Foreign Peers in College and the STEM Careers of Domestic Students

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Abstract

The number of foreign students enrolled in US higher education has increased steadily over recent decades. We examine whether foreign peers affect the likelihood domestic students complete a STEM degree and eventually work in a STEM occupation. Using administrative student records from a large U.S. research university, we exploit idiosyncratic variation in the share of foreign peers across cohorts of students attending introductory-math courses. We find that 10 extra foreign peers displace about 4 domestic students from STEM majors and occupations. However, displaced students gravitate towards relatively high earning Social Science majors, so that their potential earnings are not penalized. Our findings imply that while foreign students have higher propensity to pursue STEM majors and careers, they have little impact on the total number of STEM workers. Increases in foreign STEM graduates are offset by the reductions in domestic STEM graduates.

Key Words: immigration, peer effects, higher education, college major, STEM.
JEL Codes: I21, I23, I28, J21, J24.

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1 Introduction

Encouraging Science, Technology, Engineering, and Mathematics (STEM) education has been a long-standing goal in the United States, as STEM workers are key drivers of innovation and growth (Griliches, 1992; Jones, 1995; Kerr and Lincoln, 2010; Peri, Shih and Sparber, 2015). Higher education has been an area of particular concern, as recent decades have seen reductions in the share of degrees awarded in STEM fields, and substantial problems with retention – over 50% of intended STEM majors end up switching to non-STEM fields or dropping out (Chen, 2013). Sourcing STEM skills from abroad is one way to assuage concerns over inadequate domestic supply of STEM skills.[1] Large-scale immigration into the workforce has been accompanied by a growing presence of foreign students in higher education as family reunification and less restrictive student visa policies provide pathways for youth immigration.

This paper examines whether growing presence of foreign peers in higher education affect the likelihood that U.S. domestic students complete STEM degrees and eventually work in STEM jobs. We study this in the classroom setting, drawing on administrative student-level records from a large U.S. research university over the 2000-2012 academic years. We focus our analysis on domestic U.S. citizens who attend introductory math courses – often considered an initial gateway for STEM majors – during their first college term. We instead classify students as foreign if they have a non-US citizenship at the time of college attendance.[2] We then explore whether the share of introductory math classmates that are foreign affects the likelihood of graduating with a STEM degree and working in a STEM occupation.

Our results show that foreign peers reduce the likelihood that American students graduate with a STEM major and eventually work in a STEM occupation. A 1 standard deviation ($\approx$4 p.p.) increase in the share of introductory math classmates that are foreign reduces the probability of graduating with a STEM degree and also working in a STEM occupation by roughly 3 percentage points, or 7% of the mean. Applying our estimates to an average sized class indicates that 10 additional foreign peers displaces 4 domestic students from STEM degrees/occupations.

The displacement does not have an aggregate impact on the earnings of the domestic students. Displacement occurs among domestic students that possess a weak comparative advantage

[1] Programs like the H-1B and OPT visa explicitly aim to select STEM workers.

[2] Domestic U.S. citizens include also a minority of individuals who are born abroad: 7.7% of all U.S. citizens with some college in the cohorts of interest are born abroad and naturalized, according to own calculation using American Community Survey data. However, for the purposes of informing how STEM human capital flows into the labor market, U.S. citizenship is the most relevant margin. Naturalized citizens are more likely to be assimilated to U.S.-born students and immigration programs place large restrictions on the entry of non-citizens into the U.S. labor market.

in STEM fields relative to non-STEM fields. These students then increase their propensity of majoring/working in Social Science majors/occupations that have equally high earning potential when compared to the STEM fields they leave. Our results imply that the total number of STEM graduates/workers is left unchanged, as the increases from foreign students are offset by displacement of domestic students.

To identify our effects we leverage idiosyncratic variation in the share of a student's peers that are foreign within introductory math classes taught by the same instructor over time, similar to other studies using variation in peer composition within school-grade pairs (e.g., Hoxby, 2000; Carrell and Hoekstra, 2010; Anelli and Peri, 2019; Carrell, Hoekstra and Kuka, 2018). Our motivation follows from the ideal experiment, which varies exposure to foreign peers, while holding fixed all other classroom factors, such as the instructor, course material, and other peer characteristics. Foreign citizenship has the benefit of being a characteristic that cannot be altered by one's classmates, allowing us to identify peer effects without bias due to reflection. Focusing on students during their first-college term, helps reduce the scope for selection bias as new students have less information about the registration process, instructors, and/or their peers. Highly detailed registration actions of each student allow us to measure foreign peer composition of each class prior to the first day of instruction, to limit endogenous sorting after students observe their peers.

Balancing tests rule out selection on an array of observable background characteristics, including race, gender, and ability measures. Systematic selection out of classes by dropping after the first day of instruction also does not occur. Our estimates are robust when controlling for course-by-term effects, indicating that common shocks to a given course and academic term are not biasing our results. As introductory math classes have high enrollment caps that never bind in our setting, our estimates are not confounded by mechanical crowd-out whereby the entry of foreign students prevents domestic students from registering for the class.

Why do foreign peers encourage domestic students to pursue non-STEM majors? We probe several candidate explanations, and find a strong role for the lower-levels of English fluency social interaction brought about by foreign peers. Studies have shown foreign college students to have weaker English proficiency and engage less in communicative activities during class (e.g. Horwitz, Horwitz and Cope, 1986; Erisman and Looney, 2007; Rodriguez and Cruz, 2009; Stebleton, Huesman Jr and Kuzhabekova, 2010; Stebleton, 2011; Yamamoto and Li, 2011). Social interactions and effective communication, such as asking clarifying questions, have been linked to success in schooling and labor market outcomes (Borjas, 2000; Carrell and Hoekstra, 2010; Carrell, Hoekstra and Kuka, 2016; Deming, 2017). In a less communicative classroom environment, there are fewer positive externalities from social interactions and instructors may alter the pace or style of instruction to accommodate non-native speakers. We find this to be a likely mechanism, as analysis reveals displacement is entirely driven by foreign students with very low English proficiency.

We find less evidence for other mechanisms. Related literature has shown that class ranking impacts students' performance and choices (Murphy and Weinhardt, 2018; Elsner and Isphording, 2017) and that peers can alter the relative ranking/comparative advantage of individuals within a class or labor market. This provides an updated local signal of ability, and individuals respond by specializing in different human capital and labor market choices (Peri and Sparber, 2009, 2011; Cicala, Fryer and Spenkuch, 2017). Our data indeed show foreign students possess a strong comparative advantage in STEM. We find suggestive, but not statistically significant evidence that changes to class ranking brought about by foreign peers may lead domestic students to switch more to non-STEM fields.

We do not show any overall effect on the grade earned in the introductory math class and we find it unlikely that our results can be explained by simple distaste for taking classes alongside foreign students. Empirical checks show the individual exposure to foreign peers in the first term introductory math course is unrelated to the exposure to foreign peers in future courses and terms.

Our work contributes to three distinct lines of inquiry. First, we highlight the importance of peers on human capital investment decisions. Recent work has brought new attention to the importance of major choice, showing that the return to high paying majors rivals the high school-college wage gap (Altonji, Blom and Meghir, 2012), exceeds the return to attending selective institutions (Kirkeboen, Leuven and Mogstad, 2016; Arcidiacono, Aucejo and Hotz, 2016), and has been widening over time (Altonji, Kahn and Speer, 2014). This paper highlights that peer composition can have a large effect on investments in particular fields of study.

Second, our analysis speaks to the impacts of immigration on education within host countries. This study is the first to link exposure to foreign peers in college classrooms to eventual completion of particular fields of study. Existing studies on foreign peer impacts have solely focused on primary and secondary education, often in settings outside the United States.[3] Those focusing on higher education have generally examined extensive margin outcomes.[4] We complement work on intensive-margin outcomes (e.g., Betts and Fairlie, 2003; Cascio and Lewis, 2012; Orrenius and Zavodny, 2015; Chevalier, Isphording and Lisauskaite, 2019), bringing attention to the large growth in foreign peers within classroom settings.

Finally, our analysis on labor market outcomes demonstrate how early shocks in education can persist well into the labor market, and carry implications for how immigration of young students

[3]For example, Brunello and Rocco (2013); Gould, Lavy and Daniele Paserman (2009); Ballatore, Fort and Ichino (2015); Ohinata and Van Ours (2013, 2016); Geay, McNally and Telhaj (2013); Diette and Oyelere (2012, 2014); Conger (2015); Figlio and Özek (2017).

[4]Papers on U.S. higher education have focused on international students and enrollment or graduation (Hoxby, 1998; Betts, 1998; Borjas, 2004; Jackson, 2015; Hunt, 2017; Machin and Murphy, 2017; Shih, 2017).

may affect the aggregate supply of STEM skills. While immigration indeed adds to the pool of STEM talent, our analysis indicates that the displacement of domestic students from STEM majors/occupations is sizable enough to offset the increases in STEM graduates/workers from foreign students. Hence, our results imply that the aggregate number of STEM graduates has not increased. Furthermore, considering the higher incidence of international student-visa holders to leave the U.S. after graduating – back-of-the-envelope calculations suggest a lower-bound estimate of 35% remaining – it is likely that the aggregate number of STEM graduates may fall.[5]

The implications of our findings towards policy surrounding foreign enrollment in other institutions will vary depending on context. Our focus on introductory math courses has broad scope as the subject matter and general way of teaching calculus based courses are fairly similar across higher education institutions. However, U.S. higher education institutions are quite diverse on a wide array of attributes, which need to be considered when assessing the impact of foreign peers. The cost of switching majors, course enrollment caps, or the relative skill sets of foreign and domestic students are a few such attributes.

We proceed by describing the institutional setting and our data in the next section. Section 3 details our empirical framework and provides tests of selection on observables. Results and robustness checks are presented in section 4. Section 5 describes and tests various mechanisms underlying our main findings. Section 6 concludes.

2 Data

This paper uses administrative data from a selective U.S. university. Our data cover the breadth of students' academic records over the academic years 2000-2001 to 2011-2012. Records include all course registration activity of students, including adding and dropping courses. For each course, we observe the title, department and the identity of the instructor. Background measures include SAT scores, race, gender, nationality, and visa status. Student level outcomes include date of graduation, major at graduation, declared major (term by term), cumulative GPA, and grades in each course. In what follows, we provide more detail about the institution we study, specify the introductory math courses we focus on, and then describe the students and outcomes in our sample.

Enrollment at our institution is quite large, with undergraduate students comprising roughly

[5]The ability of international student-visa holders to work in the by U.S. is limited by immigration policy–specifically, the H-1B visa which has strict caps. In 2012, 130k H-1B visas were issued, and Ruiz (2013) provide data showing roughly 35% of H-1B visa recipients transferred from F-1 student visas. Hence, roughly 45,500 international student-visa holders were able to work in the United States. This represents 35% of the total number of 130,000 international student-visa holders graduated from U.S. universities. This may be a lower-bound as graduating students may remain in the U.S. through a different visa class, or may continue to higher levels of education.

80% of the total student body. The average SAT scores of incoming students are above the national average. Students can earn bachelor's degrees in over 100 different majors, with STEM fields (e.g. Biology, Chemistry, Mechanical Engineering) comprising half of the top 20 most popular majors. Students may enter undeclared, but are required to formally declare a major before completing two full-time years of course work. Switching majors requires obtaining approval from an advisor in the major they wish to leave and from an advisor in the major they wish to join. Approximately 50-60% of students graduate within 4 years and 80-85% graduate within in 6 years.

Our analytical sample comprises domestic students taking introductory, calculus-based, math courses during their first-term of university attendance. These courses have long been viewed as gateways to STEM degrees (Steen, 1988). All STEM majors require satisfactory completion of an introductory math course in order to progress. Within U.S. higher education, such courses generally cover uniform subject material, thereby limiting the scope for potential issues arising from differences in subject matter breadth and depth, while also enhancing the external validity of our findings. Approximately 70% of all students in our data take an introductory math course at some point during their undergraduate studies, with over 40% of domestic students enrolling during their first term. These courses have very high enrollment caps that never bind – in our sample, enrollment never exceeds 40% of the cap. This implies that students cannot be mechanically crowded-out of classes because of high demand.

Table 1 lists the math courses in our primary sample, the total number of first-term domestic students in our sample who took a given course, the average course size, and the average fraction of the course that is made up of foreign students. We consider a math course introductory if it is open to non-transfer students in their first term, satisfies the university-level requirement of a quantitative class, and counts as prerequisite for at least one STEM major. Introductory math classes are all calculus based. These courses have an average class size of 230 students. Our analysis includes high achieving students who take more advanced courses like Calculus III in their first term, but a majority of the domestic freshmen in our sample take one of the more basic courses such as Precalculus and Calculus I. On average, first-term domestic students make up 56% of the students enrolled in these introductory courses.

Foreign peer exposure is measured within classes, which are identified by a course, professor, and term. The class is a natural unit where peer interactions might occur as students attend lectures in the same physical location at the same time, and are evaluated jointly by the professor with the same exams and assignments.[6] Students are considered to be foreign if they are non-citizens and

[6]In rare instances when a single professor teaches multiple sections of the same course in a given term, the students in different sections are treated as distinct peer groups. In the data, a professor teaches two sections of the same course in the same term 6 times out of 181 different course-professor offerings.

indicate a foreign nationality. Foreign students need not be first-term freshman to be counted in our peer measure. Figure 1 shows the overall variation in the foreign share across introductory math classes. While typically ranging between 8-15%, some classes have less than 5%, and a few have greater than 20%. Using detailed registration records, we measure foreign peers in each class based on the composition of registered students on the day prior to the first day of instruction. As such, they reflect the class composition before students have been physically present in class to observe their peers, meet the professor, or examine the syllabus.

Our analytical sample is domestic students who took an introductory math course during their first enrolled term between the 2000-2001 and 2005-2006 academic years. We focus on the earlier years of our sample so that we can observe 6-year graduation rates for all students. This yields a sample of 16,830 students. Table 2 summarizes the background characteristics of undergraduate students. Columns 1 and 2 refer to all domestic and foreign students enrolled during the period under analysis (2000-2006). Column 3 describes our primary analysis sample of domestic first-term freshmen in introductory math courses. Column 4 displays statistics for foreign students in introductory math courses. While 56% of domestic students are female, only half of first-term domestic freshmen that enroll in introductory math courses are female. Domestic Asian students meanwhile are overrepresented in these classes. They comprise only 37% of all domestic students, but represent roughly half of all the first-term freshmen enrolled in introductory math courses. A similar pattern is observed for foreign students. The vast majority, nearly 80%, of all foreign students are Asian. The next most populous race groups among foreign are White students, followed by Latino students.[7]

foreign students do not appear to be substantially different in terms of ability in the general student population. One exception is that foreign students exhibit substantially lower SAT verbal scores, reflecting their lower English ability. This difference in English ability is magnified when comparing domestic first-term freshmen and their foreign peers in introductory math classes – SAT verbal scores of foreign peers are almost a full standard deviation below domestic students. Though differences in SAT verbal are the most salient, domestic freshmen outperform foreign peers in introductory math courses on all measures of background ability.

Table 3 summarizes outcome measures for our sample of students. We focus on major at graduation as it is a definitive measure of skill acquisition. Students that graduate are assigned one of three majors – STEM degree, Social Science degree, or Arts & Humanities degree – based on the university's classification of majors. We measure graduation within 6 years and those that do

[7]International students, those who have not previously lived in the United States prior to university, account for 11% of our foreign peer population. Their small sample size limits our ability to statistically distinguish effects of these two groups.

not complete within 6 years are referred to as "dropouts", however a small number may actually take 7+ years to graduate.[8]

Panel A provides a summary of academic outcomes. Approximately 82% of entering domestic freshmen graduate within 6 years, whereas 18% dropout or take greater than 6 years. While domestic students graduate with an average GPA of 3.05, foreign students perform slightly lower. Students that graduate take slightly more than 16 terms, or 5.33 years to complete their degree. Nearly half of all students attending introductory math courses earn a degree in a STEM field, with Social Science comprising less than a third. Only around 8% of students earn degrees in Arts & Humanities.

Panel B focuses on student's labor market outcomes which come from two additional sources. These data allow us to explore if there are persistent effects from peers beyond graduation. First is a measure of expected earnings from The Hamilton Project (Hershbein and Kearney, 2014) and estimated using American Community Surveys (ACS) data.[9] Every student in our data is assigned an earnings level based on the country average for their major for 1, 6, 15, and 30 years after graduation. These earnings are not student-specific (i.e. all Economics majors will be assigned the same value) and so represent a generic estimate of student labor market success after college.[10] Descriptive statics in Table 3 show that Domestic Freshmen attending intro-math courses have expected earnings along their career similar to those of their foreign peers. This suggests that on average the domestic students in our analytical sample choose majors that deliver similar earning levels in expectations.

Our second measure is a student-specific STEM occupation indicator. In conjunction with university administrators, we systematically gathered data on individual student job descriptions via publicly available information on the internet and linked it to their student records. We match occupational information for 74% of students in our analytical sample. Occupational descriptions are then matched to Standard Occupational Classification (SOC) Codes using an algorithm based on the O'NET dictionary of occupation titles. We index each occupation as STEM or non-STEM

[8]For our earlier cohorts for which we can observe graduation outcomes for up to 11 years, we find that, conditional on having not graduated within 6 years, fewer than 6% of students go on to graduate within our available timespan.

[9]Hershbein and Kearney (2014) use earnings data from the U.S. Census Bureau's American Community Surveys (ACS) between 2009 (the first wave for which college major was asked) and 2012. Earnings are defined as the sum of wages, salaries, and self-employment business income in the year prior to survey.

[10]Expected earnings and earnings profiles calculated by Hershbein and Kearney (2014) rely on the ACS cross-section of individuals from many cohorts only partially overlapping with the cohorts in our analytical sample. Using these values as outcomes for our cohorts thus implies assuming a certain degree of persistence in the returns to college major across cohorts. Moreover, average earnings by college major from the Hamilton Project are representative of the entire U.S. population of college graduates. Relying on them for our sample requires assuming that labor market outcomes for graduates from the university under analysis do not deviate substantially from those of the average U.S. graduate. Given the characteristics of this University, this is assumption is fairly reasonable.

using a classification provided by the Bureau of Labor Statistic.[11] Based on the matching, we estimate that 44% of domestic freshmen are working in STEM fields, while 50% of foreign peers students are. Based on each individual SOC code we link occupational-based expected earnings, calculated using ACS data as the average earnings of all college graduates born in the same cohorts as our students working in that occupation. Estimated earnings are very similar across the two groups.

These two measures have complementary advantages and shortcomings. The first measure has the advantage of not being subject to bias and the disadvantage of not being student-specific. The second does capture an actual observed individual labor market outcome, however it is subject to bias due to the imperfect match. The fact that these two complementary measures deliver similar estimates of expected income certainly increase the reliability of our results with respect to using only one of the two.

3 Identification and Empirical Model

We aim to identify the causal impact of foreign peers on completing a STEM degree and working in a STEM occupation. We utilize idiosyncratic variation in peer composition (Hoxby, 2000; Carrell and Hoekstra, 2010; Anelli and Peri, 2019) in introductory math classes which creates treatments that are exogenously assigned. To estimate the impact of foreign peer exposure, we estimate the following linear probability model:[12]

$$Y_{icpt} = \alpha + \beta \frac{F_{cpt}}{N_{cpt} - 1} + \sigma_{ct} + \sigma_{cp} + \gamma_1 X_i + \gamma_2 \frac{X_{cpt}^{-i}}{N_{cpt} - 1} + \gamma_3 CS_{cpt} + \varepsilon_{icpt} \tag{1}$$

Y_{icpt} represents an outcome for student i who attended a class, identified by the introductory math course c, professor p, and term t. Foreign peer exposure is measured as the share of individual i's classmates (N) that are foreign ($\frac{F_{cpt}}{N_{cpt}-1}$). We control for course-by-term indicators (σ_{ct}) and course-by-professor fixed effects (σ_{cp}), thereby forcing the remaining variation to come from changes within courses c taught by the same professor p over time t. We note that selection across course-professor pairs within a term, based on factors such as time-of-day or day-of-week, is unlikely as 98% of course-professor pairs are offered only once per term.[13] Our identifying

[11] See `https://www.bls.gov/soc/Attachment_C_STEM.pdf`. In particular, we define STEM occupations as those in categories 1 (Life and Physical science, Engineering, Mathematics, and Information Technology) and 4 (Health). The full matching process is described in detail in Appendix C.

[12] Results from logit and probit estimation (available on request) yield average marginal effects that are very similar in size. However, several papers (e.g. Greene, 2004) have cautioned against using logit or probit estimation with fixed effects as it can generate biased and inconsistent results.

[13] A concern might be that foreign and domestic students may differentially select based on time of day or day

variation–within course-professor pairs over time–might include, for example, changes in peer composition, class environment, instructor pedagogy, or course content. We focus on changes in share of foreign peers within courses-professor pairs, and argue foreign peer variation appears to be as-good-as-random.

We also control for individual characteristics (X_i) – which include race, gender, and ability variables described in Table 2 – and for peers' pre-university characteristics to account for common shocks: $\frac{X_{cpt}^{-i}}{N_{cpt}-1}$ includes peer ability measures, such as average peer SAT Math, SAT verbal, and high school GPA, and average peer race and gender composition. We also account for class size (CS_{cpt}), following Ballatore, Fort and Ichino (2015) who find important interactions between class size and foreign students inflows within Italian primary schools. Finally, ε_{icpt} is a mean-zero error term. We cluster standard errors at the professor level. We also standardize the foreign share so that the primary coefficient of interest β can be interpreted as the impact of a 1 standard deviation increase in the foreign class share on the outcome, in units of Y.

Figure 2 visually simplifies our identifying variation, by depicting the variation in the foreign share for 10 randomly sampled course-professor pairs. Each point represents the foreign share within a particular introductory math course taught by a particular professor in a given term. Connected lines facilitate visual tracking of course-professor pairs over time. To simplify our analysis by way of example, our identification compares the outcomes of freshmen students enrolled in class A, against the outcomes of freshmen who enrolled in class B. Students across these two classes took the same course (introductory calculus), with the same professor, but were exposed to very different levels of foreign peers by virtue of entering the university and enrolling in introductory math in different terms. We argue that the differences in the class compositions of A and B are driven by random fluctuations, and that students in the two classes are comparable.

3.1 Selection, Common Shocks and Reflection

Estimating peer effects can be difficult due to three main issues: selection, common shocks and reflection (Manski, 1993; Moffitt, 2000; Sacerdote, 2011). We discuss in greater detail how our data, setting, and identification strategy allow us to overcome each of these issues.

Selection of students into classes that is related to the foreign peer composition would bias our estimates. We take several precautions to guard against selection. Qualitatively, we focus on

of week, or combination of both, when more than one course-professor pair is offered in the same term. Hence, adding time-of-day, and/or day-of-week fixed effects would account for these issues. In practice, however, 98% of our course-professor pairs are offered once per term. While this may seem unusual, we note that introductory math courses are structured to be very large lecture-style classes, with enrollment often exceeding 200 students. Thus, having an instructor teach more than one introductory math course (e.g. two sections of Calc I), in a single term would likely be extremely onerous given the student load.

first-term freshmen whom have little prior experience, or knowledge about professor reputation, course detail, and peer composition at the time of registration.[14] Additionally, we measure the peer composition of students registered for each course on the day prior to the first day of instruction, before students ever physically attend class and observe their peers.

Our identifying variation in foreign peers comes from courses taught by the same professor over time. Endogenous selection in this context would manifest in students reliably predicting the current and future foreign composition, or any other characteristic correlated with the presence of foreign peers, and timing their enrollment in a course-professor pair accordingly. This is highly unlikely as instructor assignments to courses are decided only in the middle or towards the end of the prior term, often after students have already enrolled in the following term courses.[15]. Figure 2 offers visual suggestive evidence that students are unlikely to time enrollment in a course-professor pair based on passed foreign peer composition. If this was the case, we would indeed observe course-professor pairs with consistently high or consistently low share of foreign peer over terms. Figure 2 shows instead that term after term all course-professor pairs show a very idiosyncratic pattern.

We formally test for the presence of selection on observables by examining whether domestic students who enroll in the same course-professor pair, but experience varying levels of foreign peer exposure, are different along observable background characteristics. Importantly, we must test for selection, not only among first-time freshmen, but also other domestic students in the class, as selection of either group would endogenously change the classroom composition. Specifically, we estimate the following regression model:[16]

$$X_i = \alpha + \delta \frac{F_{cpt}}{N_{cpt} - 1} + \sigma_{ct} + \sigma_{cp} + \epsilon_{icpt} \tag{2}$$

The dependent variable in Equation 2 represents measures of individual background characteristics of domestic student i (X_i). Including course-by-professor and course-by-term fixed effects allows us to examine whether selection occurs within course-professor pairs.

The results of these tests are displayed in Table 4. Each column corresponds to a different individual background characteristic (X_i).[17] None of the estimates are statistically distinguishable

[14] Enrollment of freshmen for first-term courses is done online even before students are physically present on campus

[15] Given the competitive nature of student enrollment into courses, class enrollment fills up shortly after enrollment is open.

[16] We also run a similar test where the dependent variable is the foreign share, and all background characteristics of domestic students are on the right hand side. The results are shown in Table A2. The F-test has a p-value of 0.15, showing no evidence of joint significance.

[17] The sample of 25,912 include both the 16,830 domestic first-term freshmen, and other domestic students (i.e. non-first-term freshmen, sophomores, juniors, and seniors) enrolled in the introductory math courses.

from zero at any meaningful level of confidence, nor are they economically significant. The estimate in column 7, for example, indicates that a one standard deviation increase in the foreign share is associated with an increase in a domestic student's SAT math score of 1.76 points (only 0.02 of a standard deviation). Thus, the results do not provide any evidence of selection on the basis of observable background characteristics. To further limit the scope of potential selection bias in our analyses of outcomes, we include these background characteristics as controls.[18]

Our approach addresses issues of reflection that occur when explanatory peer measures can potentially be influenced by individuals. This usually is problematic when the peer measures is the average outcome of one's peers. However, we examine a peer background trait – citizenship – that is measured before students meet their peers. Thus, it is highly unlikely that domestic students could reasonably affect the citizenship status of their foreign peers before they even physically enter the classroom.[19]

Because we do not include peer outcomes, $\bar{Y}_{-icpt}$, in our specification, this also means that our model estimates a combination of the endogenous and exogenous peer effects (Carrell, Sacerdote and West, 2013; Manski, 1993). While this is a limitation common to most peer effects study – due to the challenges of having a credible source of identification to disentangle the two –, mechanisms driving peer effects are often blends of these two channels anyways, so we do not feel that estimating a combination of the two channels detracts from the model. Moreover, the aggregate peer effect we estimate is the relevant one for policy.

Common shocks represent non-peer phenomena that impact all students in a class such as teacher quality or bad lighting in a classroom. Controlling for course-by-term fixed effects accounts for both aggregate university shocks, such as changes in admission committee decisions, and course specific shocks, such as changes in grading standards, rigor, or pedagogy. Additionally, course-by-professor fixed effects help account for fixed differences, such as difficulty levels or lecture style. Finally, we include controls for other class level other peer characteristics, to absorb any common shocks that might affect the composition of students in specific classroom. Remaining class-level shocks that we are unable to account for are likely to be pseudo-random in nature and not correlated with $\frac{F_{cpt}}{N_{cpt}-1}$.

[18]We also check whether foreign students are selecting on observables based on the foreign peer composition in appendix Table A1. In Table A1, the same ten specifications as Table 4 are estimated, but instead focusing on the 3,840 foreign students taking an introductory math course. Out of ten coefficients, only one is significantly different from zero, however very small in magnitude, such that we do not believe this small amount of selection is evident to students or making a meaningful difference in the classroom environment.

[19]Additionally, because domestic and foreign students are mutually exclusive groups, our analysis does not suffer from more recent concerns of mechanical negative bias (e.g. Guryan, Kroft and Notowidigdo, 2009; Fafchamps and Caeyers, 2016).

4 Results

Table 5 shows estimates of Equation 1 looking at the effects of foreign peers in introductory math courses on major at graduation of domestic first-term freshmen. The outcome variable is an indicator equal to 1 if the student graduated with a STEM major within 6 years from enrollment, and 0 otherwise. Column 1 includes the baseline peer ability, peer race and gender composition controls. Column 2 adds a control for course size. Column 3 controls for individual characteristics. All models include course-by-term and course-by-professor fixed effects. Panel A considers domestic students. The coefficient estimates in the first row indicate that foreign peers are negatively associated with the likelihood of completing a STEM major. A 1 standard deviation rise in the foreign class share reduces the probability of graduating with a STEM major by 3 percentage points. All estimates are statistically significant at the 1% level and robust to the addition of various controls. The coefficient is roughly 7% of the mean STEM graduation rate of 48%.

By way of comparison, the magnitude of our estimate is equal in size to 1/2 of the US White-Black STEM gap and 1/5th of the STEM gap across genders.[20] We can also size our estimates by calculating the number of students displaced for a class that has all characteristics fixed at the means in our sample – 9 additional foreign students would displace 3.7 domestic freshmen from completing STEM degrees.[21] Column 4 provides a further test to ensure our foreign peer impacts are identified from exposure in introductory math courses. We include the foreign peer composition across all other classes taken by domestic first-term freshmen, excluding the introductory math class, as a control. The results are virtually unchanged. This indicates that the transmission of foreign peer impacts on STEM major choice occurs within introductory math classes, as opposed to in other courses.

Panel B considers the impacts of foreign peer exposure on foreign students. Results in all specifications are not statistically significant, perhaps due to the smaller sample size, but suggesting that foreign students do not respond to increased exposure to foreign peers. Thus, the displace-

[20]Data from the National Science Foundation show that the share of bachelors' degrees earned by White students that were in STEM fields was roughly 17% in 2011. The same share for Black students was 11%. The male STEM graduation rate in 2011 was 25% compared with only 11% for females. Hence, the White-Black STEM gap is around 6 percentage points, while the STEM gap between males and females is 14 percentage points. See (`https://www.nsf.gov/statistics/seind14/index.cfm/chapter-2/c2s2.htm#s2`).

[21]The mean size of introductory math classes is approximately 230 students. If this course had the average foreign share (approximately 13%) and the average share of domestic first-term freshmen (approximately 56%), it would comprise of roughly 30 foreign students and 129 domestic freshmen. Given that domestic freshman graduate in STEM at the mean rate of 48%, we would expect 62 STEM graduates from this group. A one standard deviation increase in foreign peers amounts to roughly 9 additional foreign students. Recall our effect is 6% of the mean graduation rate. Multiplying 0.06 times 62 (the number of domestic students expected to graduate in STEM) yields approximately 3.7 domestic students displaced from STEM.

ment we observe for domestic students is not offset by an increased likelihood of foreign students persisting in STEM.

In Table 6, we examine displacement outcomes. Column 1 contains our preferred specification from column 3 of Table 5. Columns 2 and 3 examine the likelihood of completing a Social Science or Arts & Humanities degree, respectively. Column 4 examines the likelihood of dropping out. The decline in graduating with a STEM major is offset by increases in graduating with a Social Science major. A one standard deviation increase in foreign peers is associated with a 2.2 percentage point increase in the likelihood of graduating with a Social Science major. Though the effect is imprecise, it borders on significance at the 10% level (p-value=0.15). The coefficients on graduating in Arts & Humanities and dropout are positive, but much smaller in magnitude and statistically indistinguishable from zero. In results not shown, but available upon request, we find the reduced effect of completing a STEM degree operates through a higher likelihood to switch out from STEM to Social Sciences, precisely after completing 2 years from initial enrollment.

Since STEM graduates earn more on average than non-STEM graduates[22], a decline in the probability of STEM graduation might be expected to negatively impact earnings of the domestic students. However, the aggregation of outcomes into three groups (STEM, Social Science, Arts & Humanities) may mask heterogeneity within STEM and non-STEM majors, and potentially important margins of adjustment. For example, a student may be displaced from a high earning STEM major to a very low earning Social Science major.

Lacking data on actual earnings, we link each student's major at graduation (we observe 151 different majors of graduation in our data) to measures of the expected earnings for that major, and use this as the outcome variable.[23] Major-specific expected earnings provide an alternative way to measure of the relevant qualities and characteristics of each major, and may reveal intricacies not detectable when splitting by subject-matter into STEM, Social Science, and Arts & Humanities. Where expected earnings may be useful, we also caution that average earnings presumably mask substantial heterogeneity within college major, and acknowledge that this therefore limits our ability to characterizes marginal students.

Results are shown in columns 5-8 of Table 6. Foreign peers do not appear to significantly impact expected earnings associated with majors – estimates are statistically and economically insignificant. Column 5 indicates that a one standard deviation increase in the share of foreign peers is associated with a decrease in initial earnings of $95 against a mean of $23,230 – just

[22]In our data expected earnings of STEM graduates 11-15 years after graduation are 22% higher than those of non-STEM graduates.

[23]These measures are provided by the Hamilton Project (Hershbein and Kearney, 2014) and estimated using American Community Surveys data. Data include estimates for initial earnings, earnings at 6, 11-15, and 26-30 years after graduation. Dropouts are assigned the average earnings of students with some college who did not complete a degree.

0.4%. The estimates on longer-run expected earnings are larger, but remain roughly equal to 1% of the mean. This is because domestic students gravitate towards Social Science majors that have similar earning potential to the STEM majors they leave. Appendix B elaborates on the relationship between major expected earnings and displacement.

Graduation in a STEM degree is a strong correlate for entry into STEM occupations, as fewer than 9% of all individuals with a college degree in a non-STEM field report working in a STEM occupation.[24] Displacement from STEM majors would naturally be expected to also reduce the probability of working in a STEM occupation, but not for certain. If displaced students are concentrated among those who would have counterfactually worked in non-STEM sectors with a STEM degree then their occupational sector may remain unchanged. Whether foreign peers have long run impacts on occupational choice is therefore an empirical question.

We utilize individual data on actual occupations of students, and estimate our baseline specification, replacing the outcome with indicator variables for working a STEM or non-STEM occupation. Because we are unable to link occupational data to all students, we first ensure that the likelihood of finding an occupation link is not endogenously related to the foreign peer share. This check is performed in column 1 of Table 7, where the outcome is an indicator variable equal to 1 if occupational records were matched to the student and 0 if no match was found. The results assure that the sample of students containing occupational information is not endogenously selected.

We examine whether foreign peers affect the likelihood of working in a STEM occupation after college in column 2. Results indicate that a 1 standard deviation rise in the foreign class share lowers the probability of working in a STEM occupation by 2.9 percentage points. The estimate is statistically significant and is 6.7% of the mean probability of working in a stem occupation (43%). The magnitudes of the effect on STEM occupation are nearly identical to those on major choice, indicating remarkable persistence of the impact of foreign peers on both STEM majors and STEM career paths. We caution, however, that our matching process is imperfect, and that having a binary dependent variable necessarily indicates the presence of non-classical measurement error. In order for measurement error to entirely explain our findings, however, would require that the difference in mean covariates of false positives and false negatives, weighted by their probabilities in the sample, be quite large (Meyer and Mittag, 2017). Nonetheless, at a minimum, these results lend further supporting evidence of our main findings.

Similar to our exercise using expected earnings for each major, we utilize occupational specific earnings measures to better characterize the nature of displacement from STEM occupations.[25]

[24]Authors' tabulations from individuals age 30 and under, reporting both college major and occupation in the 2009-2016 ACS.

[25]Specifically, using the 2014-2016 American Community Surveys we calculate average earnings/income measures for college-educated native-born workers from the same birth-cohorts as those observed in our student data. We then

Columns 3, 4 and 5 of Table 7 use occupation-specific average individual income, family income and average wage, respectively, as outcomes. Coefficient estimates are only marginally significant, if at all, and also economically small. The coefficient in column 5 represents a decrease of expected earnings of 1.3% with respect to the mean wage across all occupations. This indicates that domestic students are not displaced into significantly lower paying non-STEM occupations – they appear to be choosing occupations that have very similar earning power relative to the STEM occupations from which they are displaced.

4.1 Baseline Ability

To better characterize displacement from STEM we assess whether marginal students are those with relatively low baseline comparative ability or absolute ability in STEM. We define a measure of comparative advantage in STEM for each domestic student using their SAT Math and Verbal scores relative to the average SAT Math and Verbal scores of all the peers in their cohort, and use a local linear regression to look at STEM graduation on the share of foreign peers at each percentile.[26] Figure 3 plots coefficients from our main specification, and shows that students with low comparative advantage in STEM (low percentiles) experience strong displacement. The bottom third of students have an average coefficient of -0.07, while for the top third it is -0.02. Consistent with comparative advantage driving specialization, the students most at risk are those with the highest relative ability in non-STEM fields.

The bottom panel of Figure 3 presents local linear regression estimates to see if effects differ based on a measure of absolute advantage.[27] There is little difference in the effect for domestic students with high and low absolute STEM ability. All point estimates are contained within the confidence interval for all others. Using this measure, we cannot reject that students with differing absolute STEM ability are equally displaced from STEM.

match these earnings/income measures to students according to their observed occupation.

[26]To construct our measure of comparative advantage, we separately standardize students SAT math and verbal scores at the cohort level to have mean 0 and standard deviation of 1. Then, students are ranked based on the difference in their standardized math and verbal test scores. Local linear regressions of Equation 1 are estimated at every percentile using a one-standard deviation bandwidth and Epanechnikov kernel weighting. 95% confidence intervals are constructed from 250 bootstrapped repetitions, sampled at the class (i.e. math lecture) level.

[27]To measure absolute advantage, we estimate the ex-ante likelihood that a student will graduate with a STEM major. We regress STEM graduation on all background characteristics (gender, race, SAT, etc.) and year fixed effects. We then use the regression coefficients to predict each student's likelihood of graduating with a STEM major. Our measure is relatively simple, but represents the type of prediction policymakers or education administrators may use when trying to determine what factors lead to STEM persistence.

4.2 Race and Gender

Table 8 explores heterogeneity across different types of domestic students. Each estimate represents a separate regression using our preferred specification. Research on the gender gap in STEM education has uncovered various factors, such as confidence and role-models, as important for the retention of female students (e.g. Gneezy, Niederle and Rustichini, 2003; Niederle and Vesterlund, 2007; Carrell, Page and West, 2010). We assess whether foreign peers may more strongly affect domestic females relative to males. Columns 1 and 2 show that females are not strongly impacted by foreign peers. Instead, the reduction in STEM primarily comes from domestic male students.

In columns 3-5, we stratify on domestic students' race/ethnicity. Similar to the gender gap in STEM, the minority gap in STEM has also received much academic attention. Our results show that foreign peers have strong negative impacts on non-minority groups (White and Asian). In contrast, there is no detectable negative impact on minorities (Black and Latino). One interesting insight is that foreign peers appear to have strong impacts on inducing domestic minorities to remain in school rather than dropping out. This leads to domestic minorities graduating in majors with higher expected earnings, both in the short and long run. In contrast, the strong displacement of domestic Asian students (the largest ethnic group among domestic students in introductory math classes) from STEM results in movement towards Social Science, but also towards dropping out. This in turn results in significant negative impacts on expected earnings.

5 Exploring Mechanisms

Why do foreign peers lead to lower STEM completion among domestic students? We hypothesize three mechanisms. First, changes in the communicative environment within classrooms following the entry of many non-fluent English speakers may reduce the scope for knowledge spillovers that arise from questions asked during lecture, or from peer-to-peer interaction. Alternatively, instructors may respond by altering the delivery of the course, thereby affecting student's relative learning and or enjoyment.

A second hypothesis is that foreign peers in introductory math classes may provide students with a local assessment of their relative ability. As the introductory math class is often the first STEM class that students take, they may perceive their relative ability in that class as a signal of their ranking among all STEM majors. As foreign students have a comparative advantage in STEM relative to non-STEM fields, their presence may lead domestic students to update their perceptions of how their own comparative advantage in STEM ranks among other students.

The final mechanism we explore is simple distaste. If domestic students do not enjoy the presence of foreign students and/or update their beliefs about the presence of foreign workers in STEM occupations based on the foreign share observed in the introductory math courses, they may seek alternate classes or majors by means of avoidance.

5.1 Short-run impacts

Table 9 examines short-term outcomes that might provide some relevant information about when and why students get displaced. The first row examines whether foreign peers impact the likelihood of withdrawing from the course after the first day of instruction. Positive effects would indicate that students select out of math very soon after meeting their peers. Results, however, indicates there is no effect of foreign peers on the likelihood of withdrawing from the course.[28]

Row 2 shows that overall there is no impact of foreign peers on introductory math grades received by domestic first-term freshman, conditional on remaining in the class.[29] Heterogeneity analysis reveals only particular groups are affected – non-minorities and those with low comparative advantage. Further analysis on these subgroups in columns 2-8 indicates that those groups that experience displacement do see a decline in grade performance. In the bottom row, we examine whether foreign peers affect the likelihood students retake the same course in the future. Evidence indicates a small increase in the likelihood of retaking the course.

5.2 English Communication

Descriptive studies and surveys about foreign student integration in U.S. education have emphasized their lower levels of English proficiency (Erisman and Looney, 2007), and subsequent reticence and hesitance to communicate within classroom settings (e.g. Horwitz, Horwitz and Cope, 1986; Rodriguez and Cruz, 2009; Stebleton, Huesman Jr and Kuzhabekova, 2010; Stebleton, 2011; Yamamoto and Li, 2011).[30] Lower levels of communication may reduce positive externalities arising from peer-to-peer or peer-to-instructor interaction. Lower English language ability may lead instructors to alter the pace or style of instruction, or substitute time away from helping domestic students towards helping foreign students (Diette and Oyelere, 2012; Geay, McNally and Telhaj, 2013).

To empirically assess this concern, we examine whether effects are driven by foreign peers with low levels of English proficiency. Primarily, we categorize foreign students as having "low"

[28]In specifications not shown, we also separately examined immediate withdraws (one week or less into a course) and late withdraws (likely after receiving graded work) and found no significant effects.

[29]Grades have been standardized to have mean of zero and standard deviation equal to one within courses.

[30]An extensive report on foreign individuals in higher education (Erisman and Looney, 2007) found that 66% of foreign students indicated English was not their primary language.

or "high" proficiency based on whether their SAT verbal score falls below or above the median score of all foreign students in their cohort. We then repeat regressions of equation 1, splitting the overall foreign share in the class into the shares with high and low fluency.

The results from this exercise are reported in panel A of Table 10. The displacement from STEM is larger for domestic students that experience increases in foreign peers with low fluency. A one standard deviation rise in the share of peers low fluency peers reduces the likelihood of completing STEM majors by 4 percentage points. An equivalent increase in peers with high fluency has no significant effect. Peers with low fluency displace domestic students primarily towards Social Science.

As SAT Verbal scores may be an imperfect proxy for communicative ability or reticence, panel B of Table 10 provides a similar test using a different measure of English proficiency based on how distant each foreign student's home country language is from English (Chiswick and Miller, 2005).[31] Results corroborate the notion that low levels of English proficiency and classroom communication play a role. While the coefficients are not statistically different from one another, they qualitatively affirm that foreign peers that speak languages highly distant from English have a stronger displacement effect than foreign peers that speak languages similar to English.

We provide further validation of this communication/interaction channel by exploring whether the impact of foreign peers with low English fluency is exacerbated/limited by the of English proficiency of instructors. In particular, native English speaking professors might be more equipped to alter the pace of instruction to compensate for lower levels of classroom communication. Foreign professors with less English fluency may reduce peer-to-instructor interaction even further. Table 11 shows results where the shares of foreign peers with high and low English fluency are interacted with indicators for whether the instructor is a native English speaker. These estimates show that displacement is concentrated in courses with a large share of low-fluency foreign peers taught by instructors who are not native English speaker.

Overall, these results constitute robust evidence that foreign peers with lower levels of English ability drive the displacement out-of-stem. Our best hypothesis for why this is the case is alter-

[31]Measures of language distance are taken from Chiswick and Miller (2005), which measure the difficulty an English speaker faces in learning a foreign language. The scores range on a scale from 1 to 3, where 3 indicates languages close in proximity to English, and 1 indicates languages distant from English. We transform these to distance measures from English, by assigning English a value of 4 and subtracting the language proximity scores. Hence, our distance measure ranges from 0 to 3, with lower scores representing close proximity to English. Note that a score of 0 means that the primary language of a foreign student's country of origin is English. This occurs for countries such as Canada, the United Kingdom, and Australia. Foreign students are then divided accordingly to whether their linguistic distance from English is above ("high distance") or below ("low distance") the median score of all foreign students. We measure the share of foreign peers with linguistic distance scores above the median, and below the median. These two different shares are used as explanatory variables in regressions, in place of the overall foreign share.

ing the communicative environment within classrooms. Moreover, instructors might adjust their teaching style or the course content as a response to the low communicative environment triggered by the high share of foreign students with low English verbal skills.[32] All these potential mechanisms point at an altered class environment with more limited social interactions, which may result in missed peer-to-peer and peer-to-instructor exchanges, essential components of effective learning. Additionally, our estimate of displacement doubles in magnitude when domestic students are exposed to a large share of low English fluency and a foreign instructor. The importance of the communicative environment within classrooms indicates that interventions to improve English communication in the class may limit or reduce displacement from STEM majors.

5.3 Relative Ranking in STEM

The movement of domestic students away from STEM fields may be a response to competition from peers that alters one's relative ability ranking in STEM. Related literature has shown that rankings matter substantially for educational choices and outcomes (Murphy and Weinhardt, 2018; Elsner and Isphording, 2017; Cicala, Fryer and Spenkuch, 2017). In response to foreign peers, that may change relative STEM rankings within a classroom, individuals may switch to fields of study or occupations that are less quantitative in nature, and more communication-intensive, in accordance with the theory of comparative advantage (Peri and Sparber, 2009, 2011). In our context, domestic students may perceive that their comparative advantage in STEM fields falls with more foreign peers, and respond accordingly by switching to non-STEM majors.

We use SAT Math and Verbal scores to proxy for individual ability in STEM and non-STEM fields, respectively, as they have been shown to predict STEM and non-STEM major choice (Turner and Bowen, 1999). To measure the ability of each individual in STEM and how they rank relative to their peers, we utilize a traditional approach aimed at identifying individual comparative advantage (Sattinger, 1975). We define individual's ability in STEM (Non-STEM) *relative* to their cohort, by calculating the distance in standard deviations of the individual's SAT Math (Verbal) score from the average SAT Math (Verbal) score of their cohort (which is standardized to 0). Our measure of comparative advantage in STEM is then the difference between an individual's relative ability in STEM and non-STEM. We refer to this as cohort-level comparative advantage. The summary statistics presented in Table 2 indicate that foreign peers possess a comparative advantage in STEM fields. Their relative SAT Math to Verbal score is higher than that of domestic freshmen.[33]

[32] Alternatively, we cannot exclude that lower measured verbal ability is correlated with unobservable non-cognitive abilities, which in turn drive the displacement.

[33] The comparative advantage of foreign students in STEM is unlikely to be institution specific – foreign college educated individuals in the labor market are highly over-represented in STEM fields and STEM majors (Gambino and

We then also construct these measures of comparative advantage within the individual's introductory math class, by measuring individual ability relative to the class SAT averages rather than the cohort averages, which we refer to as class-level comparative advantage.[34] This allows us to first measure whether exposure to foreign peers in introductory math classes actually provides a different signal of an individual's ranking in STEM (relative to non-STEM) in the classroom relative to their actual ranking in the cohort.

Column 1 of Table 12 performs this check. We utilize our baseline specification, and replace the dependent variable with the measure of an individual's comparative advantage ranking in STEM in the class relative to the cohort. Additionally, we also control for the cohort-level comparative advantage, so that regressions are identified from individuals with the same cohort-level comparative advantage but different exposure to foreign peers. Results indicate that foreign peers drive down the average class-level comparative advantage ranking of domestic students relative to their position in the cohort, consistent with their overall higher comparative advantage in STEM.[35]

Columns 2 and 3 check whether this is a mechanism by which the estimated STEM displacement effects. Column 2 estimates effects for domestic students who had a "strong signal update" – large (above the median) declines between cohort-level and class-level comparative advantage. Domestic students who experienced a "strong signal update" responded similarly to students who had a "weak signal update", shown in Column 3. Although the displacement magnitude is larger for domestic individuals that saw small changes in comparative advantage (-0.04), it is not statistically different from the effect for those who had larger changes in comparative advantage (-0.029). Hence, we conclude that while changes in comparative advantage rank might be an operative mechanism, it appears to account only marginally for the observed displacement. This finding is also consistent with Murphy and Weinhardt (2018) who find that local (classroom) ranking signals/information are generally less likely to be important when optimizing future effort and other educational decisions.

5.4 Social Preferences

A final reason for displacement may be due to preferences over peers in the classroom. Distaste for studying alongside foreign peers would manifest in domestic students avoiding them in future courses. We replace the dependent variable in equation 1 with the foreign peer share in all classes

Gryn, 2011; Peri, Shih and Sparber, 2015).

[34]Our measure is similar to the measure of the degree of misinformation of ranking from Murphy and Weinhardt (2018), whereby the classroom ranking is a local measure that may not reflect one's ability in the cohort.

[35]This specification still holds individual and peers' SAT math and SAT verbal constant. This means that domestic students with same ability in courses with similar overall average ability can have very different within-class comparative advantage standings according to the foreign share in the course.

taken in following terms. We perform this analysis for up to 12 terms, or 4 years, since many students graduate and drop out of the sample after 4 years.

The results of this exercise are shown in Figure 4. Point estimates are indicated by the dots and 95% confidence intervals are provided for reference. The vertical axis measures the effect of a 1 standard deviation increase in the foreign peer share on the foreign peer share in all classes in future terms. The results indicate no pattern of avoidance of foreign students overall. Additional results not reported have shown no evidence of distaste when looking specifically at future Math, STEM, or non-STEM courses.

6 Conclusion

Disinterest in STEM education has generated concern over whether the U.S. will have sufficient numbers of STEM workers. At the same time, globalization has increased the number of foreign students in higher education institutions. This paper explores whether the presence of foreign peers in college affect the likelihood that domestic students obtain STEM degrees and eventually work in STEM occupations.

Using administrative records from a large U.S. research university, we find that higher exposure to foreign peers in the first-term introductory math course reduces the likelihood that domestic students eventually complete a STEM degree and pursue a STEM career. Displaced domestic students adjust by moving to Social Science majors. Displacement does not appear to substantially harm the earnings of domestic students, as they gravitate towards Social Science majors/occupations with equally high earning power.

We find compelling empirical evidence suggesting that changes to the communicative environment within the classroom as an important mechanism that generates displacement. Foreign students with low levels of English proficiency may be less likely to engage in communication in the class, leading to fewer productive peer-to-peer and instructor-to-peer interactions. Corroborating analysis finds that foreign peers who possess weak English language skills appear to have much stronger impacts than those who are fluent in English. Displacement is further exacerbated in courses with a large presence of non-fluent foreign students, and when the instructor is not a native English speaker.

Our analysis has clear implications for interventions aimed at preventing attrition from STEM majors. Interventions that improve or facilitate interaction and communication of foreign students (e.g. compulsory attendance of pre-college English courses) may help improve peer-to-peer learning and instructor-to-peer interaction. Alternatively, distributing foreign students with very low English fluency more homogenously across courses and avoiding their concentration in courses taught by foreign instructors, might reduce the negative impact on the overall class communicative environment.

Though this study was performed on a single university, our findings carry implications for aggregate welfare. Increasing numbers of foreign students – who have unconditionally higher propensity to graduate in STEM majors – are unlikely to increase the future STEM labor supply, as domestic students are displaced to non-STEM fields. Moreover, given that a portion of international STEM students are likely to return to their country after graduation – for instance because of the cap on H1-B visas –, the U.S. aggregate supply of STEM workers might actually decrease. Despite the lack of growth in the STEM workforce, however, there may be efficiency gains, as displaced students are those comparatively weak in STEM fields, and hence are being induced to move to fields in which they are comparatively stronger.

In the face of increasing globalization, understanding the impacts of foreign peers in college remains an important undertaking. This paper is the first to explore whether foreign peers affect college major and career occupational choices. Future research that further explores the mechanisms underlying such impacts would be of great value for education administrators and policymakers alike.

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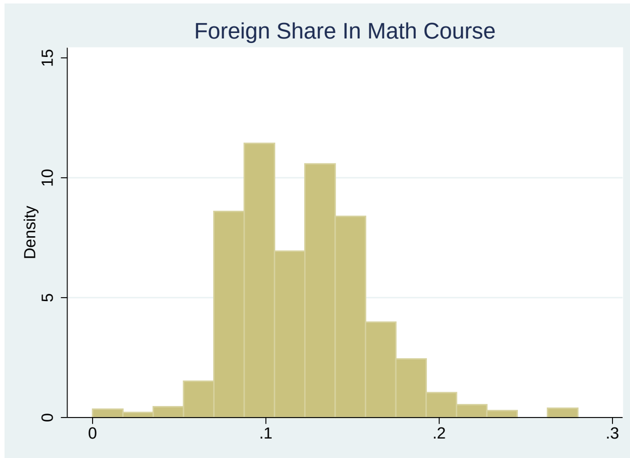
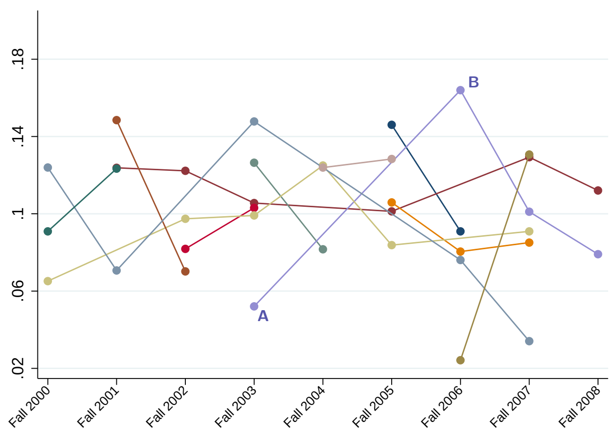
Figures & Tables

Figure 1: Variation in foreign share in introductory math courses



Note: Each observation in the distribution refers to an introductory math class in the university under analysis. Introductory math classes are defined by unique course, professor, and term combinations.

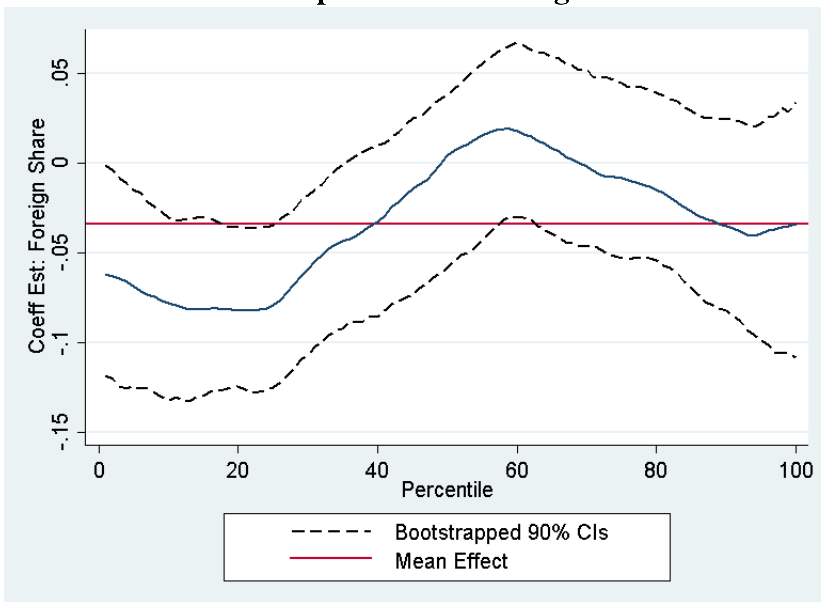
Figure 2: Foreign Share variation within professor-course pairs over time



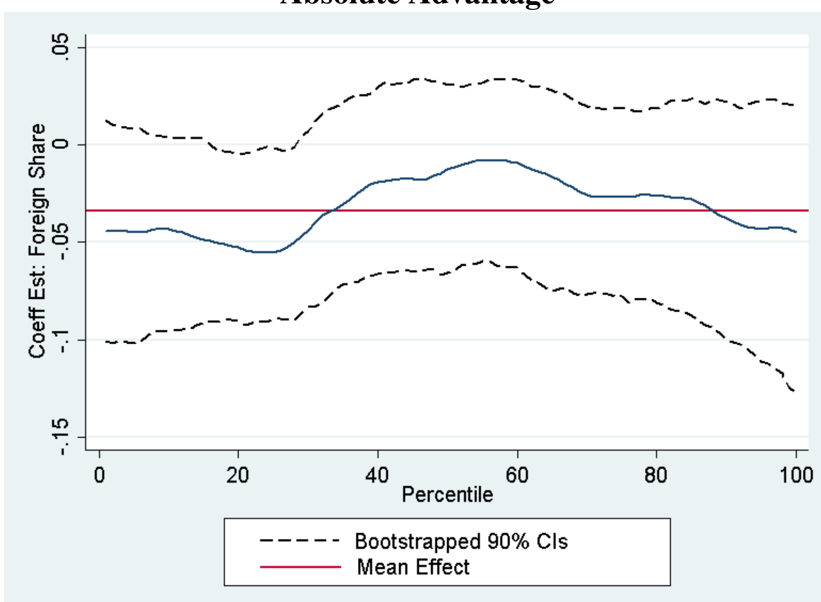
Note: Terms are displayed on the horizontal axis and share of foreign students in the class on the vertical axis. Each line represent a Calculus I course taught by the same professor. The idiosyncratic variation within across terms and within professors represents the identifying variation in our paper.

Figure 3: Local Linear Regression Results

Comparative Advantage

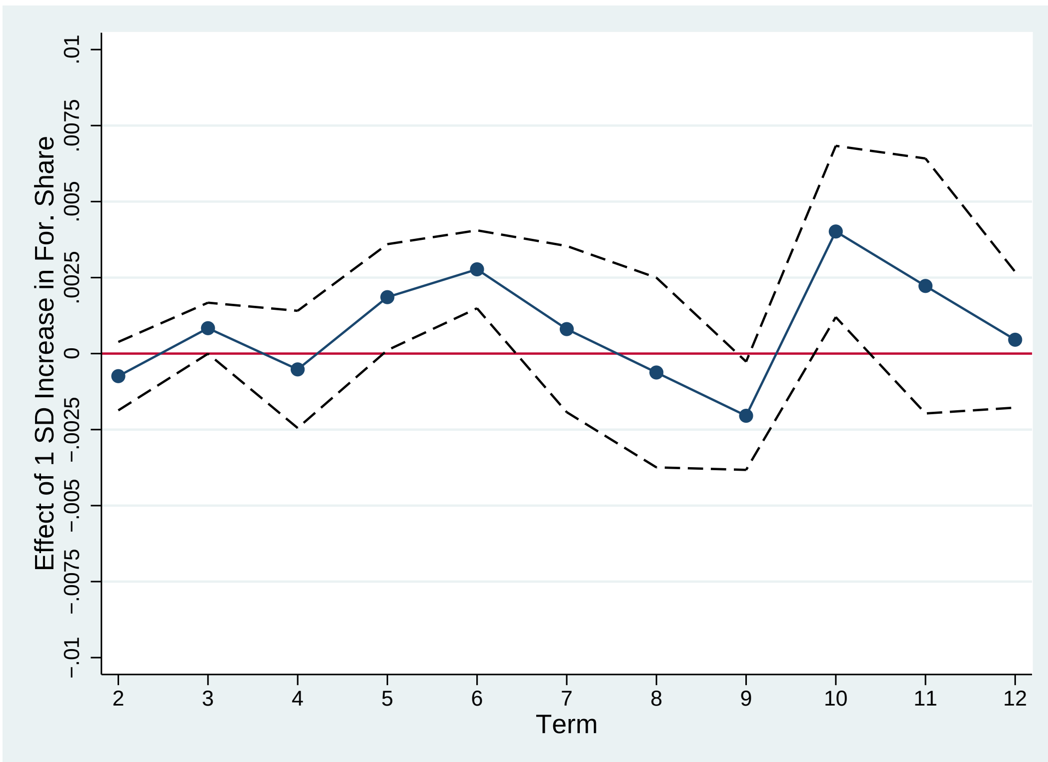


Absolute Advantage



Note: Results show coefficient estimates from local linear regressions of Equation 1 with STEM graduation as the outcome. Students in core sample are ranked from 1 to 16,830 based on a measure of comparative advantage (top) and absolute advantage (bottom). Lower percentile represents lower inclination towards STEM. Each graph plots 99 estimates from local linear regression centered at each percentile using Epanechnikov kernel weighting. Confidence intervals (dashed lines) derived from 5th and 95th percentile of 250 bootstrapped estimations, resampled at the course level. See text for details on calculation of comparative and absolute advantage. Red line shows mean effect from Column 4 of Table 5

Figure 4: Effect on Future Foreign Peer Exposure



Note: Results show coefficient estimates from regressions of Equation 1 with the outcome being the share of foreign peers in all classes in each term after the first. 95% confidence intervals are provided for reference. We show results up to 12 terms out, which represents 4 years, as many students graduate and leave the sample after 4 years.

Table 1: List of Math Courses

Title	Domestic First-Time Freshmen	Avg. Class Size	Avg. Percent Foreign
Precalculus	1,838	307	0.096
		(69.6)	(0.023)
Calculus I	7,031	247	.103
		(81.7)	(0.029)
Calculus I (Advanced)	4,965	208	0.152
		(53.9)	(0.036)
Calculus I (for Scientists)	1,287	232	0.114
		(41.4)	(0.025)
Calculus II	394	197	0.107
		(58.3)	(0.032)
Calculus II (Advanced)	922	148	0.174
		(33.7)	(0.041)
Calculus III	54	215.7	0.113
		(58.34)	(0.029)
Calculus III (Advanced)	299	148	0.152
		(43.4)	(0.041)
Calculus IV (Advanced)	40	135	0.145
		(48.0)	(0.064)
Total/Average	16,830	233	0.123
		(77.1)	(0.041)

Note: List of introductory mathematics courses offered by the university under analysis. Advanced courses cover similar material to non-advanced ones, but with greater depth. Sample includes 16,380 freshmen domestic students enrolling in introductory math courses in their first term of college attendance. Standard deviations in parentheses

Table 2: Background Summary Statistics

	(1) Domestic All	(2) Foreign All	(3) Domestic Freshmen	(4) Foreign Peers
Female	0.56	0.53	0.50	0.48
	(0.50)	(0.50)	(0.50)	(0.50)
White	0.47	0.16	0.41	0.12
	(0.48)	(0.33)	(0.48)	(0.30)
Asian	0.37	0.71	0.48	0.78
	(0.46)	(0.43)	(0.49)	(0.40)
Minority	0.15	0.13	0.10	0.11
	(0.35)	(0.32)	(0.29)	(0.30)
Black	0.03	0.02	0.02	0.02
	(0.17)	(0.13)	(0.13)	(0.13)
Latino	0.12	0.11	0.08	0.09
	(0.31)	(0.29)	(0.27)	(0.28)
High School GPA	3.70	3.70	3.76	3.72
	(0.30)	(0.26)	(0.33)	(0.30)
SAT Math	599.45	599.62	629.36	617.89
	(74.99)	(76.40)	(71.90)	(87.09)
SAT Verbal	562.90	510.62	573.83	491.18
	(79.63)	(90.42)	(84.48)	(104.15)
SAT Composite	1160.18	1105.63	1200.32	1099.42
	(136.34)	(138.31)	(135.62)	(162.82)
Composite Adm. Score	7394.68	7429.27	7510.59	7397.73
	(758.58)	(715.93)	(831.30)	(914.90)
Obs	45,293	7,165	16,830	3,840

Note: Means for enrolled students from fall 2000-fall 2006. Standard deviations in parentheses. Column 3 refers to our analysis sample of 16,830 domestic students who attended an intro math course as freshmen in the first year of college enrollment. Composite Admission Score is calculated by the admissions office using a weighted sum of various background ability and traits, which includes some measures available in our data and also other ability measures that are not available.

Table 3: Outcome Summary Statistics for Introductory Math Sample

	(1) Domestic Freshmen	(2) Foreign Peers
Panel A: Academic Outcomes		
Graduate	0.82	0.78
	(0.38)	(0.42)
Dropout	0.18	0.22
	(0.38)	(0.42)
Time to Degree (terms)	16.41	16.37
	(2.48)	(3.09)
Graduation GPA	3.05	2.96
	(0.44)	(0.45)
Graduate STEM	0.48	0.44
	(0.50)	(0.50)
Graduate Social Sciences (SS)	0.27	0.27
	(0.44)	(0.44)
Graduate Arts & Humanities (AH)	0.08	0.06
	(0.26)	(0.24)
Panel B: Labor Market Outcomes		
Exp. Earn. at Graduation	23.2	23.8
	(13.8)	(15.4)
Exp. Earn. 6yrs after Grad.	38.6	38.8
	(20.6)	(22.9)
Exp. Earn. 15yrs after Grad.	49.7	50.1
	(26.6)	(29.7)
Exp. Earn. 30yrs after Grad.	52.8	52.9
	(30.9)	(34.0)
Occupation Record Linked	0.74	0.66
	(0.44)	(0.47)
Occ. Based STEM Occupation	0.44	0.50
	(0.50)	(0.50)
Occ. Based Personal Income	63.1	62.7
	(22.0)	(21.7)
Occ. Based Family Income	14.1	14.5
	(89.9)	(98.1)
Obs	16,830	3,840

Note: In Panel A, Column 1 refers to our analysis sample of 16,830 domestic freshmen enrolling in introductory math courses in their first term of college attendance. Column 2 refers to the foreign peers of domestic freshmen enrolling in introductory math courses in their first term of college attendance. Panel B splits our analysis sample based on STEM Graduates or Non-STEM Graduates (including dropouts). All figures reported in thousands. Exp. Earn. refers to expected earnings based on a student's major according to data from the Hamilton Project. Occ. Based measures come from observation-specific occupational matching described in Appendix C.

Table 4: Exogeneity of Foreign Class Share

	(1) Female	(2) White	(3) Asian	(4) Minority	(5) Black	(6) Latino	(7) SAT Math	(8) SAT Verbal	(9) High School GPA	(10) Composite Admission Score
Foreign Sh.	-0.01	-0.01	0.01	-0.01	-0.00	-0.00	1.76	-1.08	0.01	21.11
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(1.67)	(1.97)	(0.01)	(14.53)
Mean(Y)	.49	.41	.46	.12	.02	.1	618.36	567.3	3.73	7414.36
Std(Y)	.5	.48	.48	.32	.15	.29	74.98	83.85	.32	829.08
Obs.	25,912	25,912	25,912	25,912	25,912	25,912	25,912	25,912	25,912	25,912
R-sq	0.11	0.02	0.02	0.02	0.01	0.01	0.15	0.03	0.02	0.28

Note: Sample is all domestic students attending introductory math courses. The table displays estimates from equation 2 and shows the mean and standard deviation of each outcome variable. Regressions include controls for course-by-term and course-by-professor fixed effects. Standard errors in parentheses are clustered by professor. Significance levels: *0.10, ** 0.05, ***0.01.

Table 5: Effects on STEM Graduation

	(1)	(2)	(3)	(4)
Panel A: Domestic Students				
Foreign Sh.	-0.035***	-0.036***	-0.033***	-0.034***
	(0.011)	(0.012)	(0.011)	(0.012)
Mean(Y)	.48	.48	.48	.48
Obs.	16,830	16,830	16,830	16,830
R-sq	0.05	0.05	0.10	0.10
Panel B: Foreign Students				
Foreign Sh.	0.012	-0.022	-0.003	0.009
	(0.042)	(0.030)	(0.032)	(0.029)
Mean(Y)	.44	.44	.44	.44
Obs.	3,840	3,840	3,840	3,840
R-sq	.09	0.10	0.10	0.11
Peer Chars.,σ_{cp},σ_{ct}	x	x	x	x
Course Size		x	x	x
Ind. Controls			x	x
For. Non-Math				x

Note: Panel A sample is domestic freshmen students attending an introductory math course in their first term of college. Panel B is analogous for foreign students. Regressions include course-by-term and course-by-professor fixed effects. The foreign share is standardized to have mean 0 and standard deviation 1. Peer ability includes average standardized SAT Math, SAT Verbal, and high school GPA of peers. Peer Characteristics include share of students from each race and share of females. Individual controls include a female indicator, race dummies, SAT Math and Verbal scores, and high school GPA. Foreign Share Non-Math refers to the average foreign share in non-math classes attended by first-term domestic freshmen. Standard errors in parentheses are clustered by professor. Significance levels: *0.10, **0.05 ***0.01.

Table 6: Effects on Graduation Outcomes and Expected Earnings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Grad STEM	Grad SS	Grad AH	Dropout	Earn 0	Earn 6	Earn 11-15	Earn 26-30
Foreign Sh.	-0.033***	0.022	0.0053	0.0043	-94.8	-296.8	-366.7	-566.9
	(0.011)	(0.015)	(0.0063)	(0.0091)	(325.0)	(518.9)	(640.3)	(521.3)
Mean(Y)	.48	.27	.08	.18	23230.85	38552.17	49729.47	52760.8
σ_{ct}	x	x	x	x	x	x	x	x
σ_{cp}	x	x	x	x	x	x	x	x
Peer Ability	x	x	x	x	x	x	x	x
Peer Chars.	x	x	x	x	x	x	x	x
Course Size	x	x	x	x	x	x	x	x
Ind. Controls	x	x	x	x	x	x	x	x
Obs.	16,830	16,830	16,830	16,830	16,830	16,830	16,830	16,830
R-sq	0.10	0.06	0.03	0.06	0.10	0.08	0.08	0.10

Note: Sample is domestic freshmen students attending an introductory math course in their first term of college. Regressions include course-by-term and course-by-professor fixed effects. Foreign Share is standardized to have mean 0 and standard deviation 1. Peer ability includes average SAT Math, SAT Verbal, and high school GPA of peers. Peer Characteristics include share of students from each race and share of females. Individual controls include a female indicator, race dummies, SAT Math and Verbal scores, and high school GPA. Expected earning in columns 5-8 have been assigned to each student based on their graduation major. Earnings estimates come from calculations done by the Brookings' Hamilton Project and refer to median earnings calculated on U.S. Census Bureau's American Community Survey data at different years after college graduation. Standard errors in parentheses are clustered by professor. Significance levels: *0.10, **0.05 ***0.01.

Table 7: Effects on Stem Careers and Occupation-Based Expected Earnings

	(1) Matched=1	(2) Stem Occ=1	(3) Ind Inc	(4) Fam Inc	(5) Wage
Foreign Sh.	0.010	-0.029***	-717.8	-535.4	-769.0*
	(0.009)	(0.006)	(464.7)	(1923.4)	(422.8)
Mean(Y)	0.74	0.43	62,388	140,391	59,456
σ_{ct}	x	x	x	x	x
σ_{cp}	x	x	x	x	x
Peer Ability			x	x	x
Peer Chars.	x	x	x	x	x
Course Size	x	x	x	x	x
Ind. Controls	x	x	x	x	x
Obs.	16,820	12,472	12,472	12,472	12,472
R-sq	0.43	0.03	0.02	0.01	0.02

Note: Sample is domestic freshmen students attending an introductory math course in their first term of college. Regressions include course-by-term and course-by-professor fixed effects. Foreign Share is standardized to have mean 0 and standard deviation 1. Peer ability includes average SAT Math, SAT Verbal, and high school GPA of peers. Peer Characteristics include share of students from each race and share of females. Individual controls include a female indicator, race dummies, SAT Math and Verbal scores, and high school GPA. Expected income and earnings in columns 3-7 have been assigned to each student based on their observed occupation title. Expected earnings and income are estimated for each SOC occupation code using most recent American Community Survey data on a sample that mimics the characteristics of individuals in our administrative data. Standard errors in parentheses are clustered by professor. Significance levels: *0.10, **0.05 ***0.01.

Table 8: Foreign Peer Effects on Different Domestic Groups

	(1) Female	(2) Male	(3) White	(4) Asian	(5) Minority
Grad STEM	0.00	-0.05***	-0.02**	-0.07***	0.01
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Grad SS	-0.02	0.06***	0.01	0.04**	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Grad AH	0.01	-0.01	0.01	0.00	0.03
	(0.01)	(0.01)	(0.02)	(0.00)	(0.02)
No Grad	0.01	0.00	-0.00	0.03***	-0.07***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Earn 0	58.16	135.00	-86.55	-722.00*	2288.17***
	(311.90)	(573.02)	(357.62)	(405.67)	(800.31)
Earn 6	207.00	-303.57	-165.97	-1309.33**	3338.21**
	(445.47)	(921.24)	(576.86)	(555.41)	(1270.74)
Earn 11-15	230.14	-364.49	24.24	-1918.34***	4366.76***
	(544.66)	(1156.19)	(743.25)	(658.16)	(1631.64)
Earn 26-30	-14.49	-280.05	-64.98	-1778.08**	4485.75**
	(587.69)	(1065.63)	(702.95)	(745.94)	(1935.69)
σ_{ct}	x	x	x	x	x
σ_{cp}	x	x	x	x	x
Peer Ability	x	x	x	x	x
Peer Chars.	x	x	x	x	x
Course Size	x	x	x	x	x
Ind. Controls	x	x	x	x	x
Obs.	8,355	8,475	6,483	7,667	1,606

Note: Sample is domestic freshmen students attending an introductory math course in their first term of college. Each column presents our analysis on domestic first-term freshmen, stratified by the characteristics indicated in the column headers. Minority refers to Latino and African-American students. Regressions include course-by-term and course-by-professor fixed effects. Foreign Share is standardized to have mean 0 and standard deviation 1. Peer ability includes average SAT Math, SAT Verbal, and high school GPA of peers. Peer Characteristics include share of students from each race and share of females. Individual controls include a female indicator, race dummies, SAT Math and Verbal scores, and high school GPA. Standard errors in parentheses are clustered by professor. Significance levels: *0.10, **0.05 ***0.01.

Table 9: Short-Run Effects

	(1) All	(2) Female	(3) Male	(4) White	(5) Asian	(6) Minority	(7) Low CA	(8) Hi CA
A: Drop Course								
Foreign Sh.	0.02	0.05**	-0.02	0.02	0.01	-0.01	0.01	0.02
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.04)	(0.01)	(0.02)
Mean(Y)	.12	.13	.11	.1	.13	.17	.13	.11
Obs.	16,830	8,355	8,475	6,483	7,667	1,606	8,823	8,007
R-sq	0.05	0.06	0.07	0.05	0.07	0.13	0.06	0.06
B: Std. Grade								
Foreign Sh.	-0.01	0.00	-0.02	-0.07***	0.01	0.13	-0.05**	0.05*
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.15)	(0.02)	(0.03)
Mean(Y)	.13	.18	.07	.18	.15	-.13	.04	.22
Obs.	14,801	7,286	7,515	5,866	6,672	1,328	7,687	7,114
R-sq	0.21	0.24	0.20	0.24	0.21	0.28	0.22	0.21
C: Retake								
Foreign Sh.	0.02*	0.03*	0.01	0.01	0.03**	0.03	0.02	0.02*
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)
Mean(Y)	.11	.1	.12	.1	.11	.17	.12	.1
Obs.	16,830	8,355	8,475	6,483	7,667	1,606	8,823	8,007
R-sq	0.07	0.09	0.07	0.08	0.07	0.13	0.08	0.07
σ_{ct}	x	x	x	x	x	x	x	x
σ_{cp}	x	x	x	x	x	x	x	x
Peer Ability	x	x	x	x	x	x	x	x
Peer Chars.	x	x	x	x	x	x	x	x
Course Size	x	x	x	x	x	x	x	x
Ind. Controls	x	x	x	x	x	x	x	x

Note: Sample is domestic freshmen students attending an introductory math course in their first term of college. Regressions include course-by-term and course-by-professor fixed effects. Foreign Share is standardized to have mean 0 and standard deviation 1. Panel A measures if a student dropped the intro-math course after the first day. Panel B assesses grades (e.g. A, A-, B+, etc.) in the intro math course, standardized within course-professor-term and conditional on not dropping. Panel C examines whether students retake an intro math course. Peer ability includes average SAT Math, SAT Verbal, and high school GPA of peers. Peer Characteristics include share of students from each race and share of females. Individual controls include a female indicator, race dummies, SAT Math and Verbal scores, and high school GPA. Standard errors in parentheses are clustered by professor. Significance levels: *0.10, **0.05 ***0.01.

Table 10: Testing the Classroom Communication Mechanism - Foreign Peers' Fluency

	(1) Grad STEM	(2) Grad SS	(3) Grad AH	(4) Dropout
Panel A - SAT Verbal:				
Foreign Share Low Fluency	-0.040**	0.043**	0.010**	-0.013
	(0.018)	(0.017)	(0.0051)	(0.011)
Foreign Share High Fluency	0.0027	-0.019	-0.0050	0.020
	(0.021)	(0.026)	(0.0050)	(0.013)
Panel B - Chiswick (2001) Linguistic Distance:				
Foreign Share High Distance	-0.025*	-0.0042	0.0067	0.022**
	(0.014)	(0.017)	(0.0049)	(0.0094)
Foreign Share Low Distance	-0.017**	0.019**	0.0016	-0.0049
	(0.0082)	(0.0083)	(0.0039)	(0.0055)
Mean(Y)	.48	.27	.08	.18
σ_{ct}	x	x	x	x
σ_{cp}	x	x	x	x
Peer Ability	x	x	x	x
Course Size	x	x	x	x
Ind. Controls	x	x	x	x
Peer Chars.	x	x	x	x
Obs.	16,830	16,830	16,830	16,830
R-sq	0.10	0.06	0.03	0.06

Note: Sample is domestic freshmen students attending an introductory math course in their first term of college. In Panel A we split foreign share into the share of foreign peers with SAT verbal below median (Low Fluency) and the share of foreign peers with SAT verbal above median (High Fluency). In Panel B we split foreign share into the share of foreign peers speaking languages very distant from English and the share of foreign peers speaking a language that is closer to English. All foreign shares are standardized to have mean 0 and standard deviation 1. Regressions include course-by-term and course-by-professor fixed effects. Peer ability includes average SAT Math, SAT Verbal, and high school GPA of peers. Peer Characteristics include share of students from each race and share of females. Individual controls include a female indicator, race dummies, SAT Math and Verbal scores, and high school GPA. Standard errors in parentheses are clustered by professor. Significance levels: *0.10, **0.05 ***0.01.

Table 11: Testing the Classroom Communication Mechanism - Foreign Peers'/Instructor English Fluency interaction

	(1) Grad STEM	(2) Grad SS	(3) Grad AH	(4) Dropout
For. Sh. Low FluencyX(Prof. Native English Speaker=1)	-0.018	-0.0018	0.0077	0.013
	(0.023)	(0.019)	(0.0085)	(0.014)
For. Sh. Low FluencyX(Prof. Foreign Speaker=1)	-0.061***	0.078***	0.014**	-0.032***
	(0.017)	(0.024)	(0.0064)	(0.0097)
Mean(Y)	.48	.27	.08	.18
σ_{ct}	x	x	x	x
σ_{cp}	x	x	x	x
Peer Ability	x	x	x	x
Course Size	x	x	x	x
Ind. Controls	x	x	x	x
Peer Chars.	x	x	x	x
Obs.	16,830	16,830	16,830	16,830
R-sq	0.10	0.06	0.03	0.06

Note: Sample is domestic freshmen students attending an introductory math course in their first term of college. Regressions include course-by-term and course-by-professor fixed effects. We split foreign share into the share of foreign peers with SAT verbal below median (Low Fluency) and the share of foreign peers with SAT verbal above median (High Fluency). The foreign shares are standardized to have mean 0 and standard deviation 1. The shares are interacted with a dummy taking value 1 if the Instructor is a native English speaker. Peer ability includes average standardized SAT Math, SAT Verbal, and high school GPA of peers. Peer Characteristics include share of students from each race and share of females. Individual controls include a female indicator, race dummies, SAT Math and Verbal scores, and high school GPA. Standard errors in parentheses are clustered by professor. Significance levels: *0.10, **0.05 ***0.01.

Table 12: Comparative Advantage Mechanism

	(1) Course Rank (CR)	(2) STEM, CR High	(3) STEM, CR Low
Foreign Sh.	-0.054***	-0.029**	-0.040**
	(0.016)	(0.014)	(0.017)
σ_{ct}	x	x	x
σ_{cp}	x	x	x
Cohort Rank	x	x	x
Peer Chars.	x	x	x
Course Size	x	x	x
Ind. Controls	x	x	x
Obs.	16,830	8,270	8,560
R-sq	0.61	0.11	0.10

Note: Sample is domestic freshmen students attending an introductory math course in their first term of college. In column 1 the dependent variable is a measure of within-course comparative advantage in math. In columns 2 and 3 we replicate our main specification separately for students who had a drop in within-math course comparative advantage measure (with respect to her/his own university-level comparative advantage) above and below the median drop respectively. Regressions include controls for course-by-term and course-by-professor fixed effects, peer ability, peer characteristics, course size, and individual controls. Importantly, all specifications control for the cohort-level measure of comparative advantage in math. Standard errors in parentheses are clustered by professor. Significance levels: *0.10, **0.05 ***0.01.

A Appendix Tables

Table A1: Exogeneity of Foreign Class Share: Foreign Students

	(1) Female	(2) White	(3) Asian	(4) Minority	(5) Black	(6) Latino	(7) SAT Math	(8) SAT Verbal	(9) High School GPA	(10) Composite Admissions Score
Foreign Sh.	-0.00	-0.01	0.00	0.00	-0.01	0.01	2.76	-14.19***	-0.02	-52.13
	(0.04)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(4.85)	(4.11)	(0.02)	(31.70)
Mean(Y)	.48	.12	.78	.1	.02	.09	617.89	491.18	3.72	7397.73
Std(Y)	.5	.3	.4	.3	.13	.28	87.09	104.15	.3	914.9
σ_{ct}	x	x	x	x	x	x	x	x	x	x
σ_{cp}	x	x	x	x	x	x	x	x	x	x
Obs.	3,840	3,840	3,840	3,840	3,840	3,840	3,840	3,840	3,840	3,840
R-sq	0.12	0.05	0.06	0.07	0.04	0.08	0.19	0.05	0.05	0.39

The table displays estimates from equation 2 run on Foreign Students instead of Domestic ones and shows mean and standard deviation of each variable. Regressions include controls for course-by-term and course-by-professor fixed effects. Standard errors in parentheses are clustered by professor. Significance levels: *0.1, ** 0.05, ***0.01.

Table A2: Joint Exogeneity Check

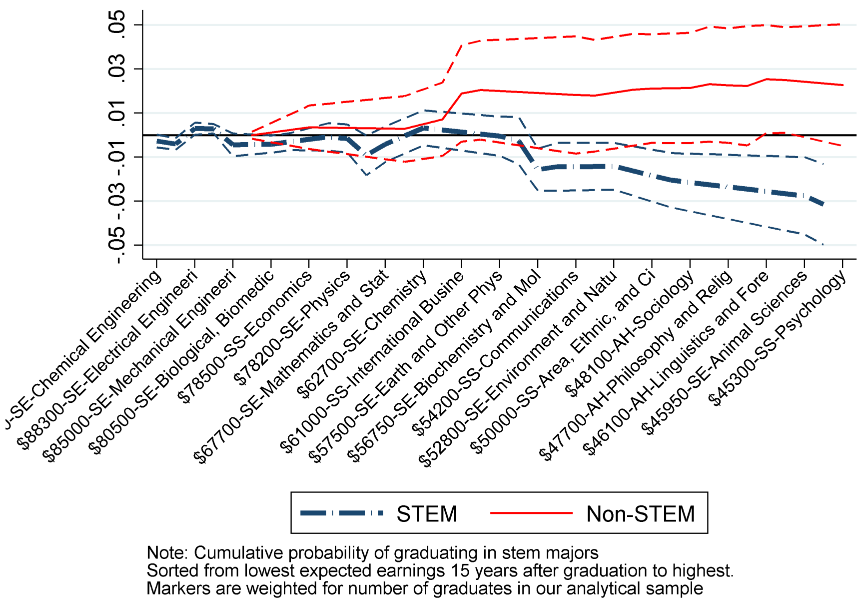
	Foreign Share
Female	-0.485
	(0.407)
Asian	0.647
	(0.449)
Minority	0.302
	(0.623)
SAT Math	0.005
	(0.004)
SAT Verbal	-0.004*
	(0.002)
HS GPA	0.751
	(0.518)
Composite Adm. Score	0.000
	(0.000)
σ_{ct}	x
σ_{cp}	x
Obs.	25,911
F-Stat	1.474
Pr $>$ F	0.19

Note: The table displays estimates from equation 1 using individual background characteristics and fixed effects. F-stat and Pr $>$ F refer to the joint F-statistic on individual background characteristics and the corresponding p-value. Standard errors in parentheses are clustered by professor. In this specification, foreign share is scaled x100 for readability. Significance levels: *0.10, **0.05 ***0.01.

B Graphical analysis of major displacement

While separate analysis for each of the 100+ different STEM and non-STEM majors is not feasible, Figure B1 visualizes the relationship between major earnings and displacement. All STEM and non-STEM majors get a rank, r, by expected earnings 11-15 years after graduation from 1 to R, with 1 being the highest-earning major. The x-axis shows where 20 of the most popular majors fall in this spectrum, but all majors are included in the analysis. Separately for STEM and non-STEM majors, for each rank, we rerun our main specification 1 with the outcome being the probability of graduating in a major ranked 1 through r. For STEM (non-STEM), each point on the figure can be thought of as the effect of a 1 standard deviation increase in foreign peers on the likelihood of graduating with a STEM (non-STEM) major with earnings ranked r or higher. 95% confidence intervals are also plotted. This shows that the bulk of the STEM displacement occurs in STEM majors with relatively low annual expected earnings (lower than $57,000). The displacement effects grows when including lower and lower earning STEM majors and reaches the 3 percentage points effect of our main estimate when including STEM majors that pay as low as $45,000 11-15 years after graduation. At the same time, the switch into non-STEM majors is driven by relatively high earning Social Science majors and is already substantial when including majors such as Business, which has expected annual earnings of $61,000. Taken together, Table 6 and Figure B1 clearly suggest that displaced students are leaving relatively low earning STEM majors and choosing relatively high earning Social Science majors.

Figure B1: Effect of Foreign Peers on cumulative Major Choice by Expected Earnings



Note: Results show coefficient estimates from regressions of Equation 1 with the outcome being probability of graduating in majors 1 to r with r being the rank position of each major in the earnings scale. Majors are ranked by expected earning 11-15 years after graduation (Earnings from the Hamilton Project using ACS data) separately for STEM ("SE" code on x axis) and non-STEM ("SS" code for Social Sciences and "AH" code for Arts and Humanities on x axis)

C Data Compilation

Occupational data for students was gathered in coordination with an administrative office from the institution. We helped devise a method to use alumni records to gather publicly available data, including job descriptions, from the internet. These data were then matched back to our main data set of student courses, grades and characteristics. To maintain the privacy of subjects in accordance with standard research guidelines, the names of students used to gather the information were never matched with our de-identified academic student records.

Using Google's search API, data on alumni was collected in a programmatic fashion. For each student, a single, uniform search was run aimed at discovering their current occupation. The script collected data contained in the first three Google results from this search. Search results often contain information beyond links in the body of the search result, including occupational descriptions. An example result is "[Student Name] - San Francisco Bay Area - Regional Sales Manager - [Company Name]". For each search, text from the top three Google results was collected.

For privacy reasons, we did not match our administrative data containing student course outcomes directly to these data. References to the student's name were removed from the results. The resulting strings of text are what we refer to as our occupational data.

In over 75% of cases, at least one of the top three results contains information that could be considered a job description. When more than one job description is present, the one from the highest search result is used. We believe that there are a non-trivial number of false positives, but have no reason to believe this will result in anything but classical measurement error. Without access to the original student names, we have no way of formally verifying the accuracy of the results. The likelihiood of a false positive should be uncorrelated with our key treatment variable of peer exposure as a first year college student. Similarly, we believe common surnames are less likely to be correctly matched, but we do not believe this should bias our results in any way beyond classical measurement error.

With the occupational data in hand, we use textual analysis to determine whether or not the occupation from the search result is likely a STEM occupation and estimated expected earnings. We use the O'NET dictionary of alternate occupation titles (https://www.onetcenter.org/dictionary/23.3/excel/alternate_titles.html) which contains a sequence of many possible occupational titles linked to each SOC code to assign our occupational data strings to a standard SOC code. Whenever an alternate title appears in multiple SOC codes, we assign the title to the SOC code that has highest probability frequency in ACS for a sample of ACS individuals that is most similar in cohort and education characteristics to our master student data file. Each match is assigned a strength from 0-100 based on the certainty of the algorithm.[36] The six-digit SOC code is then matched using a crosswalk to an O'NET occupation. We use the O'NET's definition of STEM occupations to code each observation as STEM/Non-STEM. In addition to the STEM measurement, we include the SOC measure of median salary for the occupation.

Below is an example of a single observation's matching. Two of the top three search results contained occupational information, so the first result is used. Based on job descriptions, the nearest match to "Regional Sales Manager" is SOC 41-1012 "First-Line Supervisors of Non-Retail Sales Workers". This is classified as a Non-STEM job with an average salary of $66,371.

Search Result 1	San Francisco Bay Area - Regional Sales Manager - [Company Name]
Search Result 2	.
Search Result 3	Director of Government Affairs and Associate General Counsel - [Company Name]
SOC Match	First-Line Supervisors of Non-Retail Sales Workers
SOC Code	411012
STEM	0
Salary	$66,371
Strength	90

[36]For example, search results containing the word 'lawyer' are virtually all strongly matched with SOC 231011, as this word describes very few occupations. Search results containing the word 'manager' are matched to the nearest SOC code, but are likely to have a relatively low strength due to the high number of occupations containing this term. Our models using these occupational data were tested with and without weighting based on the strength of the match and results were qualitatively similar on all dimensions.