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# Foreign Peer Effects and STEM Major Choice 


#### Abstract

Since the 1980s the United States has faced growing disinterest and high attrition from STEM majors. Over the same period, foreign-born enrollment in U.S. higher education has increased steadily. This paper examines whether foreign-born peers affect the likelihood American college students graduate with a STEM major. Using administrative student records from a large public university in California, we exploit idiosyncratic variation in the share of foreign peers across introductory math courses taught by the same professor over time. Results indicate that a 1 standard deviation increase in foreign peers reduces the likelihood native-born students graduate with STEM majors by 3 percentage points-equivalent to 3.7 native students displaced for 9 additional foreign students in an average course. STEM displacement is offset by an increased likelihood of choosing Social Science majors. However, the earnings prospects of displaced students are minimally affected as they appear to be choosing Social Science majors with equally high earning power. We demonstrate that comparative advantage and linguistic dissonance may operate as underlying mechanisms.


JEL-Codes: I210, I230, I280, J210, J240.
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## 1 Introduction

Waning interest in Science, Technology, Engineering and Mathematics (STEM) fields has remained a significant issue in the United States. In 1985, nearly 1-in-3 bachelor's degrees awarded were to students who majored in STEM. By 2010 that figure shrank to less than 1-in-4 (Figure 11. In global assessments, American primary and secondary students lag far behind students of other nations in math and science. ${ }^{1}$ During college, statistics indicate that nearly $50 \%$ of students entering as STEM majors end up switching to non-STEM majors or dropping out (Chen, 2013). While legislators have designed policies to boost the attainment and growth of STEM skills, our understanding of the factors which impact major choices remain limited.

Alongside the secular decline in the share of degrees awarded in STEM, the U.S. also sustained large inflows of foreign-born students into its colleges and universities. Figure 1 shows the share of foreign-born students in postsecondary institutions grew from 7.5\% in 1980 to $13 \%$ by 2010. Since 1965, family reunification has served as a pillar of U.S. immigration policy (Duleep and Regets, 2014, , allowing the entry of immigrant children, many of whom would eventually pursue college degrees. Very recent years have seen surges in foreign-born "international students", who are admitted solely for higher education and are legally required to return home immediately upon completion of their education. This paper proposes a new, previously unexplored factor driving STEM attrition - we examine whether foreign-born peers displace native students from STEM majors.

Dwindling STEM educational attainment, particularly during college, engenders negative economic consequences at both the individual and aggregate levels. Relatively higher average earnings associated with a STEM degree has been a long persistent feature of the U.S. skilled labor market. However, recent evidence has magnified the importance of major choice. First, the difference in earnings across high and low paying majors has been shown to be as large as the college/noncollege wage gap (Altonji, Blom and Meghir, 2012) Second, earnings inequality across majors has been growing over time Altonji, Kahn and Speer, 2014). Finally, using quasi-experimental data on students in Norway, where graduating high school students apply to college by submitting a ranking of college-major pairs, Kirkeboen, Leuven and Mogstad (2016) find that the returns to high paying majors are even greater than the returns to attending a selective institution. Therefore, factors that impact individual choices over field of study not only may have profound influence on

[^0]individual future earnings, but may also explain observed patterns in earnings inequality among skilled workers.

At the aggregate level, a shrinking supply of STEM skills may hinder economic growth. Individuals with expertise in science and engineering have been the main engine of technological progress and innovation (Griliches, 1992; Jones, 1995). Innovation and technological advance, in turn, are key drivers of economic growth. Recent evidence has linked growth in the supply of skilled scientists and engineers with greater innovation (Kerr and Lincoln, 2010) and labor market productivity (Peri, Shih and Sparber, 2015). Over the long run, changes in the types of skills produced in higher education will impact the supply of skills available in the labor market, which may ultimately affect innovation and growth.

These concerns have stimulated inquiry towards identifying factors affecting STEM major choice. At the individual level, poor preparation (Stinebrickner and Stinebrickner, 2011) or underestimation of the true returns to STEM majors (Wiswall and Zafar, 2015) have been associated with disinterest in STEM. Within higher education, studies have identified a lack of role models and improper matching of students to universities as perpetuators of gender and racial differences in STEM attainment (e.g. Carrell, Page and West, 2010, Arcidiacono, Aucejo and Hotz, 2016). Related to immigration, recent studies attribute reductions in STEM majors to inflows of foreign STEM workers (Orrenius and Zavodny, 2015, Ransom and Winters, 2016). While research on major choice continues, existing studies remain far from conclusive in elucidating the factors generating disinterest and attrition from STEM majors.

Even though foreign students comprise over $13 \%$ of all undergraduates in the U.S., the academic literature on the impacts of foreign peers has solely focused on primary and secondary education, often in other countries. While informative, the few existing studies produce conflicting findings. Using variation in PISA test scores from students across 27 countries, Brunello and Rocco (2013) find that increases in immigrant students in secondary schooling are associated with small reductions in the test scores of native-born students. Focusing on Israel after the fall of the Soviet Union, Gould, Lavy and Daniele Paserman (2009) relate the fraction of immigrants in the 5th grade to high school test scores. Their results indicate that exposure to immigrant peers in the 5th grade is associated with lower test scores during high school. Ballatore, Fort and Ichino (2015) examine Italian primary schools and find sizable negative impacts of immigrant students on native students' performance in language and math at age 7 , that also persist over time.

In contrast, several papers produce quite different findings on the impact of foreign peers. Ohinata and Van Ours (2013, 2016) study whether immigrant peers affect the test scores of native Dutch children. Using variation across classes within schools, they do not find evidence of negative impacts on reading, math, or science test scores. Similarly, Geay, McNally and Telhaj (2013)
analyze immigrant peers in England, and do not find evidence of negative impacts on native students' reading, writing, or math tests scores in primary school. Conger (2015) uses administrative data on public high school students in Florida and finds no effect of school immigrant shares on immigrant and native-born students academic performance. Finally, Diette and Oyelere (2012, 2014) examine immigrant peers in North Carolina public schools. Interestingly, their results indicate positive impacts at the middle to lower end of the ability distribution, and negative impacts towards the top. $3^{3}$

Several ideas motivate the link between foreign peers and STEM major choice. First, unconditionally, foreign students exhibit a higher predilection for STEM fields than natives ${ }_{4}^{4}$ Therefore, natives in STEM fields are likely to be exposed to more foreign peers than in non-STEM fields. Second, by virtue of their weak English proficiency, foreign students are likely to possess a comparative advantage in STEM majors. In response, native students may believe that they possess a comparative disadvantage in STEM fields and switch to non-STEM fields, similar to observed occupational switches made by natives due to immigrant competition in the workplace (Peri and Sparber, 2009, 2011). Third, recent studies have found that disruptions in the classroom environment can have lasting negative impacts (Carrell and Hoekstra, 2010; Carrell, Hoekstra and Kuka, 2016). Foreign peers may similarly alter the classroom environment due to their low English proficiency (Borjas, 2000). Instructors may slow the pace of instruction or divert attention away from natives and towards foreign students. Differently, if foreign students are less communicative, this may reduce the scope for positive externalities that arise from peer-to-peer or peer-to-instructor interactions.

This paper aims to estimate the impact of foreign peers on native STEM major choice. To do so, we utilize administrative student-level data from a large, selective public university in California, which covers the academic years 2000-01 through 2011-12. The data contains the roster of every course along with background characteristics and outcomes for each student. Our empirical design relates foreign peer exposure of U.S.-born first-term freshmen in introductory math courses to eventual graduation with a STEM/non-STEM degree.

We consider introductory math courses as an appropriate setting to look for foreign peer impacts on eventual STEM degree attainment. Such courses (see Table 11), which are primarily calculus-based, have long been considered a gateway class for STEM majors (Steen, 1988). Addi-

[^1]tionally, satisfying at least one of these introductory math courses is required for all STEM majors, and even several non-STEM majors. Thus, any individual considering majoring in STEM must take an introductory math course to keep the possibility of majoring in STEM as a viable option. Additionally, taking one of these courses also satisfies a university-wide quantitative course requirement. Therefore, in our data, $70 \%$ of all students take one of these classes at some point during their studies. ${ }^{5}$

We limit our main analysis to native freshmen in their first term of enrollment to reduce the potential for selection bias and limit the potential for foreign peer exposure in prior college courses. First-term freshmen students register during the summer before their first fall term, making it difficult for them to gain knowledge of the composition of particular classes as they fill up. For each course taught by a specific professor in a given term ("class"), we measure the composition just prior to the first day of instruction to ensure the rosters do not reflect withdrawal or additions to the class after students have had a chance to observe their peers .

Our identifying variation exploits changes in the foreign share within courses taught by the same instructor/professor over time ${ }^{6}$ Our motivation follows from the ideal experiment, which would hold fixed the instructor and course, in addition to all other factors, and only vary the share of foreign peers. The data exhibits substantial variation in the foreign share within course-professor pairs. Endogenous selection within course-professor pairs could manifest in students waiting to take an introductory math course with a particular professor when the class peer composition is preferable. However, new students are unlikely to reliably predict when a particular professor will teach a particular course in the future. Professors themselves are often not informed of future teaching assignments until late in the term prior.

We test for selection into these courses by regressing the foreign class share on individual background characteristics, including race, gender, and ability measures. These checks show no consistent evidence of selection and support the notion that the variation in the foreign share within courses taught by the same instructor is as good as random. Additionally, because introductory math classes have high enrollment caps that never bind, our estimates are not confounded by mechanical crowd-out, whereby the entry of foreign students prevents some native students from registering for the class. Further, our estimates remain robust when controlling for bias arising from contemporaneous shocks, such as increases in class size associated with more foreign peers.

We find evidence that foreign peers lower the likelihood of graduating with a STEM major.

[^2]A 1 standard deviation increase in the foreign share in the introductory math class reduces the probability of graduating in STEM by roughly 3 percentage points, or $6 \%$ of the mean. This implies that for an average-sized class, an additional 9 foreign students displaces 3.7 native freshmen from graduating with STEM majors. This finding is stable across various levels of controls and robustness checks. A placebo test assures foreign peer effects come from exposure in introductory math courses, and not in other classes.

Natives displaced from STEM ultimately graduate with Social Science majors. We find little evidence of students switching to Arts \& Humanities majors, or dropping out. To better characterize the nature of switches away from STEM majors, we link measures of expected earnings to each individual's major at graduation. Analyses which use major-specific expected earnings as the outcome indicate that native students are not displaced into lower paying majors-they appear to be choosing Social Science majors that have equal earning power relative to the STEM majors they leave. Thus, although foreign peers displace natives from STEM, they do not appear to affect their earnings prospects.

Additional analyses do not indicate any impacts on immediate, short-term outcomes such as the likelihood of withdrawing from the course, or introductory math grades. Dynamic analysis reveals that much of the formal transfer from STEM to Social Sciences majors takes place during the 2 nd and 3 rd years of college.

Further, the major choices of foreign students do not appear to be impacted by higher exposure to foreign peers. Results suggest that foreign students pursue STEM degrees at the same rate, irrespective of foreign peer composition. Thus, the displacement we observe for native students is not offset by an increased likelihood of foreign students persisting in STEM. This suggests that an increase in the presence of foreign born students in the classroom might reduce the aggregate number of STEM graduates.

We explore several potential mechanisms to explain our findings. First, foreign students may alter natives beliefs over their comparative advantage. We measure comparative advantage of each individual in STEM and non-STEM majors by comparing their baseline ability in STEM relative to non-STEM, against the average STEM to non-STEM ability of peers in their cohort. To proxy for STEM and non-STEM ability, we utilize individual SAT math and verbal scores, which have been shown to be good predictors of STEM and non-STEM major choice (Turner and Bowen, 1999). Analysis along the dimension of comparative advantage indicates the native students most affected are those with very low comparative advantage in STEM majors. Natives with middle to high values of comparative advantage in STEM do not appear to be affected. These results are consistent with the notion that natives respond according to comparative advantage.

Second, we find evidence that the low English proficiency of foreign peers may generate lin-
guistic dissonance that negatively affects the learning environment. When classes have a large share of students who cannot effectively communicate in English, this may reduce the scope for positive externalities that arise from peer-to-peer or peer-to-instructor interactions. Furthermore, instructors may have to slow instruction to accommodate non-fluent students. We examine whether linguistic dissonance may be an underlying mechanism by assigning each foreign peer a measure of the linguistic distance of the predominant language spoken in their home country from English from Chiswick and Miller (2005). Results indicate that exposure to foreign peers whose native tongues are very distant from English has a larger impact on displacement. Foreign peers whose native tongues are more similar to English, however, still have a negative and statistically significant impact on the likelihood of majoring in STEM.

Finally, the granularity of our data reveals two very different types of foreign students. Information on student visas allow us to separately identify international students from immigrant students, which include permanent residents, foreign-born U.S. citizens, and undocumented individuals. Descriptive statistics indicate that although their composition in terms of countries of origin is similar, international students are very highly selected, exhibiting background ability measures that are even higher than native students. Exploring heterogeneous impacts between these two types of foreign peers informs current issues surrounding rising international student enrollment. We find that international students actually increase the probability of STEM completion. Immigrant students are the group driving the overall negative impacts on native STEM completion.

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

### 2.1 Institutional Setting

This paper uses administrative student records from a public, land-grant university in California. This university has current enrollment over 30,000 , roughly $80 \%$ of whom are undergraduates. The institution can be characterized as a selective, Research I university that ranks consistently among the top 20 public universities in the U.S. Average SAT scores of incoming students are higher than the national average, usually by at least one standard deviation.

This university, like many postsecondary institutions, offers a wide variety of fields of study culminating in over 100 different undergraduate majors. Each year roughly 7,000 students earn
bachelors degrees, with half of the top 20 most popular majors in STEM, such as Biology, Chemistry and Mechanical Engineering. Students are required to declare a major by the time they have completed an amount of units roughly equal to two full-time years of course work. While students have flexibility in switching majors, institutional rules impose some costs-students must obtain approval from an advisor in the major they wish to leave and from an advisor in the major they wish to join.

We focus on introductory math courses, which we define as the set of math courses that are listed as satisfying a university-wide quantitative course requirement and also satisfy mathematics prerequisites required for STEM majors (see Table 1). All students, regardless of major, must satisfy a quantitative course requirement. While the list of eligible courses mainly comprises of calculus based math courses, it also includes some statistics and other math-intensive courses. All STEM majors, and some non-STEM majors, require the completion of at least one introductory math course. Many departments advise students to take introductory math in their first term. Hence, these courses do not have college-level course prerequisites, that would prevent first-term freshmen from enrolling. Taken together, these factors help generate large enrollment in introductory math courses. Approximately $70 \%$ of all students in our data take an introductory math course at some point during their undergraduate studies.

As can be seen in Table 1, the set of courses focuses on the fundamentals of calculus, although there are a few exceptions of more advanced courses on the list (e.g. Differential Equations, Vector Analysis). A majority of the native-born freshmen in our sample take one of the more basic courses (Precalculus, Calculus I, Calculus for Scientists, and Adv Calculus: Intro) as their first math course. These courses are large, with average enrollment around 230 students. Importantly, they are structured with a very high enrollment cap which never binds. In our sample, introductory math courses never exceed $40 \%$ of the cap. Thus, students cannot be mechanically crowded-out of classes when more foreign students enroll.

The academic calendar follows a trimester schedule, with instruction occurring over three terms (fall, winter, and spring). Students enroll in courses with specific instructors, and accumulate credits upon successful completion at the end of each term. Within each entering cohort, approximately $50-60 \%$ of students graduate within 12 terms ( 4 years), $70-80 \%$ in 15 terms ( 5 years), and $80-85 \%$ in 18 terms (6 years).

The registration process for first-term freshmen is distinct from the process for all other students. 7 The university organizes several optional orientations for new students in the summer prior

[^3]to their first term. During each orientation, advisers assist first-term freshmen in planning their course of study and registering for classes. Students attending earlier orientations, therefore, register before students attending later orientations. Students that do not attend orientation ultimately register online, but receive information through the mail intended to assist in course planning and registration. The non-binding high cap, however, means that students registering earlier do not have a better chance at enrolling in a given introductory math course taught by a particular instructor than those who register later.

### 2.2 Sample Construction

The administrative data contain all course registration activity for each student, which we use to construct rosters for each introductory math class, identified by the course, instructor, meeting time and term offered. We reconstruct the rosters just prior to the first day of instruction for the term. As such, they reflect the course composition before students have met the professor, examined the syllabus, or been physically present in the class with other students. Continued registration activity beyond the first day of instruction also identifies whether students add or drop the course. Registration records are then matched with student background characteristics (e.g. gender, ethnicity/race, nativity, high school GPA, etc.) and outcomes (e.g. course grade, graduation in STEM major, etc.). Finally, instructor/professor identifiers are linked to the courses in each term from online catalogs.

We measure each individual's major at graduation, which provides a more definitive measure of both choice and skill acquisition. To students who graduate we assign one of three completion outcomes - graduation with a STEM degree, Social Science degree, or Arts \& Humanities degree. Because upwards of $80 \%$ of students complete the degree within 6 years ( 18 terms), we measure graduation outcomes within 6 years. We refer to those that do not complete within 6 years as dropouts, however a small number may take 7+ years to graduate. Because the data on student outcomes ends in 2012, the fall 2006 entering cohort is the last one for which we can observe 6 year graduation outcomes. As such we limit the analysis to new freshmen enrolled in an introductory math course in fall 2000 through fall 2006. In total our sample consists of 16,830 first-term native freshmen.

Students are identified as foreign or native according to their country of origin. Foreign peer exposure is measured within classes. The class is a natural unit where peer interactions might occur as students attend lectures in the same physical location at the same time, receive the same

[^4]instruction, are given the same assignments, take the same exams, and are evaluated jointly by the professor $[8$ We adopt a standard peer measure by calculating for each native student the fraction of peers in their introductory math course that are foreign. Foreign students need not be first-term freshman to be counted in our peer measure.

Table 2 shows summary statistics of student background characteristics. Column 1 and 2 describe all native and foreign students enrolled during the period under analysis (2000-2006). Column 3 describes native first-term freshmen in introductory math courses, which represent the primary group we are interested in. Column 4 displays statistics for foreign-born peers in the introductory math courses of native first-term freshmen.

While $56 \%$ of all native students are female, only half of first-term native freshmen that enroll in introductory math courses are female. The same under-representation in the introductory math sample relative to their presence in the overall population is evident for native White and minority (Black and Latino) students. In contrast, native Asians appear to possess a strong predilection for taking introductory math courses early on. While Asians comprise only $37 \%$ of all natives, they represent roughly half of all native first-term freshmen enrolled in introductory math courses.

A very similar pattern is observed for foreign students. A large distinction is that the vast majority of all foreign-born students are Asian. Nearly $80 \%$ of foreign students in the introductory math sample are Asian. The next most populous race groups among foreign-born are White students, followed by Latino students. The predominance of Asian students likely reflect the large immigration patterns from Asian countries to California, combined with higher rates of educational attainment for Asians overall.

Measures of background ability are provided in rows 7-11. High school GPA is measured on a scale from 0 to 4 , SAT math and verbal scores range from 200-800, and the combined SAT score ranges from 0-1600. Also included is a composite score calculated by the admissions office that is a weighted sum of various background ability and traits, which include some measures available in our data and others that are not available. The academic composite index ranges from $0-14,000$. When comparing native freshman in introductory math courses to the general native student population, it is clear that those taking math in their first term are more highly selected on all ability traits. Thus, STEM majors appear to initially attract students of higher preparedness who are willing to take the gateway math course right away.

Native and 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 lower SAT verbal scores,

[^5]reflecting the fact that many learn English as a second language and are less likely to be as fluent as natives. This difference in English ability is magnified when comparing native freshmen and their foreign peers in introductory math courses- foreign students SAT verbal scores are almost a full standard deviation below that of native freshmen. The fact that foreign students in introductory math courses exhibit lower SAT verbal scores than the overall foreign student population indicates that introductory math courses likely draw interest from those with a comparative advantage in quantitative analysis. Though differences in SAT verbal are the most salient, native freshmen outperform foreign students on all measurable ability traits.

A particular advantage of our data is that it contains information on visa status and countries of origin, allowing us to explore heterogeneity among the foreign student population. We distinguish between international students on temporary visas and other foreign born students ("immigrants"), which include legal permanent residents, those with U.S. citizenship, and undocumented students ${ }^{9}$ This allows us to inform recent debates surrounding surges in international student enrollment, whereby significant controversy has led some college campuses to propose caps on the number of international students admitted. Furthermore, assessing difference between international and immigrant students is particularly important for federal immigration policy, as there are currently no caps on student visa issuance.

Columns 5 and 6 of Table 2, reveal sizable heterogeneity between international students and immigrant peers in introductory math courses. First, international students only account for $11 \%$ of foreign peers, with immigrants comprising the majority. Second, the lower ability of foreign peers relative to native freshmen is driven by immigrant students. In contrast, international students appear at least as well prepared as native freshmen, and possess an absolute advantage in quantitative ability, as their SAT math scores exceed those of native freshmen by almost 0.5 of a standard deviation. While the majority of foreign students are immigrants, these distinctions are suggestive of potential differing impacts of immigrants and international student peers in the classroom. While later analysis explores these differences, we acknowledge the small number of international students in our sample is limiting.

Table 3 summarizes the key outcomes of interest for students in introductory math courses. The top panel provides completion outcomes. Approximately $82 \%$ of entering native freshmen graduate within 6 years, whereas $18 \%$ dropout or take greater than 6 years ${ }^{10}$ While natives graduate with an average GPA of 3.05 , foreign students perform slightly lower. Students that graduate take

[^6]slightly more than 16 terms, or 5.33 years to complete their degree.
STEM is the most popular major at graduation for natives taking introductory math as firstterm freshmen, with $48 \%$ of students going on to complete a STEM degree in 6 years. Almost one-third of native freshmen taking introductory math in their first term end up graduating with a Social Science degree. Completion outcomes are similar for foreign born peers, although foreign students complete STEM degrees at a lower rate than natives. This suggests that if displacement of natives from STEM occurs, foreign students may not complete STEM degrees at equivalent rates to make up for the decline in native STEM majors.

Differences in graduation outcomes across groups can partially be explained by observing transitions between majors, measured by comparing a student's first declared major with their major at graduation. For example, if the first declared major is STEM, and they graduate with a Social Science major, they are considered to have made a STEM to Social Science transition. If they do not graduate within 6 years, they are considered to have dropped out. As our focus is on switches out of or into STEM, we only show these transitions. Statistics on transitions appear in the bottom panel of Table 3. Among students who declare STEM as their first major, only $43 \%$ end up completing a degree in STEM, indicating large attrition. Attrition appears slightly larger for foreign students. Regardless of nativity, most students who leave STEM majors end up switching towards Social Science and dropping out. A very small fraction of students switch to Arts \& Humanities majors. Additionally, a very small fraction of individuals ever make a transition from a non-STEM major to a STEM major, potentially indicating high costs of delaying pursuit of STEM degrees.

## 3 Idiosyncratic Variation

Our empirical approach addresses traditional concerns arising from the estimation of peer effects with minimal assumptions. In particular, three key issues need to be addressed: selection, common shocks and reflection (Manski, 1993; Sacerdote, 2011). Selection into or out of classes based on the peer composition could generate significant bias. Unobserved common shocks within a class would make it difficult to correctly identify the impact of foreign peers. The reflection problem confounds estimates in instances when it becomes difficult to distinguish the impact of peers on the individual, from the impact of the individual on peers. Our methodology addresses each of these issues.

Several features ensure our results are not driven by endogenous selection. As stated earlier, we examine the outcomes of natives who take introductory math courses as first-term freshmen. New freshmen, by definition, do not have actual prior educational experiences at the university. Hence, when registering for courses during the summer prior to arriving on campus, they are
unlikely to possess sufficient knowledge about the likely composition of peers required to engage in endogenous selection. Additionally, we measure the peer composition of students registered for each course, just prior to the first day of instruction. Thus, we measure foreign peers before students ever physically attend a class.

This approach does not completely guard against selection. For example, highly motivated students may be able to obtain partial or full information on the peer composition of classes before the first day of instruction. To further mitigate selection, we utilize variation in the foreign student composition within courses taught by the same professor over time. This provides credibly exogenous variation in the foreign share, as selection would have to occur within course-professor pairs across terms. This is highly unlikely as instructor assignments to courses are decided only in the middle of the prior term, so that at the start of each term, instructors themselves are not aware of what their teaching assignments will be in the future. Furthermore, a student's ability to predict peer composition in future courses taught by a particular instructor is quite limited.

It is useful to visually depict the type of variation we utilize. Figure 2 displays histograms illustrating the overall variation in the foreign share across the introductory math classes. While the foreign share ranges between $8-15 \%$, some classes have less than $5 \%$, and a few have greater than $20 \%$. Figure 3 shows the identifying variation we isolate for the analysis. Each point represents the foreign composition within a particular introductory math course taught by a particular professor. The lines linking the points allows tracking of course-professor pair over time. To allow for visual clarity, we provide a random sample of 10 professor-course pairs.

There is sizable variation over time within course-professor pairs. While some professors teach in most fall terms, some only teach sporadically. The figure also helps exemplify the experiment we have in mind. The dashed line displays the foreign share within a specific course-professor pair. This course-professor pair was only offered 4 times in our data - in the fall term of 2003, 2005, 2006, and 2008. Our analysis compares the outcomes of the native first-term freshman who happened to enroll in course-professor pair A, against the outcomes of the native first-term freshman who enrolled in course-professor pair B. While the native student in A was exposed to an environment containing 6\% foreign students, the native student in B enrolled in a class where $16 \%$ of her peers were foreign. These two native students took the same course (introductory calculus), with the same professor, but by virtue of entering the university and enrolling in introductory math in different terms, they were exposed to very different levels of foreign peers. We argue that the differences in the class compositions of A and B are driven by random fluctuations, and that the native freshmen in the two classes are comparable.

We empirically test the validity of our identification by examining whether natives who take the same course-professor pair, but experience varying levels of foreign peer exposure, are different
along observable characteristics. By analyzing whether native student background characteristics correlate with the foreign peer composition, we directly evaluate whether selection on observables is apparent. Although we only focus on the outcomes of native first-term freshmen, the test for selection is more demanding in the sense that we must test for selection across all native students in the class. Even if native first-term freshmen do not engage in selection, the selection of other native students due to foreign peer exposure would complicate the analysis. Endogenous selection of other native students could alter the composition of other peer characteristics within the class, which would then also affect our observed outcomes.

To check selection on observables, we estimate the following regression model:

$$
\begin{equation*}
C_{i}=\alpha+\delta \frac{F_{c p t}}{T_{c p t}-1}+\sigma_{c t}+\sigma_{c p}+\epsilon_{i c p t} \tag{1}
\end{equation*}
$$

Equation 1 regresses individual background characteristics of native student $i\left(C_{i}\right)$, on the share of $i$ 's peers that are foreign in the course $\left(\frac{F_{c p t}}{T_{c p t}-1}\right)$. To allow the identifying variation to come from changes in the foreign share within courses $c$ taught by the same professor $p$ across terms $t$, the model includes course-by-professor fixed effects $\sigma_{c p}$ and course-by-term indicators $\sigma_{c t}$. Standard errors are clustered at the professor level. The foreign peer share is standardized, so that the coefficients reflect the impact of a one standard deviation increase in the foreign share.

The results of these tests are displayed in Table 4. Each column corresponds to a regression of $\frac{F_{c p t}}{T_{c p t}-1}$ on a different individual background characteristic $\left(C_{i}\right) .^{11}$ The coefficient estimate in column 7, for example, indicates that a one standard deviation increase in the foreign share is associated with an increase in a native student's SAT math score of 1.76 points (only 0.02 of a standard deviation in the same score). Given the mean SAT math score is 618 and a standard deviation is 75 points, this estimate is thus economically insignificant. None of the estimates are statistically distinguishable from zero at any meaningful level of confidence, nor are they economically significant. Thus, the results do not provide any consistent 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 will include these individual background characteristics as controls to check whether their inclusion alters the estimated effects ${ }^{12}$

[^7]While selection appears unlikely, students taking the same class may be exposed to common shocks that can affect outcomes. If these vary with the foreign class share, our methodology risks confounding such shocks with the impact of foreign peers. For example, Ballatore, Fort and Ichino (2015) finds that while inflows of foreign students in Italian primary schools raised the peer composition within classes, they also increased class size. Because class size is an important determinant of educational outcomes, failing to account for the relationship between foreign peer composition and class size leads to invalid estimates.

Similar concerns are apparent with in our context. In particular, descriptive statistics in Table 2 showed key differences in baseline characteristics between native freshmen and their foreign student peers. In particular, foreign students appear less prepared in terms of background ability measures, and different in terms of racial composition. Thus, for example, increases in foreign peers will mechanically lower the average SAT verbal of peers within the class. Since studies have shown that peer ability or race can affect individual outcomes, the impact of foreign peers will be commingled with potential impacts of peer ability or race. To account for potential changes in other classroom characteristics induced by foreign peers, our analysis will include controls for peer background ability, race, and gender.

Lastly, reflection occurs when the peer characteristics being analyzed can potentially be influenced. For example, studies measuring the impact of high ability peers are at risk of problems due to reflection if peer ability is measured as the average of peers' test scores. Measuring peer ability in this way makes it difficult to separate the impact of peers on individual test scores, and the impact of the individual on peers' test scores. Examining foreign peers has the advantage of being immune to reflection concerns. This is because nativity is an immutable characteristic. Native individuals cannot affect the birth place of their foreign born peers ${ }^{13}$
classroom environment.
${ }^{13}$ Additionally, because native 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).

### 3.1 Empirical Specification

To estimate the impact of foreign peer exposure on the graduation majors of natives, we estimate a linear probability model ${ }^{[14}$ which captures the elements described earlier,

$$
\begin{equation*}
Y_{i c p t}=\alpha+\beta \frac{F_{c p t}}{T_{c p t}-1}+\sigma_{c t}+\sigma_{c p}+\gamma_{1} X_{c p t}+\gamma_{2} X_{i}+\varepsilon_{i c p t} \tag{2}
\end{equation*}
$$

Equation 2 regresses individual outcome $\left(Y_{i}\right)$ on the share of individual $i$ 's peers that are foreign $\left(\frac{F_{c p t}}{T_{c p t}-1}\right)$. We control for course-by-term indicators $\left(\sigma_{c t}\right)$ and course-by-professor fixed effects ( $\sigma_{c p}$ ). The empirical design therefore forces the identifying variation to come from changes in the foreign share within courses $c$ taught by the same professor $p$ over time $t$. An example of a violation of this strategy would be if high ability natives waited to take a course with a professor when the foreign share was low. The evidence provided earlier suggested this behavior to be unlikely.

The empirical design will also include course level controls, $X_{c p t}$, to account for potentially endogenous common course level shocks. Our baseline specification controls for peer ability, which include average peer SAT Math, SAT verbal, and high school GPA, and average peer race and gender composition. As discussed earlier, these peer composition controls help account for any confounding shocks that are concomitant with changes in the foreign share. In more saturated specifications, we control for class size, and also individual characteristics $\left(X_{i}\right)$, which include the race, gender, and ability variables described in Table 2 .

Finally, $\varepsilon_{i c p t}$ 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 $\beta$ can be interpreted as the impact of a 1 standard deviation increase in the foreign class share on the outcome, in units of $Y$.

## 4 Results

Table 5 shows the effects of foreign peers in introductory math courses on the eventual completed majors of native first-term freshmen, from Equation $2^{15}$ The outcome variable is a dummy variable equal to 1 if the student graduated with a STEM major within 6 years from the first term of

[^8]enrollment, and 0 otherwise. Column 1 includes the baseline peer ability, peer race and gender composition controls. Column 2 further includes a control for course size. Column 3 adds in individual characteristics as controls. All models include course-by-term and course-by-professor fixed effects.

The coefficients estimates in the first row indicate that foreign peers are negatively associated with the likelihood of completing a STEM major. Looking across the columns, the finding is essentially unchanged. A 1 standard deviation rise in the foreign class share lowers the probability of graduating with a STEM major by 3 percentage points, on average. All estimates are statistically significant at the $5 \%$ level. The coefficient estimates are roughly $6 \%$ of the mean STEM graduation rate of $48 \%$. By way of comparison, the difference in STEM graduation rates between White and Black students (White-Black STEM gap) is around 6 percentage points, while the STEM gap between males and females is 14 percentage points ${ }^{16}$ Thus, our effects are equal in size to $1 / 2$ of the White-Black STEM gap and 1/5th of the STEM gap across genders.

The average course size of introductory math classes is approximately 230 students. If this course had the average foreign share (approximately $13 \%$ ) and the average share of native firstterm freshmen (approximately $56 \%$ ), it would comprise of roughly 30 foreign students and 129 native freshmen. Assuming native freshman students would graduate in STEM at the mean rate of $48 \%$, then we would expect 62 of these native freshmen to go on to complete STEM degree. A one standard deviation increase in foreign peers, roughly 9 additional foreign students, would yield an expected displacement of 3.7 native student from STEM $\left[{ }^{17}\right.$

The coefficients on peer controls show that the probability of graduating with a STEM major is positively correlated with peer SAT math and negatively correlated with peer SAT verbal and High School GPA. This is consistent with empirical evidence showing that verbal test scores consistently appear with a negative sign in regression models of labor market outcomes that include math test scores (e.g. Sanders, 2015). As pointed out by Altonji, Arcidiacono and Maurel (2016), an explanation for this pattern is that conditional on SAT math, higher SAT verbal is associated with preferences for majors that pay less, but provide better non-monetary characteristics (e.g. more time flexibility) - typically the non-STEM majors. A similar reasoning may also be valid for peer high school GPA, with those peer students having a higher GPA conditional on SAT math score preferring non-STEM majors.

[^9]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 native 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.

Given that native freshmen appear to be displaced from STEM, we assess whether foreign students are also displaced to understand if foreign peers are impacting total number of STEM majors. Table A4 replicates Table 5, but examines the outcomes of foreign students. Results in all specifications are insignificant, suggesting that foreign students do not respond to increased exposure to foreign peers. Thus, the displacement we observe for native students is not offset by an increased likelihood of foreign students persisting in STEM ${ }^{18}$ As a result, we should expect the total number of STEM graduates to decline with the share of foreign-born students in the class.

In Table 6, we examine what outcomes displaced natives are pushed towards ${ }^{19}$ We utilize our preferred specification from column 3 of Table 55, which includes all peer composition and individual level controls, which is reprinted in column 1. Columns 2 and 3 examine the likelihood of completing a Social Science degree and Arts \& Humanities degree, respectively. Column 4 examines the likelihood of dropping out, where the outcome is an indicator equal to one if the student failed to graduate within 6 years.

The estimates show that the decline in graduating with a STEM major is offset by similar 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. The coefficients on graduating in Arts \& Humanities and dropout are positive, but much smaller in magnitude. None of the coefficients, however, are statistically significant.

In columns 5-8 of Table 6 we estimate the implications of this displacement from STEM on earning potential. The aggregation of outcomes into four groups (STEM, Social Science, Arts \& Humanities, Dropout) masks heterogeneity within STEM and non-STEM majors, and potentially important margins of adjustment. For example, a native may be displaced from a high earning STEM major to a very low earning Social Science major or vice versa. Given that the students in the sample comprise over 100+ different majors, separate analysis for each STEM or non-STEM major is not feasible. Instead, we utilize the expected earnings associated with each major, which provides a sufficient statistic for much of the relevant qualities and characteristics of majors.

[^10]For each native student, we link their major at graduation to measures of the average expected earnings for that major. 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. We then regress these earnings measures for natives on their foreign peer exposure in introductory math courses.

The results on earnings are negative in sign, but statistically indistinguishable from zero. Furthermore, they appear economically significant. For example, the estimate in 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 $\$ 23,230$-less than $0.5 \%$. ${ }^{20}$ The estimates on longer-run expected earnings are larger, but remain roughly equal to $1 \%$ of the mean. Our findings suggest that displaced students are leaving relatively low earning STEM majors, choosing relatively high earning non-STEM majors, or a combination of the two.

Next, we examine when student's movement away from STEM majors occurs. For each native student, we observe their reported majors term-by-term. We group these majors into four categories: STEM, Social Science, Arts \& Humanities, or Undeclared. For each term, we create dummies indicating whether a native student declared a major in one of these categories. We then estimate equation 2, replacing the dependent variable with term by term major dummies. ${ }^{21}$ The coefficients are then displayed in Figure 4. The vertical axis measures the coefficient estimate (i.e. the impact of a one standard deviation increase in foreign peers), and the horizontal axis measures the term of enrollment, where 1 represents the first term, 2 represents the second term, and so on. Since our main results are for completion within 6 years, we perform this analysis for 6 years (18 terms).

The figure shows native students begin to choose STEM majors with lower probability in their 6th-11th terms. The decline in STEM major choice is offset by increases in the likelihood of declaring Social Science majors. While native students are exposed to foreign peers in their term 1 math class, the likelihood of choosing Social Science majors does not increase until the 6th term (end of the 2nd year). This lag may in part be due to bureaucratic costs associated with changing majors. This delayed switching may also be indicative of the cumulative nature of changing majors. While high foreign exposure is a contributing factor for deciding to avoid STEM majors, it might

[^11]not be a relevant factor for deciding which alternative major to pursue. It could take several terms to search for the desired Social Science major and formally register in that major.

Table 7 lexamines more immediate, short-term outcomes to see if they shed light on why STEM displacement might be occurring. We first examine whether share of foreign peers impact the likelihood native first-term freshmen withdraw 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. Column 1, however, indicates there is no effect of foreign peers on the likelihood of withdrawing from the course. ${ }^{22}$

Column 2 shows no impact of foreign peers on introductory math grades received by native first-term freshman, conditional on remaining in the class. Grades have been standardized to have mean of zero and standard deviation equal to one within courses. In Column 3 we consider impacts on end of first-term GPA. The point estimate on GPA is positive and marginally significant, but relatively small in magnitude.

One potential explanation for these two results is native students marginally shifting effort away from introductory math and towards their other classes. On average, foreign students are negatively selected in math courses (see Table 22). Under curved grading, a higher share of foreign peers might allow a native student to achieve the same grade with less effort. After receiving a signal of their grade (e.g. a first midterm), students may then substitute effort towards other courses. However, there might be a number of possible mechanisms, and our data do not allow us to examine them, so this explanation is speculative.

Columns 4-6 explore near term progression in STEM, and avoidance of foreign students. Columns 4 and 5 evaluate whether foreign peers in introductory math affect the likelihood native freshmen take another math course or STEM course, respectively, in the following term. The results do not indicate any near term impacts on STEM progress.${ }^{23}$ Column 6 examines whether the share of foreign peers in introductory math is related to the share of foreign peers among all classmates in the following term. If native students attempt to avoid foreign students, this might explain their movement away from STEM fields. The findings, however, do not indicate any avoidance behavior.

Overall our findings indicate that foreign peers displace natives from STEM. As a result, natives appear to switch to Social Science. However, native students appear to be choosing Social Science majors that possess equally high earning power relative to the STEM majors they abandon. Analysis of immediate outcomes do not reveal any detectable contemporaneous impacts that

[^12]might lead to discouragement from STEM fields. Additionally, the increased likelihood of choosing Social Science majors does not occur immediately following the introductory math course, but instead takes several semesters to materialize. Given these findings, we now explore the potential underlying mechanisms at work.

## 5 Exploring Mechanisms

Why do foreign students lead to lower STEM completion among natives? We consider heterogeneity in the estimated effects and explore possible mechanisms underlying the results. Changes in native outcomes may be in line with responses along the basis of comparative advantage. Similarly, the lower English language ability of foreign students may alter the learning environment. Such mechanisms are not mutually exclusive and may operate contemporaneously. We explain these hypotheses in greater detail, and perform empirical analyses to test the prevalence of these mechanisms.

### 5.1 Comparative Advantage

The movement of native students away from STEM fields may be a response to changing comparative advantage. Literature on the labor market impacts of immigration have found evidence of native adjustments based on comparative advantage. For example, immigration that reduces native comparative advantage in manual and quantitative tasks leads natives to move towards occupations requiring more communication-intensive skills (Peri and Sparber, 2009, 2011). Within the context of higher education natives who originally thought of pursuing STEM fields might update their choice when exposed to many foreign students with comparative advantage in STEM.

The summary statistics suggest that foreign peers may indeed possess a comparative advantage in STEM fields. Their relative SAT Math to Verbal score is higher than that of native freshmen. Given that SAT Math and Verbal scores have been shown to be decent predictors of STEM and non-STEM major choice (Turner and Bowen, 1999), we believe relative scores are a good proxy for comparative ability in STEM and non-STEM fields. This feature is unlikely to be institution specific - foreign-born college educated individuals in the labor market are highly over-represented in STEM fields and STEM majors (Gambino and Gryn, 2011, Peri, Shih and Sparber, 2015).

If comparative advantage is an underlying mechanism, one would expect to see strong responses among native students who are marginal. Native students who originally possess very strong comparative advantages in STEM fields are unlikely to change their choice of major given exposure to many foreign peers. In contrast, those natives who possess middle-to-low comparative advantage in STEM fields are the ones who should be changing to non-STEM majors. Thus,
analyzing differential impacts on natives based on comparative advantage in STEM fields should serve as a test of this mechanism.

We empirically assess this idea using a local linear regression. We define a measure of comparative advantage in STEM for each native 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 regress STEM graduation on the share of foreign peers at each percentile.${ }^{24}$ Figure 5 plots coefficients from our main specification, and shows that students with low comparative advantage in STEM (low percentiles) experience strong displacement from STEM. 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.

We also consider whether students respond to absolute advantage. To measure absolute advantage, we estimate the ex-ante likelihood that a student will end up 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.

The bottom panel of Figure 5 presents local linear regression estimates based on absolute advantage. There is little difference in the effect for natives 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 are equally displaced from STEM.

### 5.2 Linguistic Dissonance

Though our data comes from a single university, national studies have similarly concluded that foreign-born college students overall appear to be negatively selected. In particular, foreign students lack English proficiency, come from low income backgrounds, require high levels of financial assistance, and are likely to work part-time during college (Erisman and Looney, 2007), ${ }^{25}$ The

[^13]lower levels of preparedness in foreign student populations are also evident prior to college, and have motivated several studies examining the impacts of foreign students in primary education. ${ }^{26}$

A key feature of foreign students is their lack of English proficiency. A large presence of non-fluent speakers may foster linguistic dissonance within the classroom that could generate negative peer effects in several ways. Limited English speakers may lead teachers to slow the pace of instruction (Diette and Oyelere, 2012). Similarly, if foreign students require more assistance, instructors may substitute time away from helping native students towards helping foreign students (Geay, McNally and Telhaj, 2013). Qualitative studies suggest that low English language ability, alongside other factors, may lead foreign students to be more reticent in class (e.g. Rodriguez and Cruz, 2009; Stebleton, Huesman Jr and Kuzhabekova, 2010; Stebleton, 2011; Yamamoto and Li, 2011). Lack of communication in class would reduce the amount of productive externalities that arise when students ask each other for clarification, or when they ask the instructor questions.

Testing for linguistic dissonance requires measures of English language fluency. We proxy for this by assigning a measure of language distance from English to each foreign student. This involves first identifying the national language of each country. Next, for each national language, we link in measures of linguistic distance from Chiswick and Miller (2005). ${ }^{27}$ We then assign linguistic distance scores to foreign students according to their country of origin. 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.

The results from this exercise are reported in Table 8- Panel A. The displacement from STEM is larger for native students that experience increases in peers that come from countries whose spoken language is highly distant from English ("high distance"). A one standard deviation rise in the share of peers from high distance countries reduces the likelihood of completing STEM majors by 2.5 percentage points. An equivalent increase in peers from low distance countries only reduces

[^14]the likelihood of completing STEM majors by 1.7 percentage points. However, despite being 50\% larger in magnitude, the effects for high distance foreign peers are not statistically different from those for low distance foreign peers at conventional levels. Thus, the evidence provides some support for linguistic dissonance, though it is not definitive.

Note, however, that high distance foreign peers are positively and significantly associated with an increased likelihood of dropping out. Differently, low distance foreign peers appear to be pushing natives towards Social Science. The association of high distance foreign peers with dropping out, and low distance foreign peers with Social Science majors, has implications for the impacts on expected earnings. High distance foreign peers induce a reduction in expected earnings, explained by the increase in the likelihood of dropping out. For low distance foreign peers, earnings estimates are actually (insignificantly) positive. This underscores that natives exposed to low distance foreign peers are making relatively efficient major choices when it comes to earnings potential.

### 5.3 International Students vs. Immigrants

Though traditionally comprising a very small fraction of foreign-born students, recent surges in international students on temporary visas have generated substantial controversy. For example, facing backlash from increasing international enrollment, the University of California System recently proposed caps on international student admissions.$^{28}$ Our data allow us to test whether international peers have differential impacts than immigrant peers. Separately examining the impacts of these two types of foreign students is particularly relevant for policy, as the international student visa program remains uncapped, and recent years have seen unprecedented inflows of international students.

To test for differences between immigrants and international students, we split the foreign share into two components: the share of peers that are immigrants and the share of peers that are international students. We then perform regressions of Equation 2, including both the immigrant share and international student share, instead of the overall foreign share ${ }^{29}$ The results, reported in Table 8-Panel B, reveal interesting heterogeneity.

Immigrants appear to be driving the displacement of natives from STEM majors. A one standard deviation increase in immigrant peers lowers the probability of graduating with a STEM degree by nearly 5 percentage points. The displacement from STEM is entirely offset by graduation in Social Science.

[^15]The impact of international student peers on STEM completion is actually positive and significant. A one standard deviation increase in international student peers raises the likelihood of graduating in STEM by 1.5 percentage points. Recall from Table 2 that international students possess very high background ability relative to immigrant students, and also relative to native first-term freshmen, which is especially salient in SAT Math scores. Thus, there might be productive externalities from students that particularly excel in math. However, the small number of international students, and the small amount of variation they exhibit in the data prevent us from exploring these avenues more deeply.

### 5.4 Other explanations

Overall the evidence provides support for comparative advantage and linguistic dissonance as possible underlying mechanism. We cannot rule out many alternative mechanisms, such as instructor adjustments ${ }^{30}$ We conclude our analysis with some interesting findings which may hint at potential further mechanisms for future explorations.

Table 9 explores whether there are heterogeneous responses across different types of native students. Much 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 native females relative to males. For example, linguistic dissonance may more strongly deter females. In this sense, foreign peers may exacerbate the gender gap in STEM. Columns 1 and 2, however, show that females are not strongly impacted by foreign peers. Instead, native males are the group that is negatively impacted.

In columns 3-5, we stratify on native 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 native minorities to remain in school rather than dropping out. This leads to native minorities graduating in majors with higher expected earnings, both in the short and long run. In contrast, the strong displacement of native Asian students from STEM results in movement towards Social Science, but also towards dropping out. This in turn results in significant negative impacts on expected earnings associated with their outcomes.

As a final check, Table A6 of the appendix examines the impact of foreign peers on future

[^16]social connections. Another potential mechanism could be that foreign peers alter the effort or engagement in a course, resulting in students being more/less likely to form social ties ${ }^{31}$ We generate a proxy measure for an individual's social connections future terms, however, results from this exercise show negligible effects.

These interesting findings suggests possible alternative mechanisms at work. For example, it is possible that the presence of very low ability foreign peers provides a confidence boost for minority students. Alternatively, native Asian students may be particularly affected by negative spillovers if they are the group that interacts most often with foreign peers, which is possible given that $80 \%$ of foreign students are also Asian. The strong impact on males, rather than females, indicates some forces at work that have differential impact across genders. Finally, many of these heterogeneous results may be explained by differences in preferences for foreign peers. We leave deeper exploration of the mechanisms of foreign peer effects for future endeavors.

## 6 Conclusion

Disinterest in STEM throughout the education pipeline has been a great concern in the U.S. for several decades. At the same time, globalization has increased the number of foreign-born students in higher education institutions. This paper explores whether the rising presence of foreign-born peers can explain high native attrition rates from STEM majors in college.

Using administrative records from a large, selective public university, we find that higher exposure to foreign peers in the freshman first-term introductory math course reduces the likelihood of eventually completing a STEM degree. Displaced natives adjust by moving to Social Science majors. Additionally, we do not find strong evidence that foreign peers lead natives to switch to Arts and Humanities majors, or drop out of college. In terms of future earnings, the displacement does not appear to substantially harm the native students. This suggests that displaced native students might be moving from relatively low-earning STEM majors to relatively high-earning Social Sciences majors.

Our results are identified from idiosyncratic variation in foreign peers within courses taught by the same professor over time. Focusing on native first-term freshmen helps assuage selection concerns, as they register for classes in the summer prior to formally entering the college. We also

[^17]measure the class composition from registration records of students enrolled just prior to the first day of instruction. This ensures the students in our class have not had the opportunity to observe their peers and then withdraw. Balancing tests demonstrate that there appears to be little selection along observable characteristics. Results remain robust to controls for common shocks to classes that might alter peer ability, peer race/gender, or class size. Finally, we show that findings are due to exposure in introductory math classes and not other classes taken during the first-term.

To further elucidate these findings, we find evidence in support of two mechanisms that lead foreign peers to discourage natives from STEM. First, although foreign students appear absolutely worse than natives in baseline STEM and non-STEM ability, they appear to possess a baseline comparative advantage in STEM fields, measured by relative SAT Math to Verbal scores. As such, natives exposed to many foreign peers early on may update their priors regarding comparative advantage. A local linear regression analysis of the effects of foreign peers at each percentile of the comparative advantage spectrum shows that natives that initially exhibit very low comparative STEM ability are strongly impacted by foreign peers. In contrast, natives that initially display high comparative advantage in STEM appear much less affected.

Secondly, foreign students possess very low levels of English proficiency. As such, their presence may generate linguistic dissonance within the classroom environment, which in turn may affect learning. Fewer productive interactions, or changes in the pace of instruction to accommodate non-fluent students, may increase disinterest in STEM among native students. Analysis provides qualitative support that foreign students whose native language is very distant from English appear to have stronger impacts than those whose native tongue is close to English.

From a policy perspective, our analysis also shows the importance of distinguishing between immigrant and international students on temporary visas. This is particularly relevant as recent large inflows of international students have led some campuses to consider capping the number of international students admitted. We find that immigrants peers appear to be the group responsible for the displacement of natives from STEM. In contrast, international student peers appear to have a small crowd-in effect, increasing the likelihood natives graduate in STEM.

Though this study was performed on a single university, our findings carry implications for aggregate welfare. Our results may indicate that a foreign peers induce specialization based on comparative advantage, without negative consequences for individual earnings potential. While this could be efficiency enhancing. our results also indicated that the total number of STEM graduates is likely to fall-the displacement we observe for native students is not offset by an increased likelihood of foreign students persisting in STEM. The aggregate welfare implications are further amplified if foreign-born students exhibit high return migration rates. Though evidence on return migration rates of foreign-born college students are very limited, recent immigration-related
policies may be dissuading foreign students from attending college in the U.S ${ }^{32}$ The future U.S. aggregate supply of STEM skills may shrink substantially.

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

[^18]
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## Figures \& Tables

Figure 1: Trends in STEM Majors and Foreign Enrollment

(b) Foreign Enrollment as Share of Total

Note: Data on bachelor's degrees awarded by field of study come from the Integrated Postsecondary Education Data System (IPEDS). Data on foreign-born enrollment in higher education comes from the 1990, 2000 Censuses, and the 2001-2014 ACS. Data represents foreign-born individuals resident in the U.S. and enrolled in undergraduate studies. Because the year 1990 is missing college attendance, we instead calculate the number of students that have at least a high school degree, but less than a bachelor's degree that are enrolled in school. International Student data series comes from Institute of International Education, "International Students by Academic Level" (2016) and represents alien foreign born students enrolled in undergraduate studies.

Figure 2: 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 3: Foreign Share variation within professor-course pairs over time


Note: Terms are displayed on the horizontal axis and share of foreign born student in the class on the vertical axis. Each line represent a course taught by the same professor (e.g. Calculus I taught by a specific professor over multiple Fall terms). The idiosyncratic variation across terms of each course taught by the same professor represents the identifying variation in our paper.

Figure 4: Impact of Intro Math Foreign Peers on Major Choices in Future Terms


Note: The horizontal axis measures terms, where 1 indicates an individual's first term. The vertical axis measure the impact of a one standard deviation increase in foreign peers on the likelihood of declaring a particular major category at every term. Term 18 indicates 6 years from the first term.

Figure 5: Local Linear Regression Results

## Comparative Advantage




Note: Results show coefficient estimates from local linear regressions of Equation 2 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 95 th percentile of 250 bootstrapped estimations, resampled at the course level. See text for details on calculation of comparative and absolute advantage.

Table 1: List of Math Courses

| Title | Native <br> First-Time <br> Freshmen | Avg. <br> Class <br> Size | Avg. <br> Percent <br> Foreign |
| :--- | :---: | :---: | :---: |
| Adv Calculus: Intro | 4,965 | 208 | 0.152 |
|  |  | $(53.9)$ | $(0.036)$ |
| Adv Calculus: Multi Variable | 922 | 148 | 0.174 |
|  |  | $(33.7)$ | $(0.041)$ |
| Adv Calculus: Differential Equations | 299 | 148 | 0.152 |
|  |  | $(43.4)$ | $(0.041)$ |
| Adv Calculus: Vector Analysis | 40 | 135 | 0.145 |
|  |  | $(48.0)$ | $(0.064)$ |
| Calculus for Scientists | 1,287 | 232 | 0.114 |
|  |  | $(41.4)$ | $(0.025)$ |
| Calculus I | 7,031 | 247 | .103 |
|  |  | $(81.7)$ | $(0.029)$ |
| Calculus II | 394 | 197 | 0.107 |
|  |  | $(58.3)$ | $(0.032)$ |
| Calculus III | 54 | 215.7 | 0.113 |
|  |  | $(58.34)$ | $(0.029)$ |
| Precalculus | 1,838 | 307 | 0.096 |
|  |  | $(69.6)$ | $(0.023)$ |
| 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 native students enrolling in introductory math courses in their first term of college attendance. Standard deviations in parentheses

Table 2: Background Summary Statistics

|  | (1) | (2) | (3) | (4) | (5) | (6) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Native All | Foreign All | Native Freshmen | Foreign Peers | Imm <br> Peers | $\begin{aligned} & \text { Intl } \\ & \text { Peers } \end{aligned}$ |
| Female | $\begin{gathered} 0.56 \\ (0.50) \end{gathered}$ | $\begin{gathered} 0.53 \\ (0.50) \end{gathered}$ | $\begin{gathered} 0.50 \\ (0.50) \end{gathered}$ | $\begin{gathered} 0.48 \\ (0.50) \end{gathered}$ | $\begin{gathered} 0.48 \\ (0.50) \end{gathered}$ | $\begin{gathered} 0.49 \\ (0.50) \end{gathered}$ |
| White | $\begin{gathered} 0.47 \\ (0.48) \end{gathered}$ | $\begin{gathered} 0.16 \\ (0.33) \end{gathered}$ | $\begin{gathered} 0.41 \\ (0.48) \end{gathered}$ | $\begin{gathered} 0.12 \\ (0.30) \end{gathered}$ | $\begin{gathered} 0.12 \\ (0.30) \end{gathered}$ | $\begin{gathered} 0.12 \\ (0.29) \end{gathered}$ |
| Asian | $\begin{gathered} 0.37 \\ (0.46) \end{gathered}$ | $\begin{gathered} 0.71 \\ (0.43) \end{gathered}$ | $\begin{gathered} 0.48 \\ (0.49) \end{gathered}$ | $\begin{gathered} 0.78 \\ (0.40) \end{gathered}$ | $\begin{gathered} 0.77 \\ (0.40) \end{gathered}$ | $\begin{gathered} 0.78 \\ (0.39) \end{gathered}$ |
| Minority | $\begin{gathered} 0.15 \\ (0.35) \end{gathered}$ | $\begin{gathered} 0.13 \\ (0.32) \end{gathered}$ | $\begin{gathered} 0.10 \\ (0.29) \end{gathered}$ | $\begin{gathered} 0.11 \\ (0.30) \end{gathered}$ | $\begin{gathered} 0.11 \\ (0.30) \end{gathered}$ | $\begin{gathered} 0.10 \\ (0.28) \end{gathered}$ |
| Black | $\begin{gathered} 0.03 \\ (0.17) \end{gathered}$ | $\begin{gathered} 0.02 \\ (0.13) \end{gathered}$ | $\begin{gathered} 0.02 \\ (0.13) \end{gathered}$ | $\begin{gathered} 0.02 \\ (0.13) \end{gathered}$ | $\begin{gathered} 0.02 \\ (0.13) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.11) \end{gathered}$ |
| Latino | $\begin{gathered} 0.12 \\ (0.31) \end{gathered}$ | $\begin{gathered} 0.11 \\ (0.29) \end{gathered}$ | $\begin{gathered} 0.08 \\ (0.27) \end{gathered}$ | $\begin{gathered} 0.09 \\ (0.28) \end{gathered}$ | $\begin{gathered} 0.09 \\ (0.28) \end{gathered}$ | $\begin{gathered} 0.08 \\ (0.26) \end{gathered}$ |
| High School GPA | $\begin{gathered} 3.70 \\ (0.30) \end{gathered}$ | $\begin{gathered} 3.70 \\ (0.26) \end{gathered}$ | $\begin{gathered} 3.76 \\ (0.33) \end{gathered}$ | $\begin{gathered} 3.72 \\ (0.30) \end{gathered}$ | $\begin{gathered} 3.71 \\ (0.31) \end{gathered}$ | $\begin{gathered} 3.79 \\ (0.27) \end{gathered}$ |
| SAT Math | $\begin{aligned} & 599.45 \\ & (74.99) \end{aligned}$ | $\begin{aligned} & 599.62 \\ & (76.40) \end{aligned}$ | $\begin{aligned} & 629.36 \\ & (71.90) \end{aligned}$ | $\begin{aligned} & 617.89 \\ & (87.09) \end{aligned}$ | $\begin{aligned} & 611.64 \\ & (87.31) \end{aligned}$ | $\begin{aligned} & 667.00 \\ & (67.66) \end{aligned}$ |
| SAT Verbal | $\begin{aligned} & 562.90 \\ & (79.63) \end{aligned}$ | $\begin{aligned} & 510.62 \\ & (90.42) \end{aligned}$ | $\begin{aligned} & 573.83 \\ & (84.48) \end{aligned}$ | $\begin{aligned} & 491.18 \\ & (104.15) \end{aligned}$ | $\begin{gathered} 486.25 \\ (104.19) \end{gathered}$ | $\begin{aligned} & 529.88 \\ & (95.44) \end{aligned}$ |
| SAT Composite | $\begin{aligned} & 1160.18 \\ & (136.34) \end{aligned}$ | $\begin{aligned} & 1105.63 \\ & (138.31) \end{aligned}$ | $\begin{aligned} & 1200.32 \\ & (135.62) \end{aligned}$ | $\begin{aligned} & 1099.42 \\ & (162.82) \end{aligned}$ | $\begin{aligned} & 1088.71 \\ & (162.29) \end{aligned}$ | $\begin{aligned} & 1195.38 \\ & (133.69) \end{aligned}$ |
| Composite Adm. Score | $\begin{array}{r} 7394.68 \\ (758.58) \\ \hline \end{array}$ | $\begin{aligned} & 7429.27 \\ & (715.93) \end{aligned}$ | $\begin{aligned} & 7510.59 \\ & (831.30) \end{aligned}$ | $\begin{array}{r} 7397.73 \\ (914.90) \\ \hline \end{array}$ | $\begin{aligned} & 7390.23 \\ & (884.44) \end{aligned}$ | $\begin{gathered} 7456.56 \\ (1125.18) \\ \hline \end{gathered}$ |
| Obs | 45,293 | 7,165 | 16,830 | 3,840 | 3,406 | 434 |

Note: Means for enrolled students from fall 2000-fall 2006. Standard deviations in parentheses. Column 3 refers to our analysis sample of 16,830 native 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

|  | $(1)$ <br> Native <br> Freshmen | $(2)$ <br> Foreign <br> Peers |
| :--- | :---: | :---: |
| Graduation Outcomes in 6 Yrs |  |  |
| Graduate | 0.82 | 0.78 |
|  | $(0.38)$ | $(0.42)$ |
| Dropout | 0.18 | 0.22 |
|  | $(0.38)$ | $(0.42)$ |
| Time to Degree | 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 |
|  | $(0.26)$ | $(0.24)$ |
| Major Transitions |  |  |
| STEM $\rightarrow$ STEM | 0.43 | 0.39 |
|  | $(0.49)$ | $(0.49)$ |
| STEM $\rightarrow$ SS | 0.14 | 0.12 |
|  | $(0.34)$ | $(0.32)$ |
| STEM $\rightarrow$ AH | 0.04 | 0.04 |
|  | $(0.20)$ | $(0.19)$ |
| STEM $\rightarrow$ Dropout | 0.14 | 0.16 |
| SS $\rightarrow$ STEM | $(0.35)$ | $(0.37)$ |
| AH $\rightarrow$ STEM | 0.02 | 0.02 |
|  | $(0.13)$ | $(0.13)$ |
| Obs | 0.01 | 0.01 |
|  | 16.830 | $(0.12)$ |

Note: Column 1 refers to our analysis sample of 16,830 native native freshmen enrolling in introductory math courses in their first term of college attendance. Column 2 refers to the foreign peers of native freshmen enrolling in introductory math courses in their first term of college attendance. Transitions refer to the fraction of students who had a different major at graduation from their first declared major.
Table 4: Exogeneity of Foreign Class Share

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ | $(6)$ | $(7)$ | $(8)$ | $(9)$ | $(10)$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Female | White | Asian | Minority | Black | Latino | SAT | SAT | High <br> Composite |  |
|  |  |  |  |  |  |  | Math | Verbal | School <br> Admission |  |
|  |  |  |  |  |  |  |  |  | GPA | Score |
| Foreign Sh. | -0.01 | -0.01 | 0.01 | -0.01 | -0.00 | -0.00 | 1.76 | -1.08 | 0.01 | 21.11 |
|  | $(0.01)$ | $(0.01)$ | $(0.01)$ | $(0.01)$ | $(0.00)$ | $(0.01)$ | $(1.67)$ | $(1.97)$ | $(0.01)$ | $(14.53)$ |
|  |  |  |  |  |  |  |  |  |  |  |
| $\operatorname{Mean}(Y)$ | .49 | .41 | .46 | .12 | .02 | .1 | 618.36 | 567.3 | 3.73 | 7414.36 |
| $\operatorname{Std}(Y)$ | .5 | .48 | .48 | .32 | .15 | .29 | 74.98 | 83.85 | .32 | 829.08 |
| $\sigma_{c t}$ | x | x | x | x | x | x | x | x | x | x |
| $\sigma_{c p}$ | x | x | x | x | x | x | x | x | x | x |
| 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 native students attending introductory math courses. The table displays estimates from equation 1 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

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ |
| :--- | :---: | :---: | :---: | :---: |
| Foreign Sh. | $-0.035^{* * *}$ | $-0.036^{* * *}$ | $-0.033^{* * *}$ | $-0.034^{* * *}$ |
|  | $(0.011)$ | $(0.012)$ | $(0.011)$ | $(0.012)$ |
| Peer SAT Math | $0.448^{* * *}$ | $0.450^{* * *}$ | $0.392^{* * *}$ | $0.400^{* * *}$ |
|  | $(0.081)$ | $(0.078)$ | $(0.056)$ | $(0.057)$ |
| Peer SAT Verbal | $-0.146^{* * *}$ | $-0.144^{* * *}$ | $-0.148^{* * *}$ | $-0.150^{* * *}$ |
|  | $(0.048)$ | $(0.049)$ | $(0.047)$ | $(0.047)$ |
| Peer HS GPA | $-0.162^{* * *}$ | $-0.165^{* * *}$ | $-0.119^{* *}$ | $-0.123^{* *}$ |
|  | $(0.056)$ | $(0.054)$ | $(0.051)$ | $(0.051)$ |
| Mean $(Y)$ | .48 | .48 | .48 | .48 |
| $\sigma_{c t}$ | x | x | x | x |
| $\sigma_{c p}$ | x | x | x | x |
| Peer Chars. | x | x | x | x |
| Course Size |  | x | x | x |
| Ind. Controls |  |  | x | x |
| For. Non-Math |  |  |  | x |
| Obs. | 16,820 | 16,820 | 16,820 | 16,820 |
| R-sq | 0.05 | 0.05 | 0.10 | 0.10 |

Note: Sample is native freshmen students attending an introductory math course in their first term of college. 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 native 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 |
| $\sigma_{c t}$ | x | x | x | x | x | x | x | x |
| $\sigma_{c p}$ | 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 native 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 Bureaus 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: Short-Run Effects

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ | $(6)$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Withdraw | Grade | GPA | Math T+1 | STEM T+1 | For Sh. T+1 |
| Foreign Sh. | -0.01 | -0.01 | $0.04^{*}$ | -0.00 | -0.01 | -0.03 |
|  | $(0.01)$ | $(0.02)$ | $(0.02)$ | $(0.01)$ | $(0.01)$ | $(0.02)$ |
| Mean $(Y)$ | .12 | .13 | 2.78 | .87 | .93 | 0 |
| $\sigma_{c t}$ | x | x | x | x | x | x |
| $\sigma_{c p}$ | x | x | x | x | x | x |
| Peer Ability | x | x | x | x | x | x |
| Peer Chars. | x | x | x | x | x | x |
| Course Size | x | x | x | x | x | x |
| Ind. Controls | x | x | x | x | x | x |
| Obs. | 16830 | 14792 | 16830 | 16830 | 16830 | 16830 |
| R-sq | 0.061 | 0.21 | 0.23 | 0.080 | 0.049 | 0.33 |

Note: Sample is native 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. Withdraw measures if a student withdrew from the intro-math course after the first day. Grade is the letter grade received (e.g. A, A-, B+, etc.) in the intro math course. GPA refers to the overall GPA at the end of first term. Math T+1 and STEM T+1 refer to whether the student took a Math or STEM class in the following term. For Sh. T+1 is the average foreign share among all peers in courses attended in the following term (standardized to have mean 0 and sd 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 8: Heterogeneity Among Foreign Peers

|  | (1) Grad STEM | (2) <br> Grad SS | (3) <br> Grad AH | (4) <br> Dropout | (5) <br> Earn 0 | (6) <br> Earn 6 | (7) <br> Earn 11-15 | $\begin{gathered} \hline(8) \\ \text { Earn 26-30 } \end{gathered}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Panel A - Language Dissonance: |  |  |  |  |  |  |  |  |
| High Engl Dist Share | $\begin{gathered} -0.025^{*} \\ (0.014) \end{gathered}$ | $\begin{aligned} & -0.0042 \\ & (0.017) \end{aligned}$ | $\begin{gathered} 0.0067 \\ (0.0049) \end{gathered}$ | $\begin{gathered} 0.022^{* *} \\ (0.0094) \end{gathered}$ | $\begin{aligned} & -385.2 \\ & (352.2) \end{aligned}$ | $\begin{aligned} & -942.2^{*} \\ & (522.7) \end{aligned}$ | $\begin{gathered} -1167.9^{*} \\ (634.3) \end{gathered}$ | $\begin{aligned} & -758.0 \\ & (598.4) \end{aligned}$ |
| Low Engl Dist Share | $\begin{aligned} & -0.017^{* *} \\ & (0.0082) \end{aligned}$ | $\begin{aligned} & 0.019^{* *} \\ & (0.0083) \end{aligned}$ | $\begin{gathered} 0.0016 \\ (0.0039) \end{gathered}$ | $\begin{aligned} & -0.0049 \\ & (0.0055) \end{aligned}$ | $\begin{gathered} 68.6 \\ (184.5) \end{gathered}$ | $\begin{gathered} 116.8 \\ (291.7) \end{gathered}$ | $\begin{gathered} 145.8 \\ (367.7) \end{gathered}$ | $\begin{aligned} & -164.0 \\ & (407.4) \end{aligned}$ |
| Panel B - International vs. Immigrant: |  |  |  |  |  |  |  |  |
| Immigrant Stud. Share | $\begin{gathered} -0.047^{* * *} \\ (0.012) \end{gathered}$ | $\begin{gathered} 0.046^{* * *} \\ (0.016) \end{gathered}$ | $\begin{gathered} 0.0010 \\ (0.0068) \end{gathered}$ | $\begin{aligned} & -0.00011 \\ & \hline(0.0084) \end{aligned}$ | $\begin{aligned} & -146.1 \\ & (336.2) \end{aligned}$ | $\begin{gathered} -273.7 \\ (534.4) \end{gathered}$ | $\begin{gathered} -346.5 \\ (679.6) \end{gathered}$ | $\begin{gathered} -1095.1^{* *} \\ (486.2) \end{gathered}$ |
| Int' ${ }^{\prime}$. Stud. Share | $\begin{gathered} 0.015^{* *} \\ (0.0075) \end{gathered}$ | $\begin{gathered} -0.031^{* *} \\ (0.012) \end{gathered}$ | $\begin{gathered} 0.0070 \\ (0.0053) \end{gathered}$ | $\begin{aligned} & 0.0071 \\ & (0.012) \end{aligned}$ | $\begin{gathered} 60.9 \\ (318.1) \end{gathered}$ | $\begin{gathered} -79.2 \\ (508.1) \end{gathered}$ | $\begin{gathered} -85.5 \\ (636.6) \end{gathered}$ | $\begin{gathered} 690.5 \\ (561.3) \end{gathered}$ |
| $\operatorname{Mean}(Y)$ | . 48 | . 27 | . 08 | . 18 | 23230.85 | 38552.17 | 49729.47 | 52760.8 |
| $\sigma_{c t}$ | X | X | X | X | X | X | X | X |
| $\sigma_{c p}$ | 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 | 16,320 | 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 native 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 speaking languages very distant from English and the share of foreign peers speaking a language that is closer to English. In Panel B we examine separate impacts of immigrant students and international students with temporary student visas, such as F1 or J1. 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 9: Foreign Peer Effects on Different Native Groups

|  | (1) | (2) | (3) | (4) | (5) |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Female | Male | White | Asian | Minority |
| Grad STEM | $\begin{gathered} 0.00 \\ (0.01) \end{gathered}$ | $\begin{gathered} -0.05^{* * *} \\ (0.02) \end{gathered}$ | $\begin{gathered} -0.02^{* *} \\ (0.01) \end{gathered}$ | $\begin{gathered} -0.07^{* * *} \\ (0.01) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ |
| Grad SS | $\begin{aligned} & -0.02 \\ & (0.02) \end{aligned}$ | $\begin{gathered} 0.06^{* * *} \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ | $\begin{aligned} & 0.04^{* *} \\ & (0.02) \end{aligned}$ | $\begin{gathered} 0.03 \\ (0.02) \end{gathered}$ |
| Grad AH | $\begin{gathered} 0.01 \\ (0.01) \end{gathered}$ | $\begin{aligned} & -0.01 \\ & (0.01) \end{aligned}$ | $\begin{gathered} 0.01 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.00 \\ (0.00) \end{gathered}$ | $\begin{gathered} 0.03 \\ (0.02) \end{gathered}$ |
| No Grad | $\begin{gathered} 0.01 \\ (0.01) \end{gathered}$ | $\begin{gathered} 0.00 \\ (0.02) \end{gathered}$ | $\begin{gathered} -0.00 \\ (0.01) \end{gathered}$ | $\begin{gathered} 0.03^{* * *} \\ (0.01) \end{gathered}$ | $\begin{gathered} -0.07^{* * *} \\ (0.02) \end{gathered}$ |
| Earn 0 | $\begin{gathered} 58.16 \\ (311.90) \end{gathered}$ | $\begin{gathered} 135.00 \\ (573.02) \end{gathered}$ | $\begin{gathered} -86.55 \\ (357.62) \end{gathered}$ | $\begin{aligned} & -722.00^{*} \\ & (405.67) \end{aligned}$ | $\begin{gathered} 2288.17^{* * *} \\ (800.31) \end{gathered}$ |
| Earn 6 | $\begin{gathered} 207.00 \\ (445.47) \end{gathered}$ | $\begin{aligned} & -303.57 \\ & (921.24) \end{aligned}$ | $\begin{aligned} & -165.97 \\ & (576.86) \end{aligned}$ | $\begin{gathered} -1309.33^{* *} \\ (555.41) \end{gathered}$ | $\begin{aligned} & 3338.21^{* *} \\ & (1270.74) \end{aligned}$ |
| Earn 11-15 | $\begin{gathered} 230.14 \\ (544.66) \end{gathered}$ | $\begin{gathered} -364.49 \\ (1156.19) \end{gathered}$ | $\begin{gathered} 24.24 \\ (743.25) \end{gathered}$ | $\begin{gathered} -1918.34^{* * *} \\ (658.16) \end{gathered}$ | $\begin{gathered} 4366.76^{* * *} \\ (1631.64) \end{gathered}$ |
| Earn 26-30 | $\begin{gathered} -14.49 \\ (587.69) \\ \hline \end{gathered}$ | $\begin{gathered} -280.05 \\ (1065.63) \\ \hline \end{gathered}$ | $\begin{gathered} -64.98 \\ (702.95) \\ \hline \end{gathered}$ | $\begin{gathered} -1778.08^{* *} \\ (745.94) \\ \hline \end{gathered}$ | $\begin{aligned} & 4485.75^{* *} \\ & (1935.69) \\ & \hline \end{aligned}$ |
| $\sigma_{c t}$ | X | x | X | X | x |
| $\sigma_{c p}$ | 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 |
| R-sq | 0.09 | 0.10 | 0.10 | 0.10 | 0.17 |

Note: Sample is native freshmen students attending an introductory math course in their first term of college. Each column presents our analysis on native first-term freshmen, stratified by the characteristics indicated in the column headers. Minority refers to Latino and AfricanAmerican 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, ${ }^{* *} 0.05{ }^{* * *} 0.01$.

Appendix
Table A1: Exogeneity of Foreign Class Share: Foreign Students

|  | (1) <br> Female | (2) White | (3) Asian | (4) <br> Minority | (5) Black | (6) <br> Latino | $\begin{gathered} \hline \hline \text { (7) } \\ \text { SAT } \\ \text { Math } \end{gathered}$ | $\begin{gathered} \hline \hline(8) \\ \text { SAT } \\ \text { Verbal } \end{gathered}$ | (9) High School GPA | (10) <br> Composite <br> Admissions <br> Score |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Foreign Sh. | $\begin{gathered} -0.00 \\ (0.04) \end{gathered}$ | $\begin{gathered} -0.01 \\ (0.02) \\ \hline \end{gathered}$ | $\begin{gathered} 0.00 \\ (0.02) \end{gathered}$ | $\begin{gathered} 0.00 \\ (0.02) \end{gathered}$ | $\begin{aligned} & -0.01 \\ & (0.01) \end{aligned}$ | $\begin{gathered} 0.01 \\ (0.01) \end{gathered}$ | $\begin{gathered} 2.76 \\ (4.85) \end{gathered}$ | $\begin{gathered} -14.19^{* * *} \\ (4.11) \end{gathered}$ | $\begin{aligned} & -0.02 \\ & (0.02) \end{aligned}$ | $\begin{gathered} -52.13 \\ (31.70) \\ \hline \end{gathered}$ |
| Mean $(Y)$ | . 48 | . 12 | . 78 | . 1 | . 02 | . 09 | 617.89 | 491.18 | 3.72 | 7397.73 |
| $\operatorname{Std}(Y)$ | . 5 | . 3 | . 4 | . 3 | . 13 | . 28 | 87.09 | 104.15 | . 3 | 914.9 |
| $\sigma_{\text {ct }}$ | x | x | x | x | x | x | x | x | x | x |
| $\sigma_{c p}$ | 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 1 run on Foreign Students instead of Natives 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: Effects on STEM Graduation - Probit

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ |
| :--- | :---: | :---: | :---: | :---: |
| Foreign Sh. |  |  |  |  |
| 1.5 sd below mean | $-0.024^{* * *}$ | $-0.025^{* *}$ | $-0.025^{* *}$ | $-0.027^{* *}$ |
|  | $(0.007)$ | $(0.012)$ | $(0.012)$ | $(0.012)$ |
| 1 sd below mean | $-0.024^{* * *}$ | $-0.025^{* *}$ | $-0.025^{* *}$ | $-0.027^{* *}$ |
|  | $(0.007)$ | $(0.012)$ | $(0.012)$ | $(0.012)$ |
| 0.5 sd below mean | $-0.024^{* * *}$ | $-0.025^{* *}$ | $-0.025^{* *}$ | $-0.027^{* *}$ |
|  | $(0.007)$ | $(0.012)$ | $(0.012)$ | $(0.013)$ |
| At mean | $-0.024^{* * *}$ | $-0.025^{* *}$ | $-0.025^{* *}$ | $-0.026^{* *}$ |
|  | $(0.007)$ | $(0.012)$ | $(0.012)$ | $(0.012)$ |
| 0.5 sd above mean | $-0.024^{* * *}$ | $-0.025^{* *}$ | $-0.025^{* *}$ | $-0.026^{* *}$ |
|  | $(0.007)$ | $(0.011)$ | $(0.011)$ | $(0.012)$ |
| 1 sd abovemean | $-0.024^{* * *}$ | $-0.025^{* *}$ | $-0.025^{* *}$ | $-0.026^{* *}$ |
|  | $(0.007)$ | $(0.011)$ | $(0.011)$ | $(0.012)$ |
| 1.5 sd above mean | $-0.024^{* * *}$ | $-0.025^{* *}$ | $-0.025^{* *}$ | $-0.026^{* *}$ |
|  | $(0.007)$ | $(0.011)$ | $(0.011)$ | $(0.012)$ |
| Mean $(Y)$ | .48 | .48 | .48 | .48 |
| $\sigma_{c t}$ | x | x | x | x |
| $\sigma_{c p}$ | x | x | x | x |
| Peer Ability | x | x | x | x |
| Peer Chars. |  | x | x | x |
| Course Size |  |  | x | x |
| Ind. Controls |  |  |  | x |

Note: Sample is Native freshmen students attending an introductory math course in their first term of college enrollment. Table reports marginal effects from probit estimation. Values reported are marginal effects for values of foreign share at intervals (in standard deviations) relative to the mean, holding all other covariates at the mean. Standard errors in parentheses are clustered by professor. Significance levels: ${ }^{*} 0.10,{ }^{* *} 0.05 * * * 0.01$.

Table A3: Effects on STEM Graduation - Logit

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ |
| :--- | :---: | :---: | :---: | :---: |
| Foreign Sh. |  |  |  |  |
| 1.5 sd below mean | $-0.024^{* * *}$ | $-0.026^{* *}$ | $-0.026^{* *}$ | $-0.027^{* *}$ |
|  | $(0.007)$ | $(0.012)$ | $(0.012)$ | $(0.012)$ |
| 1 sd below mean | $-0.024^{* * *}$ | $-0.026^{* *}$ | $-0.026^{* *}$ | $-0.027^{* *}$ |
|  | $(0.007)$ | $(0.012)$ | $(0.012)$ | $(0.013)$ |
| 0.5 sd below mean | $-0.024^{* * *}$ | $-0.026^{* *}$ | $-0.026^{* *}$ | $-0.027^{* *}$ |
|  | $(0.007)$ | $(0.012)$ | $(0.012)$ | $(0.013)$ |
| At mean | $-0.024^{* * *}$ | $-0.026^{* *}$ | $-0.026^{* *}$ | $-0.027^{* *}$ |
|  | $(0.007)$ | $(0.012)$ | $(0.012)$ | $(0.013)$ |
| 0.5 sd above mean | $-0.024^{* * *}$ | $-0.025^{* *}$ | $-0.025^{* *}$ | $-0.027^{* *}$ |
|  | $(0.007)$ | $(0.011)$ | $(0.011)$ | $(0.012)$ |
| 1 sd abovemean | $-0.024^{* * *}$ | $-0.025^{* *}$ | $-0.025^{* *}$ | $-0.027^{* *}$ |
|  | $(0.007)$ | $(0.011)$ | $(0.011)$ | $(0.012)$ |
| 1.5 sd above mean | $-0.024^{* * *}$ | $-0.025^{* *}$ | $-0.025^{* *}$ | $-0.027^{* *}$ |
|  | $(0.007)$ | $(0.011)$ | $(0.011)$ | $(0.012)$ |
| Mean $(Y)$ | .48 | .48 | .48 | .48 |
| $\sigma_{c t}$ | x | x | x | x |
| $\sigma_{c p}$ | x | x | x | x |
| Peer Ability | x | x | x | x |
| Peer Chars. |  | x | x | x |
| Course Size |  |  | x | x |
| Ind. Controls |  |  |  | x |

Note: Sample is Native freshmen students attending an introductory math course in their first term of college. Table reports marginal effects from logit estimation. Values reported are marginal effects for values of foreign share at intervals (in standard deviations) relative to the mean, holding all other covariates at the mean. Standard errors in parentheses are clustered by professor. Significance levels: ${ }^{*} 0.10,{ }^{* *} 0.05 * * * 0.01$.

Table A4: Effects on STEM Graduation - Foreign Students

|  | $(1)$ | $(2)$ | $(3)$ |
| :--- | :---: | :---: | :---: |
| Foreign Sh. | -0.022 | -0.003 | 0.009 |
|  | $(0.030)$ | $(0.032)$ | $(0.029)$ |
| Mean $(Y)$ | .44 | .44 | .44 |
| $\sigma_{c t}$ | x | x | x |
| $\sigma_{c p}$ | x | x | x |
| Peer Ability | x | x | x |
| Peer Chars. | x | x | x |
| Course Size |  | x | x |
| Ind. Controls |  |  | x |
| For. Non-Math |  |  | x |
| Obs. | 3,840 | 3,840 | 3,840 |
| R-sq | 0.10 | 0.10 | 0.11 |

Note: Sample is foreign freshmen students attending an introductory math course in their first term of college. Regressions include course-by-term and course-byprofessor fixed effects. The 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. Foreign Share Non-Math refers to the average foreign share in non-math classes attended by first-term native freshmen. Standard errors in parentheses are clustered by professor. Significance levels: $0.10,{ }^{* *} 0.05 * * * 0.01$.
Table A5: Effects on Graduation Major, Robustness Controlling for Foreign Share in Non-Math Courses

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ | $(6)$ | $(7)$ | $(8)$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Grad STEM | Grad SS | Grad AH | No Grad | Earn 0 | Earn 6 | Earn 11-15 | Earn 26-30 |
| Foreign Sh. | $-0.0328^{* * *}$ | 0.0223 | 0.00531 | 0.00403 | -98.56 | -296.9 | -368.9 | -565.4 |
|  | $(0.0113)$ | $(0.0151)$ | $(0.00620)$ | $(0.00885)$ | $(315.5)$ | $(503.4)$ | $(621.7)$ | $(505.4)$ |
| Foreign Sh Non-Math Courses | x | x | x | x | x | x | x | x |
| Mean $(Y)$ | .48 | .27 | .08 | .18 | 23230.85 | 38552.17 | 49729.47 | 52760.8 |
| $\sigma_{-} t c$ | x | x | x | x | x | x | x | x |
| $\sigma_{-c p}$ | 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 | 0.1003 | 0.05979 | 0.02838 | 0.05738 | 0.09971 | 0.07896 | 0.07904 | 0.09606 |

Note: Sample is Native freshmen students attending an introductory-math course in their first term of college enrollment. Regressions include controls for 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,
 female indicator, race dummies, SAT Math and Verbal scores, and high school GPA. Standard errors in parentheses are clustered by professor. Significance levels: *0.1, **0.05 ***0.01.

Table A6: Impacts on Social Connections

|  | $\mathrm{T}+1$ | $\mathrm{~T}+2$ | $\mathrm{~T}+3$ |
| :--- | :---: | :---: | :---: |
| Any Future Course - All |  |  |  |
| Foreign Sh. | 0.354 | 0.172 | 0.031 |
|  | $(0.241)$ | $(0.166)$ | $(0.105)$ |
| Mean(Y) | 7.10 | 6.18 | 3.78 |
| Obs. | 16,830 | 16,830 | 16,830 |
| Any Future Course - Native |  |  |  |
| Foreign Sh. | 0.218 | 0.080 | 0.006 |
|  | $(0.209)$ | $(0.139)$ | $(0.086)$ |
| Mean(Y) | 6.15 | 5.36 | 3.31 |
| Obs. | 16,830 | 16,830 | 16,830 |
| Future Math Course |  |  |  |
| Foreign Sh. | -0.069 | -0.013 | -0.000 |
|  | $(0.089)$ | $(0.074)$ | $(0.076)$ |
| Mean(Y) | 4.98 | 3.41 | 1.16 |
| Obs. | 14,132 | 14,132 | 14,132 |
| $\sigma_{c t}$ | x | x | x |
| $\sigma_{c p}$ | x | x | x |
| Peer Ability | x | x | x |
| Ind. Ability | x | x | x |
| Peer Chars | x | x | x |
| Ind. Chars | x | x | x |
| Course Size | x | x | x |

Note: Sample is Native freshmen students attending an introductory math course in their first term of college. The dependent variable is the total number of overlapping students in future course discussion sections. Discussion sections are 20-50 student subsets of courses that meet once per week with a teaching assistant. For our primary sample, we count how many peers from their introductory are registered for the same discussion sections in future terms. Registering for the same discussion section is our proxy a social tie between students. Columns 1, 2, 3 look one, two and three terms into the future, respectively. Row 1 considers both foreign and native peers from intro math courses. Row 2 considers overlaps only with native students. Row 3 limits the sample to those students who take another math course at some point and counts only overlaps in math courses. Regressions include controls for course-by-term and course-byprofessor fixed effects, number of natives in the initial course, peer ability, peer characteristics, course size, and individual controls. Standard errors in parentheses are clustered by professor. Significance levels: $* 0.10$, **0.05 ***0.01.


[^0]:    ${ }^{1}$ See PISA (2015), for example.
    ${ }^{2}$ Altonji, Blom and Meghir (2012) show that even after conditioning on basic demographics and potential experience, the log wage gap between Mathematics/Computer Science majors relative to General Education majors ( 0.638 $\log$ points for males, $0.722 \log$ points for females) is even larger than the college vs. high school wage gap ( $0.577 \log$ points).

[^1]:    ${ }^{3}$ There have been a small number of inquiries into postsecondary education, however studies remain focused solely on international students. Furthermore, the key question of interest in this literature has been over whether international students crowd natives out of or into higher education (Hoxby, 1998, Borjas, 2004, Shih, 2016a). We are not aware of any studies that have examined impacts on intensive-margin outcomes in college.
    ${ }^{4}$ Recent statistics show that nearly $40 \%$ of foreign bachelor's recipients major in STEM, while the comparable figure for natives is only 31\%. See NSF Science and Engineering Indicators 2012: https://www.nsf.gov/statistics/seind12/c2/c2s2.htm

[^2]:    ${ }^{5}$ The remaining $30 \%$ that do not ever take one of these classes are very likely to be "never-takers", who know early-on that they have no desire to major in STEM. They satisfy the quantitative course requirement through another class (e.g. Statistics).
    ${ }^{6}$ Similar identifying strategies that rely on idiosyncratic variation include Carrell and Hoekstra (2010), Hoxby (2000) and Anelli and Peri (2016)

[^3]:    ${ }^{7}$ Non-freshmen students register for courses online in the prior term (or in summer for the fall term). Registration dates and times are allotted to students as follows. Students are divided into 4 bins according to accumulated credits normal for freshmen, sophomores, juniors, and seniors. Registration occurs according to bin rank-students in the senior bin register first, followed by the junior bin, followed by the sophomore bin, and finally the freshmen bin.

[^4]:    Within each bin, however, students are randomly assigned a registration date and time. Thus, while a junior will almost certainly register before a sophomore, there is no guarantee ex-ante that one sophomore will register before another sophomore.

[^5]:    ${ }^{8}$ 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.

[^6]:    ${ }^{9}$ Unfortunately, our data do not allow us to distinguish further between foreign-born permanent residents, citizens, and undocumented students. However, it is unlikely that the foreign peers we study contain many undocumented immigrants as much research has shown that undocumented persons disproportionately come from South and Latin America, with very few from Asia.
    ${ }^{10}$ For ease of exposition, we refer to these students throughout as "dropouts".

[^7]:    ${ }^{11}$ The sample of 25,912 include both the 16,830 native first-term freshmen, and other native students (e.g. sophomores, juniors, and seniors) enrolled in the introductory math courses.
    ${ }^{12} \mathrm{We}$ 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 SAT Verbal is significantly different from zero. A one standard deviation increase in foreign peers in a class is associated with a 14 point lower SAT Verbal score. Despite the statistical significance, the magnitude is relatively small (one-tenth of a standard deviation), such that we do not believe this small amount of selection is evident to students or making a meaningful difference in the

[^8]:    ${ }^{14}$ We performed robustness checks using logit and probit to evaluate the assumption of the linearity of the conditional expectation function. Results from logit and probit estimation, reported in the appendix tables A2 and A3. reveal that marginal effects are very similar in size to estimates from OLS, and consistent across the distribution of the foreign share. However, several papers (e.g. Greene, 2004) have shown that using logit or probit estimation with fixed effects can lead to biased and inconsistent results. Hence, we present our analysis using a linear probability model.
    ${ }^{15}$ Among the various control variables used, we only report coefficients for peer ability measures due to space constraints. Results of the coefficients on other control variables are available upon request from the authors.

[^9]:    ${ }^{16}$ 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. See the https://www.nsf.gov/ statistics/seind14/index.cfm/chapter-2/c2s2.htm\#s2.
    ${ }^{17}$ Multiplying 0.06 times 62 (the number of natives expected to graduate in STEM) yields approximately 3.7 natives displaced from STEM.

[^10]:    ${ }^{18}$ Due to no apparent "own" effect of foreign share on the likelihood of foreign students persisting in STEM in any of our specifications, we focus analysis and additional specifications on native students. Additional specifications for the foreign-born population are available upon request.
    ${ }^{19}$ In appendix Table A5 we show robustness checks for controlling for the foreign peer share in non-math courses taken by the native first-term freshmen.

[^11]:    ${ }^{20}$ Alternatively, this magnitude represents $1.3 \%$ of the average earnings gap of STEM vs non-STEM majors (around $\$ 7000$ annually at labor market entrance).
    ${ }^{21}$ To avoid compositional changes due to graduation or drop out, we use the following procedure. Each student's majors are observed until the term they graduate or dropout. If a student graduates or drops out prior to the 18th term, we assign their final major to all terms after their last term until the 18th term. Thus, the estimated coefficients will be identified only on individuals who either choose a non-STEM major, or switch away from a STEM major.

[^12]:    ${ }^{22}$ 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.
    ${ }^{23}$ This is consistent with the dynamic results of Figure 4 which shows the formal declaration of non-STEM majors does not begin to appear until the end of the 2nd year.

[^13]:    ${ }^{24}$ 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 2 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.
    ${ }^{25}$ An extensive report on foreign-born individuals in higher education (Erisman and Looney, 2007) found that 53\% delayed entry into college after high school, $33 \%$ supported dependents, $66 \%$ indicated English was not their primary language, and $62 \%$ were in the two lowest income quintiles.

[^14]:    ${ }^{26}$ Such studies include Gould, Lavy and Daniele Paserman (2009), Diette and Oyelere (2012, 2014), Ohinata and Van Ours (2013, 2016), Geay, McNally and Telhaj (2013), Brunello and Rocco (2013), and Ballatore, Fort and Ichino (2015).
    ${ }^{27}$ We utilize linguistic distance scores from Chiswick and Miller (2005). These range on a scale from 1 to 3, where 3 indicates languages close in proximity to English, and 1 indicates languages distant from English. While the details of how linguistic distance are described in Chiswick and Miller (2005), the measure is based on the difficulty an English speaker faces in learning the foreign language. 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.

[^15]:    ${ }^{28}$ See http://www.latimes.com/local/lanow/la-me-ln-uc-limit-nonresident-students-20170306-story.html for further details.
    ${ }^{29} \mathrm{We}$ also standardize the immigrant share and international student share, so that coefficients are can be interpreted as the impact of a 1 standard deviation increase.

[^16]:    ${ }^{30}$ For example, information on instructor evaluations would allow us to assess whether native students perceive changes in instruction quality when the foreign peer share is high. Unfortunately, this data was unavailable.

[^17]:    ${ }^{31}$ Specifically, each course has several different registration numbers associated with it. For example, a math course with 200 students, has around 10 different "sections" of the math course, which denotes different teaching assistant for the course. We measure the number of peers from introductory math that are enrolled together with an individual, not only in the same course, but the same section in the following term. This measure is our proxy for social interaction, since two students in the same introductory math course registering for the same section the following term is less likely to have occur by chance than those same two students registering for the same course.

[^18]:    ${ }^{32}$ For example, recent research indicates that restrictive immigration policies can reduce foreign student enrollment (Shih, 2016b). Recent reports indicate a decline in college applications from international students, potentially due to several recent immigration policies. See, for example, https://www.insidehighered.com/news/2017/03/13/nearly-4-10-universities-report-drops-international-student-applications.

