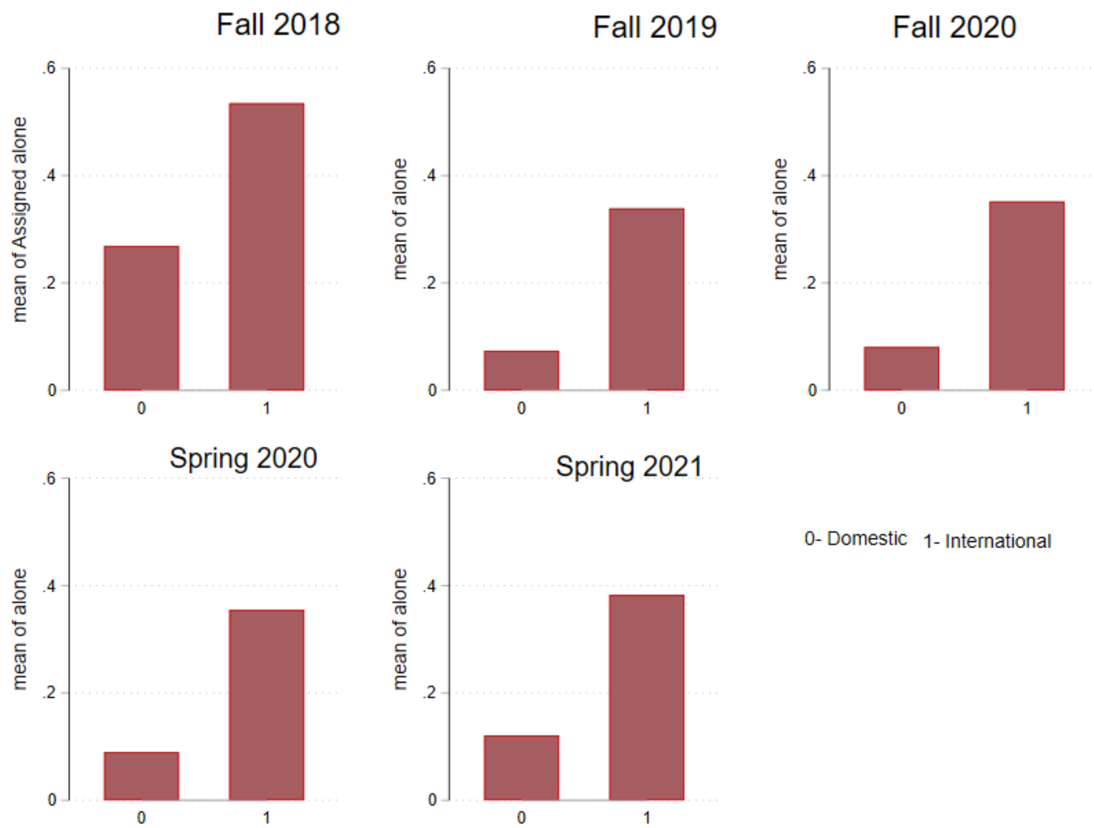

Figure 8: Bar chart of mean student-level loneliness by semesters

The left bar represents the fraction of domestic students who were on average alone in a class of the semester. Sample sizes can be different as follow-up samples differ after the Fall 2018 (i.e., some students did not attend). The right bar represents the fraction of international students who were alone in a course in that semester. The semester names are marked above the sub-plots.

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Appendix

Identifying the Mechanism Behind Positive "Lone" Effects

1. Regression 1: Interaction of "Alone" Assignment and Ability

(a) Regress grade on the interaction of "Assigned Alone" and ability (high/medium/low) dummies.

(b) Check if the coefficient (β) of the interaction is significant.

- Yes: List the corresponding ability group in the set of ability groups potentially driving the positive lone effect.
- No: Disregard that ability group.

2. Regression 2: Omit Each Ability Group

(a) For each ability group in the set derived from Regression 1, omit the ability group.

(b) Regress grade on "Assigned Alone" without the omitted ability group.

(c) Check if the treatment effect reverses or disappears.

- Yes: The omitted ability group drives the positive lone effect. Store this ability group as the "Driver Ability Group."
- No: The omitted ability group does not drive the effect.

3. Regression 3: Interaction of Driver Ability and Fraction of Racial Peers

(a) Regress grades on the interaction of the "Driver Ability Group" and the fraction of racial peers of each ability (in separate regressions).

(b) Regress grade on "Assigned Alone" without the omitted ability group.

(c) Identify which interaction coefficient is significant.

- Yes: The significant coefficient indicates which fraction of racial peers by ability level interacts with the "Driver Ability Group" to drive the positive lone effect.
- No: Not relevant as a mechanism of the lone effect

Race/ethnicity	N	Mean
Asian	1396	.185
Black	603	.491
Hispanic	1133	.335
White	199	.176
Others (US)	1325	.315

Figure 9: Map of *assigned alone* students by country of citizenship

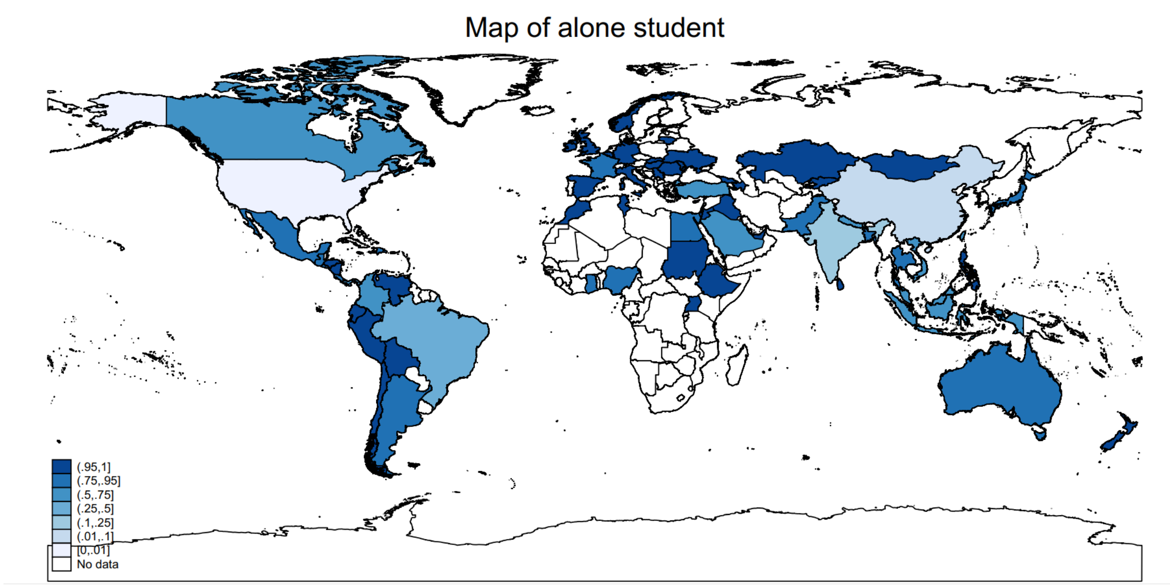


Figure 10: Map of *alone* students by country of citizenship

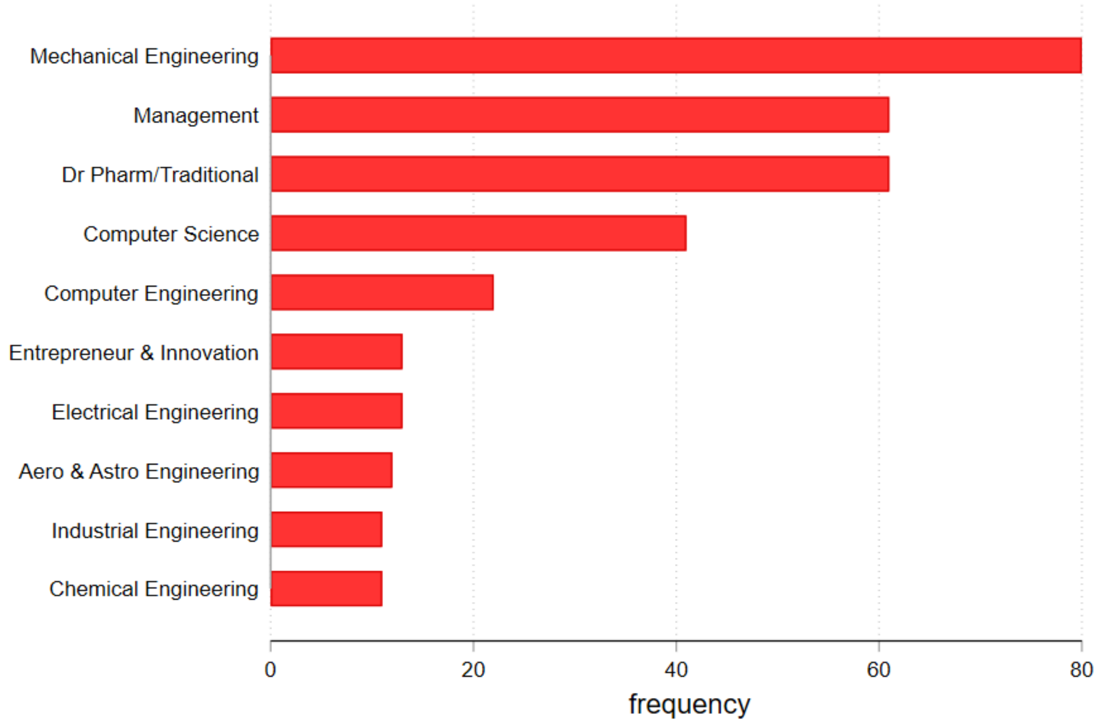


Figure 11: Popular majors of graduates with Asian race (all terms)

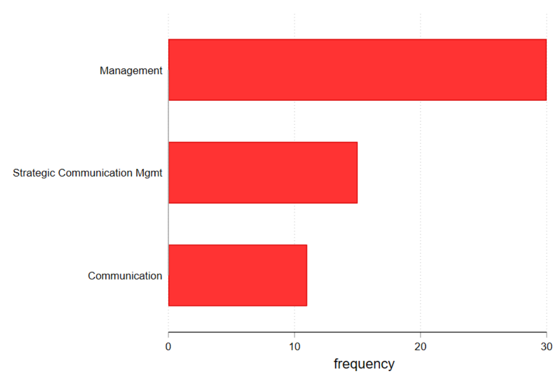


Figure 12: Popular majors of graduates with Black race (all terms)

Figure 13: Popular majors of graduates with Black race by graduation terms

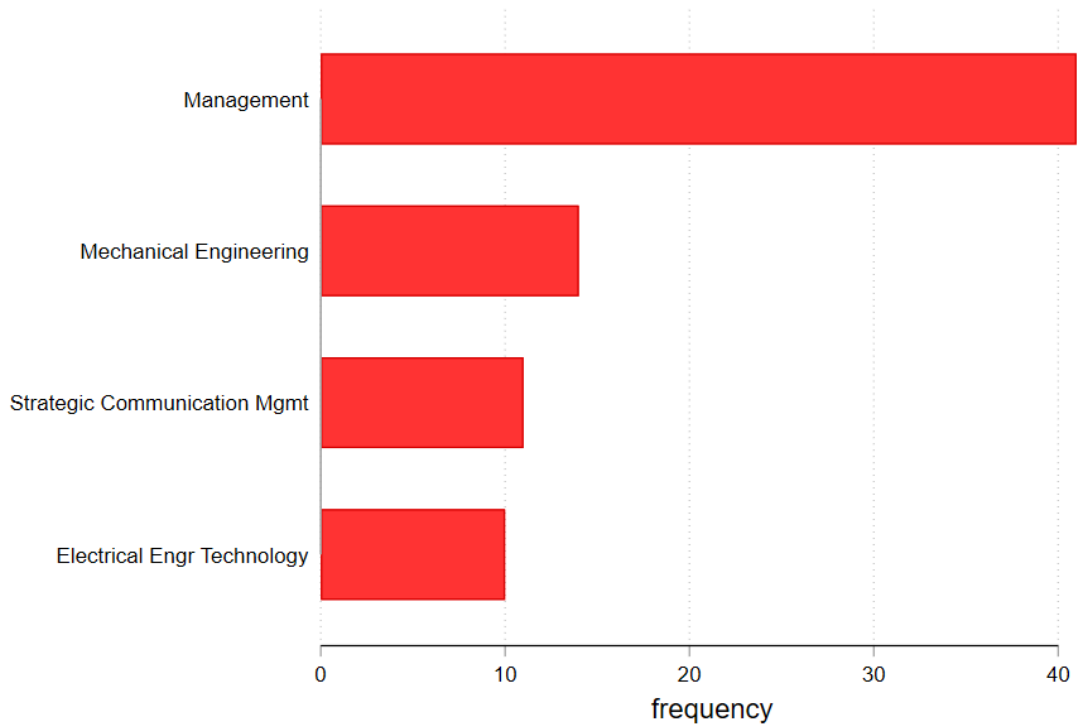


Figure 14: Popular majors of graduates with Hispanic ethnicity (all terms

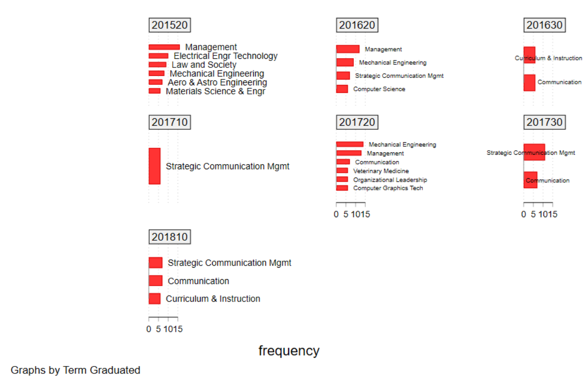


Figure 15: Popular majors of graduates with Hispanic ethnicity by graduation terms

Figure 16: Popular majors of graduates with White race by graduation terms

Table A1 Course drops

	Naiive	Reduced-form	
	(1)	(2)	(3)
	beginning to census period	census to end period	beginning to end period
assigned_alone	-0.0016	0.0015	0.0010
	(0.0012)	(0.0052)	(0.0053)
pr(assigned_alone)	0.0008	0.0113	0.0113
	(0.0007)	(0.0090)	(0.0090)
_cons	0.0185	-0.0291	0.0185
	(0.0193)	(0.0916)	(0.0794)
Course and race/ethnicity FE	x	x	x
Major FE	x	x	x
N	5039	5173	5039
R^2	0.200	0.161	0.168

Notes: Cluster Robust standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table A2 Treatment effects of graduating with historic salary in top 25th percentiles (College of Engineering sample)

	International	Black	Hispanic	Asian	White
	(1)	(2)	(3)	(4)	(5)
	b/se	b/se	b/se	b/se	b/se
(mean) enrolled_alone_r	0.0165	0.2565	-0.0355	0.0136	0.5443
	(0.1138)	(0.2139)	(0.1354)	(0.1105)	(0.3773)
(mean) enrolled_alone_rsim	0.1506	0.5012	0.0902	0.1332	0.0097
	(0.2100)	(0.3789)	(0.2554)	(0.2233)	(0.6465)
Observations	235	52	123	269	21
R^2	0.197	0.184	0.047	0.023	0.298

Notes: Cluster Robust standard errors in parentheses.
$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table A3 Treatment effects of graduating with a major popular among current racial students

	All	Indian/Chienese	All	Asian	Black	Hispanic	White
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Assigned alone	0.0935*	-0.4520*	0.0284	0.0422**	-0.0178	-0.0323	-0.0944
	(0.0501)	(0.2327)	(0.0276)	(0.0213)	(0.0277)	(0.0450)	(0.0764)
pr(Assigned alone)	-0.0843	0.9670***	0.0004	-0.0154	0.0113	-0.0065	0.0466
	(0.0791)	(0.3047)	(0.0521)	(0.0362)	(0.0401)	(0.0734)	(0.0508)
Observations	510	32	1083	496	99	262	122
R^2	0.575	0.468	0.489	0.852	0.851	0.846	0.643
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Cluster Robust standard errors in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table A4 Treatment effects of graduating with a high-paying major (College of Engineering sample)

	International	Black	Hispanic	Asian	White
	(1)	(2)	(3)	(4)	(5)
(mean) enrolled_alone_r	-0.0317	-0.3100	0.1126	-0.0410	0.1537
	(0.0887)	(0.2045)	(0.1065)	(0.0713)	(0.1846)
(mean) enrolled_alone_rsim	-0.0129	0.5198	-0.0240	0.2411**	0.0678
	(0.1563)	(0.3202)	(0.1935)	(0.1007)	(0.1271)
Observations	212	40	107	239	19
R^2	0.136	0.141	0.092	0.027	0.112

Notes: Cluster Robust standard errors in parentheses.
$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table A5 Treatment effects of graduating with a high-paying engineering major (College of Engineering sample)

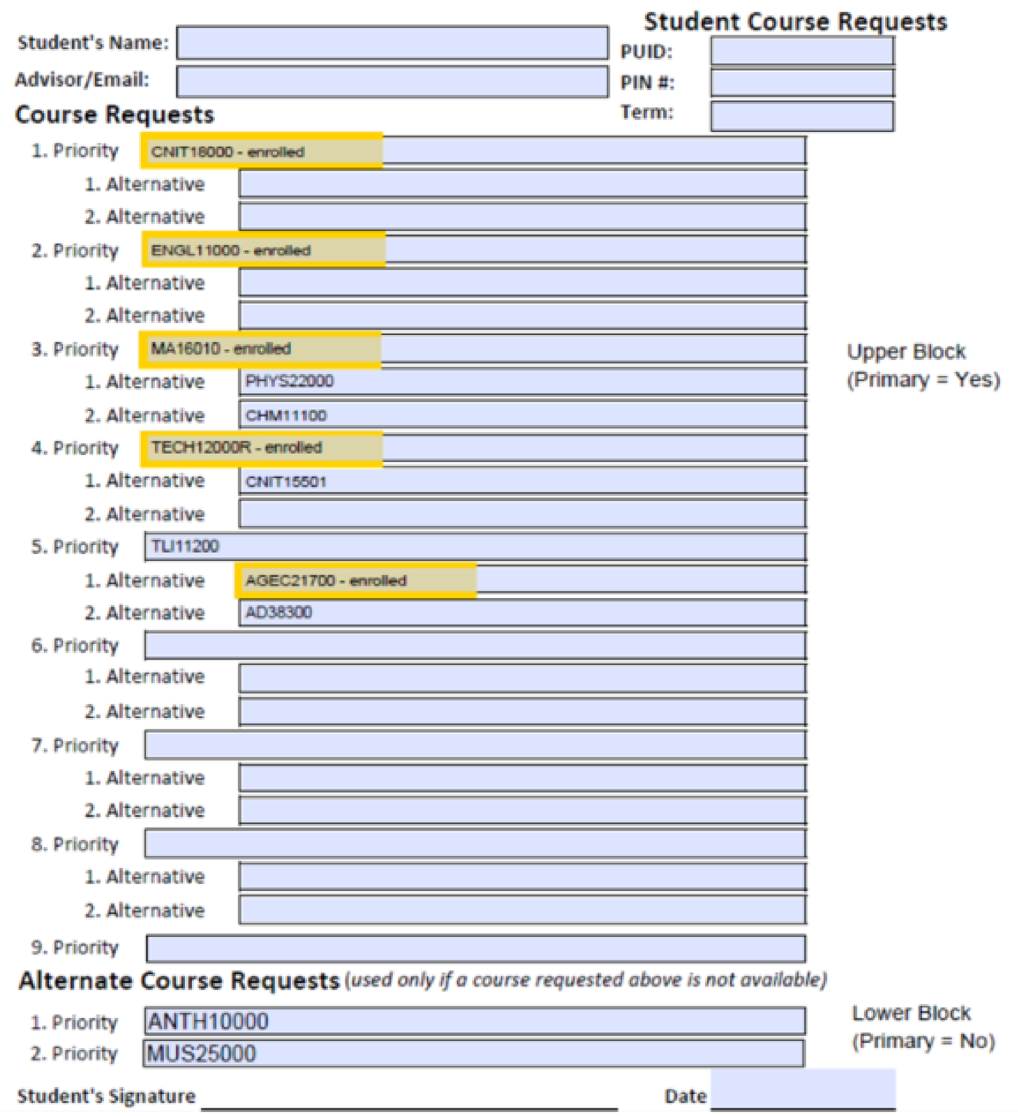
	International	Black	Hispanic	Asian	White
	(1)	(2)	(3)	(4)	(5)
Assigned alone	-0.0453	-0.1042	-0.0238	0.1849*	0.6217**
	(0.1111)	(0.2261)	(0.1416)	(0.0951)	(0.2349)
pr(Assigned alone)	0.0714	0.1350	-0.1504	0.1798	0.0621
	(0.1802)	(0.4020)	(0.2723)	(0.1500)	(0.2509)
Observations	235	52	123	269	21
R^2	0.178	0.184	0.067	0.035	0.344
Demographic controls	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes

Notes: Cluster Robust standard errors in parentheses.
$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Appendix A2. Course Registration and the Assignment

Students submit their course preferences well ahead of the first class of the semester (Figure 1). When submitting the course requests, they know which instructors will teach which section of the courses. Given that known information, a student fills out the course request form, where she submits her preference orders for the courses (Fig. 2). It is possible to choose courses strategically but once I control the course preferences, being *assigned alone* is random.

The course assignment algorithm used at the university is called Batch Registration (Muller et al., 2010). A distinctive feature of this algorithm is that course and section assignments are random once students' course preferences are taken into account. On the course request form, students can choose up to eight different priority blocks of courses in chronological order. For



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

Figure 17: Course request form

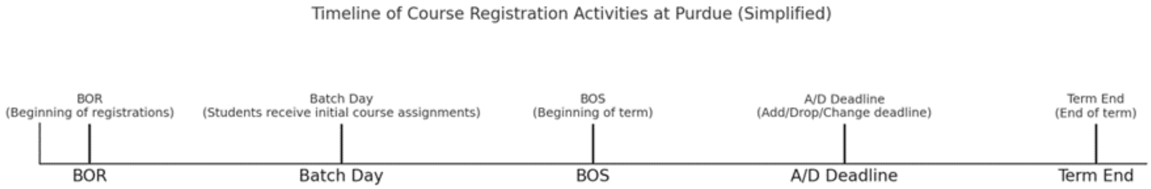


Figure 18: Course registration timeline

each block, the first course listed is the main course in that priority order. The Q function assigns higher weights to top-priority orders, with the priority number raised to the power of 0.9. If the course is the first choice in a given priority block, the value of *alternative* equals zero which is raised as the power to a fractional weight (0.5). When the primary course is not available for assignment, the algorithm chooses the lowest possible alternative so that the Q function is maximized. To do so, the algorithm picks a student on a random basis and fills her request for a given course. So, the source of randomness in course assignments originates from the random order in which students are selected.

Due to university-wide course demand, course availability, and student preference issues, there can be differences between the treatment and the instrument. In addition to that, students strategically requesting courses and choosing their priority order is plausible, making it difficult to ensure that course assignments are truly random.

Under each priority, students select one primary course and up to two alternative courses. If the primary course in a priority block cannot be assigned to the student due to capacity or scheduling conflicts, the algorithm will select one of the alternatives listed in the same priority block. The batch registration algorithm maximizes the following Q function (Mumford et al., 2023).

$$Q = \sum_i \sum_c (.9^{priority_i} * .5^{alternative_i})$$

Let us consider an example. The form has five priority blocks.

- If all the five primary courses are assigned as shown on the form, Q=.9+.9^2 +.9^3 +.9^4 + .9^5=3.686.
- If the student is enrolled for all the courses as shown on the form except CNIT18000 by the algorithm, Q=2.786. Comparing with the first bullet point above, the higher the

number of courses the student is enrolled/assigned, the higher is Q

- If the student is enrolled for all the courses as shown on the form except the course in priority 2 (i.e., ENGL11000), Q=2.876. Compared to the second bullet point above, assigning courses situated at a higher priority order (e.g., priority 1) than assigning a lower priority course (priority 2), yields a larger Q.

- If the student is enrolled for all the courses as shown on the form except the primary course in priority 3 (i.e., MA16100) and assigned the first alternative to the primary course, $Q = 0.9 + 0.9^2 + (0.9^3 \times 0.5^1) + 0.9^4 + 0.9^5 = 3.321$. Compared to the first bullet point above, assigning courses an alternative course rather than assigning a primary course for any priority block yields a smaller Q.

The algorithm solver has four constraints to consider. First, each course and section has seat limits. Second, one student cannot enroll in two or more overlapping sections. The third constraint is a distance conflict which arises when two sections are located too far apart for students to arrive. The fourth constraint is the reserved seats for students with pre-declared majors. The algorithm solver works in five steps that is briefly described in Mumford et al. (2023)