ESSAYS ON IMMIGRATION & EDUCATION ECONOMICS

by

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I would like to end with a verse from the Bible that sums up my experience in this program: *If any of you lacks wisdom, let him ask of God, who gives to all liberally and without reproach, and it will be given to him. (James 1:5, NKJV)*

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ABBREVIATIONS

Chapter 1

STEM	Science, Technology, Engineering, and Math
OPT	Optional Practical Training
Int.	International
SCI	Science
ENGR	Engineering
MGMT	Management
LIB	Liberal Arts
LCM	Lower than C-minus
hsgpa	highschool gpa
ratio int.	Share of international students among total number

Chapter 2

CBP	County Business Pattern
IPEDs	Integrated Postsecondary Education Data System
CBSA	Core Based Statistical Area
DID	Difference in Difference
OLS	Ordinary Least Squares

Chapter 3

Imm.	Immigrant Share
Frac.	fractionalization index
HS	Highschool

ABSTRACT

My three chapters are all related to the study of immigrants in how they impact the US economy. The first two chapters look at international students in particular and how they impact their domestic peers and the local college towns they reside in. The third chapter looks at immigrant workers and their effect on native workers' propensity to consolidate to form labor unions.

To be specific, the first chapter, titled *How International students Affect Domestic Students' Achievement: evidence from the OPT STEM-extension*, looks at the role of immigrants in shaping the educational outcome of domestic students pursuing STEM degrees in the United States. By utilizing the mass influx of international students after an immigration policy change (OPT-STEM-extension) in 2008, I investigate the peer effects that international students have on grades, attrition, and first-year salary of STEM graduates. I account for the common selection issues present in the peer-effects literature by looking at the yearly exogenous change in international student share in a specific course-instructor pair and controlling for rich individual ability and demographics. This was made possible by having access to administrative data of a land-grant university with one of the highest international student enrollments in the US. I find that international students tend to lower grades and persistence of domestic students in STEM. Still, this negative effect is more than compensated for in the increase in salary due to spill-over effects in learning for those who persist and graduate.

My research aims to eventually aid policymakers in both the local educational institutions and the federal government. To this end, I have extended my analysis of international students by shifting my focus outside the classroom to the local economies of the college campuses. In my second chapter, titled *International Students' Effect on Local Businesses*, I use the zip code-level Census data on small businesses to see how the influx of international students affected the regional college campuses. I find that international students have a significantly positive effect on job creation in the local economy. To my knowledge, this is the first data-driven-causal analysis of international students on local businesses in the US.

My third chapter is a co-authored work with Alex Nowrasteh and Artem Samiahulin titled *Immigrants Reduce Unionization in the US.* Here we attempt to relate immigrants to a more traditional labor economics topic: labor unions. Although there is a vast amount of literature on unions, we found that the literature that causally estimates immigrants' effect on unions is severely lacking in the US setting. Using a combination of representative data such as the CPS, Census, and the ACS, we show that immigrants accounted for about one-third of the decline in unions since the 1980s. We based our paper on the theoretical model of Naylor and Cripps 1993 and borrowed George Borjas's skill-cell method for our empirical method.(Borjas 2003)

1. HOW INTERNATIONAL STUDENTS AFFECT DOMESTIC STUDENTS' ACHIEVEMENT: EVIDENCE FROM THE OPT STEM-EXTENSION

1.1 Introduction

Economists have long been interested in the impact of immigrants on native workers' labor market outcome[1]. More recently, this analysis has been taken to the human capital acquisition phase (education phase). The question then becomes how immigration affects academic outcomes of domestic students. This question is especially important as academic outcome is a precursor to labor market outcomes. In the post-secondary education phase, domestic take-up of STEM is of particular concern as US citizens and permanent residents earning bachelors in science and engineering have not shown an increase and there are evidences that more students are avoiding highly technical STEM fields.[2] Insofar as the returns to a STEM degree is higher than non-STEM degree, the continual shying away from the hard sciences among domestic students is problematic as jobs increasingly reward highly technical fields such as computer science, engineering, and quantitative finance.[3] This implies that students are losing out on building key human capital that the economy demands in STEM fields and, in turn, technological growth will stall as firms have trouble finding skilled labor in their innovation frontier.[4]. On the individual level, taking up hard sciences are one of the few ways people move up the social mobility. Recent literature has focused on how taking (or lackthereof) of STEM majors contributes to bridging the inequalities in returns to college.[5]

Starkly contrasting the downward trend of STEM take-up among domestic students, there has been an upward trend of International students in recent decades in US higher

[1]↑ Borjas 1999Peri and Sparber 2011S. P. Kerr, W. R. Kerr, and Lincoln 2015 Peri, Shih, and Sparber 2015

[2]↑According to the Integrated Postsecondary Education Data System (IPEDS) , international undergraduate student enrollment in U.S. colleges rose 115% from 2003 to 2012, compared to a 10% increase in its domestic counterpart.

[3]↑altonji2012heterogeneity quantifies the premium technical fields offers compared to non-technical fields, wiswall2015determinants shows how labor market incentives of certain high paying majors such as STEM and Business induces students to switch majors

[4]↑deming2018stem shows how technological progress largely depends on the younger generation's take up of STEM

[5]↑ Some recent work shows how the gender wage gap is attributable to preferences for higher paying STEM majors among males more so than females. (Jiang 2021,Blau and Kahn 2017)

education. The types of international students that come to the US to study are from countries that better prepare students in Math and Science.[6] In particular, in between 2008 and 2016, the enrollment has sky-rocketed from 600,000 to over 1million.[7] As international students generally come to the US to major in highly technical fields, and at many large R1 universities,[8] they account for a sizable portion in enrollment, especially in STEM majors and they generally have higher comparative advantage in STEM than their fellow domestic peers in the same major.[9] This raises the question of how the two groups interact in a classroom setting under the same instructor, and in turn, how being exposed to more international peers affect one's labor market outcome upon graduating. In this paper I attempt to answer just this by causally estimating the effect of international students on domestic students' academic outcome in STEM fields in the college level, and the direct labor market outcome in terms of first year salary from these fields. My paper is distinguished from past related research in three main ways:

- I use a shock to the international student enrollment that took place as a result of a policy change in 2008. (OPT STEM-extension)
- Using rich admin data, I directly match a student' academic outcome and first year salary that is collected from the same student.
- I employ a tournament model with rank-concerns to study how higher competency in math drives the peer effects (as opposed to lower competency in communication ability).

From the data from the university whose administrative data I am using, I find that a 10 pp. increase in the share of international students in STEM courses decrease grades by about 0.06 on a 4-point scale. This effect is more clearly seen in courses that generally have a strict distribution of letter grades, or "curved" classes. There is little evidence that the

[6]↑The 3 largest internatonal student groups are Chinese, Indians, and South Koreans; China and Korea rank 1 and 7 in the Math PISA score while the US ranks 37.NCES

[7]↑please refer to figure 1 second panel.

[8]↑R1 universities are considered "Research-heavy institutions by the Carnegie Classificationcarnegie

[9]↑In the admin. data I am using they typically account for 20 to 30 percent of the total population depending on major, and their ACT math 3 points higher out of 36 compared to their domestic peers in same majors.

negative effect is through the lack of communication ability of internationals but the evidence is clear that it is through the big gap in the latent math ability between the domestic and international students. The lowering or the "crowding out" to lower grade has implications in persistence in STEM majors. On the other hand looking at salary outcome, international students help domestic students; a 10pp increase in share of internationals in a matriculating engineering major cohort increases salary by about a thousand dollars. In the theory section I attempt to explain why we find negative results in grades but positive results in salary. To this end, I reinterpret the tournament model with rank-concerns first devised by Hopkins and Kornienko 2004 and further refined by Tincani 2017.The rest of this section details relevant literature and the policy shock that I am using.

1.1.1 *Relevant Literature*

The study of international students' effect is part of the larger literature on how immigrants and immigrant children affect native's educational outcomes and decision. The literature on the effects of immigrants on domestics' educational outcome generally shows short-term negative effects. There are two main channels through which this may happen. The first channel is the general cultural discrepancy and the language deficiency of international students. For example Borjas 2000 shows how foreign born teaching assistant tend to adversely affect undergraduate academic performance in Economics due to lower verbal abilility compared to their domestic peers. Chin, Daysal, and Imberman 2013 documents how increase in bilingual peers necessitates school resources to accomodate them by creating separate programs, and Anelli, Shih, and Williams 2017 shows that linguistic dissonance is between international and domestic students is one factor that contribute to higher attrition among domestics out of STEM.

Although the language difficulties is a significant driver of negative peer effects, in settings where the international student is highly skilled, the larger channel of the effect may be the discrepancy in innate quantitative abilities of the two group. Generally, international students who come to the US major in STEM and as colleges compete to admit and retain the brightest talents, domestic students who under-perform in STEM fields compared to their international counterpart may be crowded out as the number of available openings in a given major is usually inelastic in the short run (Bound and Turner 2007). To this end, Barnett, Sonnert, and Sadler 2012 shows how immigrants earn higher grades on college calculus classes which are gateway classes to succeed in hard science and engineering majors. Hoxby 1998 shows that immigrants appear to displace Blacks and Hispanics from selective institutions. In a series of papers, Borjas shows the influx of international students in science and engineering majors reduces the number of domestics in the same majors, especially Whites (Borjas 2004,Borjas 2009). Most recently, Anelli, Shih, and Williams 2017 shows with a California school data that foreign-born peers crowd-out domestic students in STEM majors; one of their mechanisms being the comparative advantage of foreign born students in math.

Anelli, Shih, and Williams 2017 is the paper that is most closest to my paper in terms of methodology and data. Anelli, Shih, and Williams 2017 divides foreign students into two groups 1)International students and 2) foreign-born immigrants. Due to the nature of the institution they are analyzing, the main driver of the effect is the latter group whose math ability (as proxied by test scores) are lower than their domestic counterpart. My paper complements the paper's findings as I solely focus on the former group which is international students on student visas. These groups typically have higher math skills and may have a crowding-out effect both in the extensive margin (admission in to selective institutions), and intensive margin(increasing the attrition of domestic STEM majors).

The main reason why the literature on immigrant/international students primarily focuses on the verbal channel is due to the main driver of recent immigration from Spanish speaking countries.[10]. The recent surge in international students in US colleges are from a vastly different types of students; they are generally from a higher socioeconomic ladder in their respective countries and well prepared for college in the US.[11] Because of this trend, it has become easier to identify how the differential math skill of immigrant peers affect stu-

[10]↑For example, in Figlio et al. 2021, 61 percent of immigrant children in Florida schools were of Hispanic origin

[11]↑Both the evidence from PISA and the Admin data show this (NCES (accessed November 15, 2018))

dent outcome. The gradual increase in international students who fall into aforementioned category has gradually increased since the early 2000s, but starting in 2008 and up till 2016, it has sky-rocketed to unprecedented levels. I detail this shock in the next part.

1.1.2 *The Shock (OPT STEM-extension)*

Although both international students on student visas and immigrants are considered "immigrant" students in the general sense, I only focus on international students in this paper instead of immigrants or children of immigrants. In the literature, international students and immigrants or immigrant children are generally not distinguished; the former are in the US on a student visa while the latter are children of immigrants or are on their way to permanently settling in the US. I focus on this narrow sample of immigrants in higher education because of the unique policy change that has dramatically increased the number of international students on student visas; the policy change in the duration of Optional Practical Training.

Optional Practical Training(hereby OPT) is a program by the Dept. of Homeland Security that allows US educated foreigners to work in a US firm with their student visas for up to 12 months. Typically, foreigners need to secure a working visa such as (h1b) in order to work full time but the OPT obviates the need to go through the somewhat labyrinthine process of getting a working visa. [12]. OPT has been in existence since the early 1990s, but lobbyists from large tech firms have tried to convince the congress to increase the duration of it to be able to retrain foreign talent for a longer period and attract foreign workers to pursue a US degree in related fields. These corporations were mainly concerned about retaining talents in STEM fields as the demand for technical expertise grew larger than the supply of eligible native candidates. In 2008, the efforts by tech lobbyists paid off and the duration of OPT was extended for an additional 24 months, totaling 3years for international students graduating in STEM fields in the US. I will call this extension the OPT STEM extension, and this is the policy shock that I am utilizing in my paper.

The OPT STEM-extension was a powerful incentive mechanism for foreigners who were on the margin of pursuing a US college education. As most foreigners who pursue a US

[12]↑typically, applicants compete through a lottery from a limited number of yearly allotment

college education want experience working in the US, the policy change has dramatically increased foreigners who wanted to pursue a US education primarily in STEM fields. This is illustrated in Figure **??** and Figure 1.1. In the upper panel of Figure **??**, we see that international students on OPT dramatically increases sometime after 2008. In Figure 1.1, I break down international students by the two main student visa types they hold. F-1 visa is typically chosen for those who are full time students while J-1 visa is typically for those who are temporarily visiting as exchange students or scholars. The stipulation of the OPT policy says that only full time students who are on a F-1 Visa are eligible for OPT. J-1 visa holders are also eligible to work in the US through a separate job training program called the Academic Training(AT) that allows work for up to 18months. While the OPT was extended to 3 years in 2008, AT has not experienced such extension and hence we see a dramatic increase in the take up of F-1 visas as opposed to J-1 after 2008. This gives strong evidence that the OPT-STEM extension has had a labor market incentive for foreigners considering an education in the US. [13]

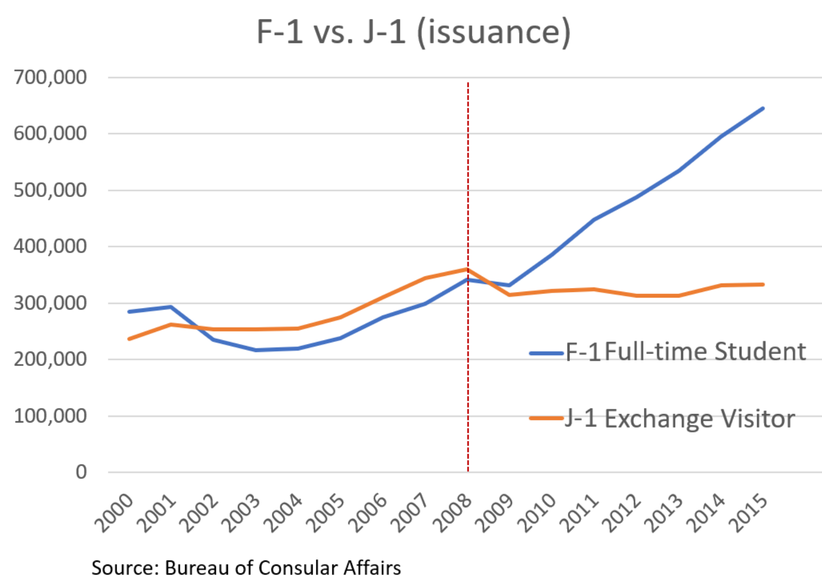

Figure 1.1. F-1 vs. J-1

[13]↑Please refer to the Dept. of Homeland Security Website for detailed info.u.s.

The enrollment effect of OPT STEM-extension has been studied and confirmed. Amuedo-Dorantes, Furtado, and Xu 2018 uses the National Survey of College Graduates to show that foreign-borns who graduate after 2008 have shown to graduate in STEM at a higher rate than those who graduated before 2008. Amuedo-Dorantes, Shih, and Xu 2020 show that not only has the OPT STEM-extension increased enrollment but increased the quality of the students who enrolled in US colleges based on the selectivity of institutions they attend. However, no paper has yet to study the causal effect that such increase in international students has had on domestic students' academic and labor market outcome. Past literature on the effects of international students were limited in their analysis due to the small sample size of true international students in the institution they are analyzing.[14] The closest one that attempts to causally estimate at the post-secondary phase is the Anelli, Shih, and Williams 2017 paper, but the paper mainly focuses on the immigrant group and not those on student visas.[15]. The benefit of using the OPT-STEM extension period is that there is large and a dramatic influx of international students which allows for exogenous shock and identifying variation in the shares of international students in differnete classroom settings. In sum, I bridge the gap in the immigration literature by using a unique international student shock to causally estimate the impact of international students on domestic students' achievements. In the next section I will detail my theoretical framework.

1.2 Theoretical Framework

In many literature that looks at the impact of immigrants on domestic student's outcome, the main driver of the negative peer effect is through disruption in learning due to lower communication skills and the diverging of school resources away from domestic students to help lower performing immigrant students. The aspect of increased competition between students brought by international students is not closely examined as the setting is mainly primary and secondary education and the types of immigrants that have generally seen an increase in these settings.

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[14]↑by *true* I refer to those students on student visas as opposed to immigrants in general.

[15]↑The paper does distinguish between the two groups, but the low sample size of international students on study visas prevents from doing a detailed analysis until more recently

In this theory section, I abstract away from the aforementioned channel through communication difficulties and explicitly consider the channel through increased competition between domestic and international students. The explicit assumption here is that international students generally have higher latent math ability than their domestic counterpart. This assumption is generally true however in research heavy universities and the university that I am analyzing. In order to put the problem in a competition framework I define exactly what the students are competing for. I claim that in my setting, college students who take the same course are competing for higher grades. This is especially true for so-called "weed-out" courses in hard STEM courses in early years of college (Freshman and Sophomore) and courses whose grade distribution strictly follows a set distribution.

To start, letter grades were originally meant to reflect the progress of one's educational achievement; an objective measure of proficiency in the subject. For better or for worse it has now become largely a measure of relative performance. Students and instructors generally use their class room peers as reference groups by which they measure their success. Therefore in one's utility function from education, there is an 1) own-achievement component and 2) a rank component. The former is determined by an objective measure of human capital that one has accumulated, and the latter is purely determined by how much one has accumulated relative to others. This bears a lot of resemblance to the framework created by Hopkins and Kornienko (2004) where they theoretically showed why people tend to overspend on goods that show his status even when it doesn't bring in direct utility. Tincani (2017) applied their model in an educational setting where students are putting in effort in classrooms with peers of different abilities and how rank-concerns create competition. In this theoretical section, I borrow the foundational work of Hopkins and Kornienko 2004, modify the Tincani 2017's application to fit my specific setting where domestic students are competing along with international students. [16]

To start, there are three main assumptions:

1. Their utility is increasing in own-achievement.

[16]↑For more studies on how tournament setting and rank-concerns create peer effects refer to Gill et al. 2019,Lazear and Rosen 1981,Brown 2011,Frank 1985,Sacerdote 2011

2. Their utility is increasing in their ranks.

3. There is minimal spillovers in learning.

4. International students' are on a higher distribution of math ability.

students differ in type a which is the productivity of effort (or ability). Type a is distributed in the c.d.f. $G(.)$ on $[\underline{a}, \overline{a}]$. The distribution of a is common knowledge. The cost function $c(\text{e}; a)$ is where higher a incurs lower cost for every effort, e (i.e., $\frac{\delta c(\text{e};a)}{\delta a} < 0$). Type a will be informally referred to as ability and in our data it is proxied by the students' ACT math component.

Effort increases achievement which is given by $y(\text{e}) = p(\mu)\text{e}$ where μ is the average ability of peers and e is effort. $(p(\mu))$ captures the technological spillover of your peer's ability as the returns to your effort is larger with higher ability peers. One example of this is a student asking relevant questions in class or helping a struggling peer do better in exams.In courses where students are competing for higher grades or when the coures size is very large, this parameter is irrelevant.[17]

The utility function is the product of two utility from own-achivement and rank:

$$U = V * R$$

$V(y, c)$ which is the utility for own-achievement is a function of achievement and cost. The utility from rank R can be rewritten as the c.d.f of achievement of your peers $F_y(y)$ from [0,1]. This is the fraction of students whose achievement is lower than your own. Because one's effort determines one's achievement $F_y(y)$ is identical to the c.d.f. of effort provision ($F_y(y)$=$F_\text{e}(\text{e})$).

Students choose effort level to maximize utility. At the symmetric Nash equilibrium of the game, equilibrium strategy is $\text{e}^*(a)$ and it is differential w.r.t. to a and has an inverse

[17]↑For this reasons this parameter will be very small or irrelevant in weed out courses in math and sciences in the 100 and 200 level where students are highly competitive and there is little to no interaction between students. This parameter becomes more important as students declare their specific fields and start interacting personally in smaller classes to work on homeworks or group projects. In the data, these classes generally appear in the 300-400 level.

function $a(\mathrm{e}^*)$. Therefore, rank in equilibrium can be rewritten as $G(a(\mathrm{e}^*))$. student i's utility is then $V_\mathrm{i}(y_\mathrm{i}, a_\mathrm{i})G(a(\mathrm{e}_\mathrm{i}^*))$.

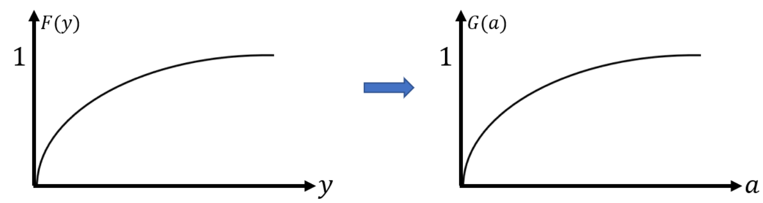

Figure 1.2. Distributional Equivalence

Taking the first order condition w.r.t. effort, we have the following:

$$\underbrace{V_1 p(\mu)}_{\text{Mg. learning}} + \underbrace{\frac{V(y,c)}{G(a(\mathrm{e}_\mathrm{i}^*))} g(a(\mathrm{e}_\mathrm{i}^*))(-a^{'}(\mathrm{e}_\mathrm{i}^*))}_{Mg.\Delta rank} = \underbrace{-V_2 \frac{\delta c}{\delta \mathrm{e}^*}}_{\text{Mg.Cost}} \tag{1.1}$$

This equation shows that the marginal utility of learning together with the marginal utility of increased rank is equal to the marginal cost of effort in the symmetric Nash equilibrium of the game. Further assuming that the marginal cost function is convex so that it takes more cost to increase the same amount effort at an already higher effort level than lower ($\frac{\delta(Mg.Cost)}{\delta \mathrm{e}^*} > 0$). Using this relationship, we can make implications on how effort level changes as we change the change ability distribution $G(.)$. We can derive several testable propositions:

- **Prediction 1**: With the influx of international students, there is an overall shift of the ability distribution to the right so that the new distribution G_B first order stochastic dominates by the old one G_A ($G_A > G_B$). In such case, we will see an increase in effort provision across all ability spectrum.

The more formal proof of this proposition is outlined in Hopkins and Kornienko 2004, but to give the readers an intuition on the results, take Figure 1.3 as an example. The top two graphs exemplify ability distribution of domestic and international students respectively. The bottom graph shows what the distribution may look like with the combination of the two. You can see that it is similar to the case with only domestic students but the distribution has shifted slightly to the right with the right significantly higher density towards the right

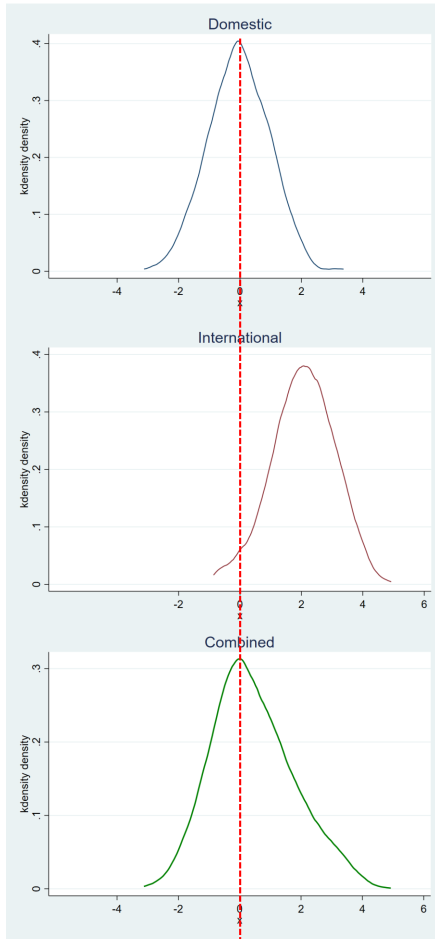

Figure 1.3. Combination of the Two dist.(simulation)

of zero. This will cause students of all ability levels to increase more effort as it has become more difficult to secure a higher rank, or grade.

Going back to equation (1.1), we can see that a shift of distribution from G_A to G_B causes the marginal utility of increased rank ($Mg.\Delta rank$) to get bigger. In such scenario, the F.O.C of Nash equilibrium strategy shows that the Marginal cost of effort ($Mg.Cost$) is higher and hence the effort level is higher in equilibrium. ($\frac{\delta(Mg.Cost)}{\delta e^*} > 0$).

- **Prediction 2**: Let us first divide the ability distribution so that we have 3 types: low, middle, and high. With the influx of international students, there is an increase in the density of students to right of the ability distribution. In such case, there is an overall increase in effort provision but the increase is higher among the higher distribution as the density of peers with similar ability ($g(a)$) is higher. The middle type will have less increase in effort compared to the high type, and the increase among those who are in the very low end is uncertain.

Going back to equation 1, we see that an increase in density $g(a)$, all else equal, increases the marginal returns to increased rank and hence increases effort (similar to the logic in proposition 1). The intuition is that if you have peers that are more similar to you a small increase in effort will get you far ahead of them and increase your chances of a higher rank (grade). Using data from our focal institution, in figure 3, we see that ACT score has gone up overtime with the influx of international students with the highest increase in density coming from the upper end of the distribution. Figure **??** gives evidence that the increase in density in the upper distribution is driven by international students as they, on average, have higher latent ability in Math. For the middle type, the density of peers has neither increased nor decreased so the rate of change of effort provision will be lower to that of high types. For the low types, on one hand, there is less number of peers among the lower end so that utility from increased rank is lower. On the other hand, the probability of zero rank ($G(.) = 0$) is higher in which case it is better to put in higher effort to avoid this fate.
To illustrate what could happen with the influx of international students with higher ability, in Figure **??** , I have simulated 1000 observations of domestic students and 300 observations of international students whose ability is distributed to the right of the domestic. In the third panel of Figure **??** , we see that the influx of international students creates a resulting distribution that is similar to the first panel (domestics), but with a fatter right tail which indicates the higher types have more people they are competing with than before the influx.

Equivalent real-life variables to model parameters

To summarize, in the data, I use ACTmath as the proxy for students' ability. Grades in individual courses are ranks. That is controlling for the domestic students' ability and the structure of the course, if grades decreased, then it is an indication that some exogenous factor has crowded them out to a lower distribution of Grades and hence the student's utility from rank decreases proportionally. The exogenous change in the distribution is the influx of international students with higher math ability. Finally, effort provision is best measured by the salary data. Given that the ability measure and demographic characteristic of domestics students are kept constant over time, if domestic students with higher shares of international peers earn a higher salary, then it is indication that they have put in a higher effort that translates to higher accumulation of human capital that the labor market rewards. The strong assumption is that the spill over effect in learning that effects salary is trivial and the salary increase mostly driven by individual's higher effort provision due to competition.

1.3 Data and Methodology

1.3.1 Data

Figure 1.4. Trend of ACT math Scores by College

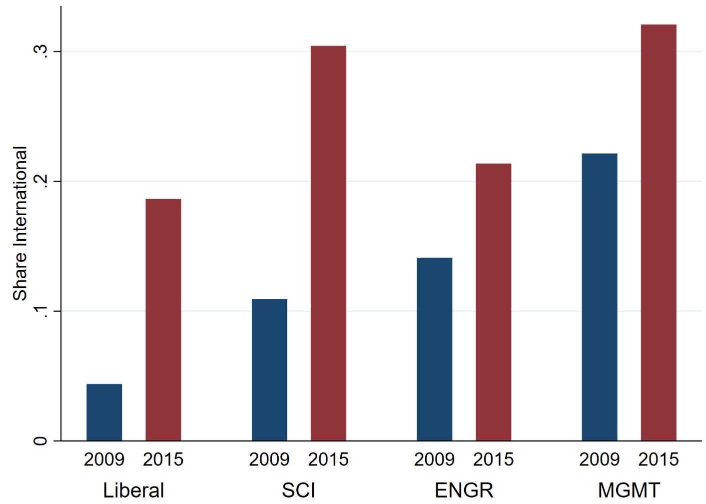

Figure 1.5. Increase in Share Int. by College

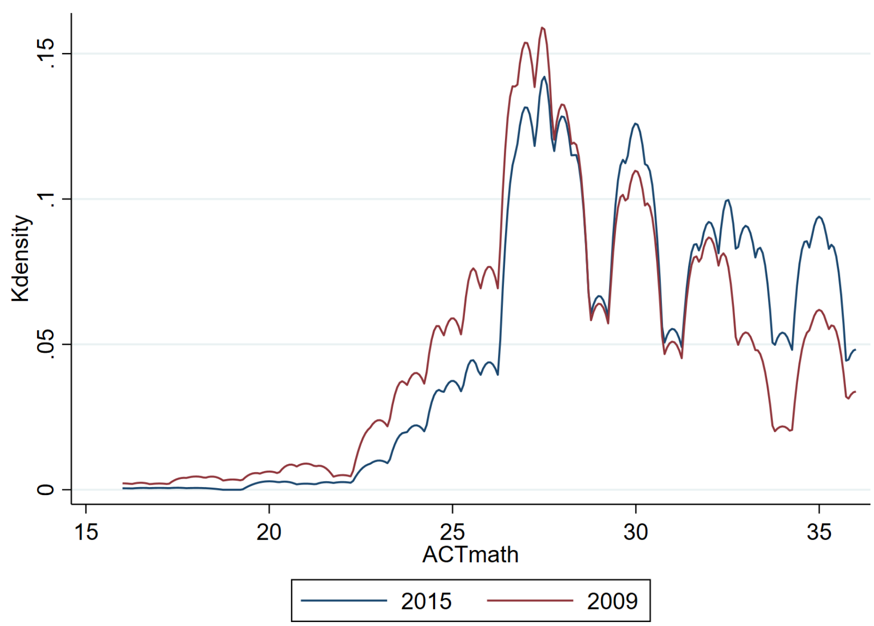

Figure 1.6. Density of ACTmath across Time

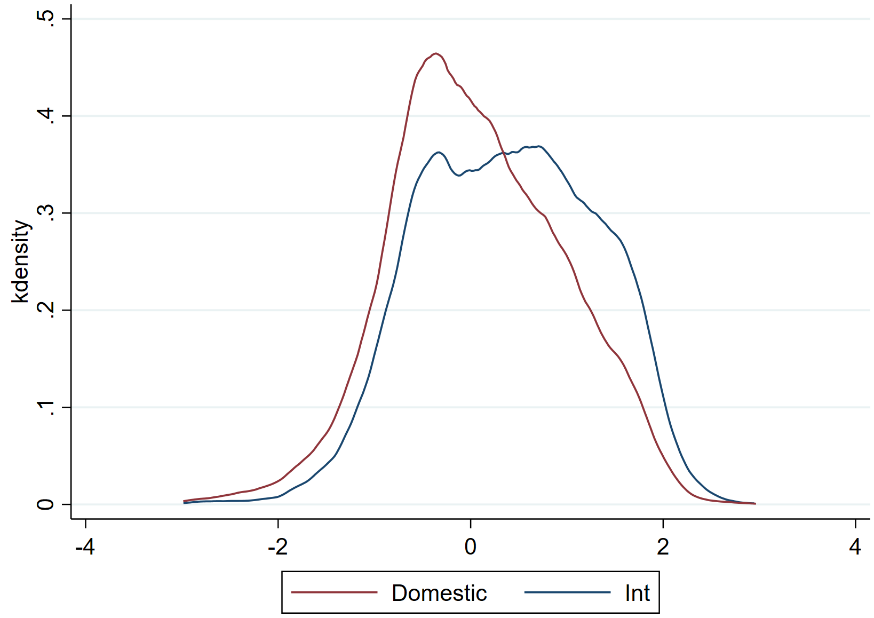

Figure 1.7. Density of Std. Diff in ACTmath by Nativity

The main dataset I use is an administrative data from a large public university in the Midwest region of the US. There are helpful characteristics about the said institution that aids the analysis. First, it is a land grant university that focuses heavily on STEM education which attracts international students high in math skills from all over the globe in a large scale. It is home to about 40,000 students 15% of whom are internationals. Secondly, the domestic student body is a relatively homogeneous group of people mostly consisting of local residents who would have had little exposure to international student peers before they entered college. For example, according to the institution's website about 70 percent of domestic students are from the same state that the school resides in which has 1 percent of immigrants overall. The scale of the international student body that domestic students are suddenly exposed to will allow the peer effects to be strong and identifiable.[3] For each semester starting Fall of 2008, the data show all the courses offered in that year with the information of each students taking the course. For most of my analysis I only focal period is from Fall 2008 to Spring 2015. This is when the increase in international students was

[3]↑Although these are some added benefits of using the data from this specific school, it is not the main identification strategy of the paper as there is no way to formally prove and identify specific domestic students who are suddenly exposed to international students when they enter this particular college.

the largest and also the data becomes more sparse for students who are enrolled after Spring 2015. The data also contains a rich set of individual characteristics that include students' gender, race, test scores, and majors. It also has useful outcome measures such as grades in each course, graduation major, and salary of students' first job upon graduating; albeit only 1 out of 3 graduates reported it.[18].

Sample Restrictions

Although looking at all majors and courses are helpful, it is useful to limit our scope to certain courses taken by students in certain majors to see if the effect of competition is more clearly seen in courses and types of students who align more to our model environment in our previous section. For this reason, I have started my analysis with a pool of all students, but eventually narrowed my analysis down to just engineering students. This is helpful as we are keeping constant the types of students that interact with international students (engineering students are take core science courses). The fact that engineering is the most popular major(1/5 students pursue engineering in this shcool) and that students who major in engineering are the most competitive in terms of math ability creates an apt environment to see how the two groups interact.

Ability Differences

The summary statistics on some key variables in shown in Table 1.1. Several take-aways from the Table 1.1 is that international students generally flock to engineering at a higher rate and have a higher math ability as proxied by their ACT math score. They also have lower verbal ability compared to their domestic peers. Also, the salary of engineers are higher on average; in fact, out of all majors, engineering majors have the highest salary in this institution. In Figure 1.4, I have taken the average of the ACT math scores of international and domestic students by year and by all courses offered in the specified colleges; SCI is for science, ENGR is for engineering, MGMT is for management, and CLA is for College of Liberal Arts. There is a general increase in the average math score over time for this

[18]↑In the appendix, I show if there is any selection of students who take the survey based on observable characteristics and show that it isn't a threat to trustworthiness of the data

Table 1.1. Summary Statistics

	All Students		Engineering Matriculants	
	Domestic	Inter.	Domestic	Inter.
Female	0.45	0.34	0.25	0.19
Non resident	0.29	n/a	0.52	n/a
Black	0.032	n/a	0.019	n/a
Hispanic	0.036	n/a	0.041	n/a
Asian	0.056	n/a	0.078	n/a
ACT math	24.5	29.8	29.2	30.7
ACT reading	44.5	38.35	52	41.2
Hsgpa	3.55	3.50	3.79	3.61
Salary(inflation ad.)	57,000	66,700	68,400	70,600
GPA(undegrad)	3.16	3.21	3.18	3.20
Observations	51,310	6,422	6,565	1,600

Note: means are for all courses taken either by domestics or international students. International student's race is not recorded precisely hence I have omitted them. Engineering matriculants are all students who have entered into a first-year engineering program. The observation numbers are for the general population for each column. Some variables such as hsgpa is dramatically lower for international students as many of them have not attended highschool that goes by the 4 point system.

Table 1.2. Persistence in the Discrepancy of Math Ability

DV: ACTmath	(1) original	(2) demo	(3) Term_College	(4) courseID
International (0,1)	5.432***	5.409***	4.332***	3.724***
	(0.0137)	(0.0129)	(0.0126)	(0.0123)
Demo.control		x	x	x
Term+ College FE			x	x
CourseID FE				x
>=				
Observations	1,420,745	1,420,745	1,420,744	1,420,565
R-squared	0.100	0.229	0.312	0.383

Note: Demographic control include gender, nonresident domestic, black, Hispanic, and Asian. Standarderrors in parentheses **p<0.01, ** p<0.05, * p<0.1

institution; however, we see that the gap between two scores of the two groups (int, and dom) persists over time.

In Figure 1.5, we see that across all colleges, there has been an influx of international students from 2009 to 2015, but the increase has been mostly seen in science coureses (SCI)[19]. Figure 1.6 illustrates most clearly the model prediction of what happens when there is an influx of international student whose ability is on a higher distribution. Figure 1.7 shows that the distribution of students ability has shifted to the right and that the right tail has become fatter with higher ability students concentrated score range that is above 30. This happened in tandum with the increase in international students as we have seen in Figure 1.5. Figure 1.7 shows that the general shift in the ability distribution is driven by international students. The Figure shows the distribution of students in hard STEM courses (math and physics) in terms of the standardized distance of their ACT math score to the mean of the specific course

[19]↑There are not many courses with the ENGR heading as many required coureses of engineering majors are in the college of Science

they are taking. We see that within a course, international and domestic students have very different distribution as predicted by the model. [20]. To quantify the average discrepancy in the math ability of the two groups across all majors and courses, I have run a regression with *ACTmath* on the dependent variable with the i*nternational* dummy which indicates that the student is either international or domestic. We see in column 1 of Table 1.2 that the two groups have an unconditional difference of ACTmath score of about 5.4. Once we control of demographic factor, term, college, and couresID fixed effects, the difference still remain and it is about 3.7 which is sizable given that 1 standard deviation of ACTmath score of all engineering majors are about 3.5; international students are a whole standard deviation above their domestic counterpart who are taking the same courses and under the same broad major category.

The evidences from the data clearly indicate that international and domestic students' math ability are on a different distribution, the former being higher in however we slice the data. Although the summary statistics I have discussed that show the ability differences between the two groups cannot be generalized to all institutions, I presume this trend can be generalized to other large land-grant universities with large STEM programs.

1.3.2 Methodology

I employ two main strategies to get a causal estimate of international students. The first is conveniently focusing on the post 2008 period when the OPT STEM-extension caused a shock to international student enrollment. The second one is controlling the unit of analysis to a instructor-course pair so that we are keeping constant the type of class and the grading criteria of instructors overtime.

The focal time period is between 2008 and 2016 which is after the OPT-STEM extension when there was a massive influx of international students across US colleges. Figure 1.1 shows the evidence for this increase. The graph shows a trend line of total number of Visas issued by the US immigration office for the respective Visa categories. Both F-1 and J-1 Visas are given to foreigners who want to study in the the US. However, the former allows

[20]↑I have only used math and physics courses, but this dichotomy is seen even with the inclusion of all other subjects both in STEM and non STEM

them to work in a US firm after graduation while the latter prohibits them. J-1 Visas are usually for cultural exchange or short term visits. One can see why there is a spike in F-1 Visa after 2008 compared to J-1; it is due to the newly promulgated legislation that allows international students to extend their working period in the US after graduation. This spike is also consistent with past work on the impact of OPT STEM extension on international student enrollment (Amuedo-Dorantes, Furtado, Xu, et al. 2018,Shih 2017).

In the literature that looks at the impact of immigration, the dependent variable is domestic outcome such as employment or wages and it is regressed on the share (ratio) of foreign workers in an industry or region. Whatever effect the domestic worker receives works through the share or "ratio" of the foreign workers that they are interacting within a defined setting.[5] I borrow this framework in my analysis; in this case, the domestic worker will be replaced by domestic students and the foreign worker will be replaced with international students.

My benchmark regression is:

$$Outcome_{\text{ict}} = \beta RatioInt_{ct} + X_{\text{i}} + \mu_t + \gamma_c + \rho\zeta_{ct} + \epsilon_{\text{ict}} \tag{1.2}$$

Variable Definition:

- $Outcome_{\text{ict}}$: Academic outcome of domestic student i in course-by-prof.(CBP) pair c that they are taking at time t. Outcomes are **Grades and Salary**[21]
- $RatioInt_{ct}$: It is simply the number of international students(Int) over total number of students($Total$) in course-by–prof pair c: ($RatioInt_{ct} = \frac{Int}{Total-1}$).[6]
- X_{i}: controls (race, gender, and own ability measure (ACT, hsgpa))
- μ_t : term fixed effects (without summer)
- γ_c: course-by-prof.(CBP) fixed effects.

[5]↑ This is called the linear-in-means specification since the explicit assumption is that the dependent variable is linearly correlated with the mean of the independent variable; in our case the share of internationals.
[21]↑I also look at attrition, retake rates, failure rates, but the primary dependent variables I use are Grades and Salary
[6]↑I subtract one from the denominator to exclude the domestic student i from the total.

- $\rho\zeta_{ct}$: Avg. ACT math score, Avg. highschool GPA, and Classsize of a course-by-prof.(CBP) in time t. [22]

($Outcome_{ict}$) is academic outcomes of domestic student i in course-by-prof.(CBP) pair c that they are taking at time t. When I refer to "class," it means a specific c in a given term. Outcomes are **Grades and Salary.** I regress these on my explanatory variable ($RatioInt_{ct}$) which is simply the number of international students(Int) over total number of students($Total$) in courseID-Prof pair c: ($RatioInt_{ct} = \frac{Int}{Total-1}$).[7] ($X_i$) controls for race, gender, and test scores. (μ_t) is term fixed effects (without summer). (γ_c) is CBP. fixed effects. Finally, for some specifications, I control for student i's peer characteristics($\rho\zeta_{ct}$), which include ACT math and reading scores of others in the class, and a variable indicating class size. I detail below how all these terms constitute my identification strategy.

The linear-in-means specification of this form is biased due to the endogenous peer group selection as detailed in Manski.[8] It becomes a problem when the ratio of international students in a class is not random, but correlated with what is in the error term that also affects domestic outcome. An example might be instructors that attract more international students and who happens to also affect the learning of domestic students; the literature calls this the "correlated effect." Another potential issue is when there are certain demographic, or individual characteristics correlated with international students that I am not controlling for. For example I could erroneously attribute the effects to be coming from increased share of international students, when in fact, it may be coming from an increase in the share of males in classroom assuming most international students are male. The literature calls this the "contextual effect." Next, I will explain how I have addressed both the correlated and the contextual effect.

[22]↑ I omit this for most of my specification as we are identifying our effect off of the differences between the peer's ability

[7]↑I subtract one from the denominator to exclude the domestic student i from the total.

[8]↑Although the mechanical set up of the equation does not allow for the reflection problem(simultaneity), the correlated(omitted variable) and the contextual effects(lack of controls) still needs to be addressed.

1.3.3 Correlated effects

Many peer effects literature exploit exogenous shocks that reduce any potential omitted variables that are correlated with both the outcome and explanatory variable. The best way to eliminate this bias is to run a randomized experiment where the experimenter has full discretion in how the peer group is formed. An example of this is randomized roommate assignment in college dorms.However, such experiments are hard to run in large scales and also has ethical boundaries in other settings. Another common approach is to use policies that more or less endogenously varies the composition of peer groups. Examples can be the Boston METCO program, and other desegregation policies that brings in exogenous variation in peer composition. The assumption in this identification strategy is that these policies introduce exogenous shocks to the peer composition once we control for all observable characteristics of the students. The strategy I use in this paper is the latter where I use the OPT STEM extension as an exogenous influx of international students in a classroom in US colleges including the one I am analyzing. As with most variation that relies on a policy change, the identification is messy. for instance, it is hard to identify which international students came as a result of the policy change and which of them would have come anyways (always responders); including the latter group with the former group will violate exogenity. Therefore, I reinforce my identification by relying on a rich set of fixed effects. To be specific, by including the CBP fixed effects(γ_c), I allow the identifying variation to come from the changes in the international student ratio ($RatioInt_{ct}$) within a specific course taught by a specific professor. I call the unique Course-by-professor(or CBP) pair as c in my regression.[9] Furthermore, I control for the term fixed effects (μ_t) that will control for any term-specific trends in both the outcome (grade, graduation, and salary), and the explanatory variable ($RatioInt_{ct}$).

[9]↑A potential bias will remain if high ability domestic student strategically wait for the optimal term when the class has the lowest share of internationals. However, this is unlikely as it is hard to predict next year's share of international students in a certain CBP pair.

1.3.4 Contextual effects

Another threat to my identification is the contextual effect. This is minimized by controlling for rich individual characteristics to allow apples-to-apples comparison of domestic students across terms within the CBP pair. First, (X_{i}) controls for basic demographic characteristics that include dummies for Gender; Black; Asian(domestic) and non-resident domestic. In addition, the term includes own-ability measures as proxied by the individuals' scores in ACT math and reading. By controlling for their test scores, the ability of domestics students we are comparing across time are fixed constant. I also control for ($\rho\zeta_{ct}$) which are characteristics of a students' peers in the courses they are taking. These include others' ACT scores in math and reading, and class size. By controlling for ($\rho\zeta_{ct}$) I am essentially holding fixed the students' ability and the average ability of her peers across terms within the CBP pairs. [10]

1.3.5 Testing for Selection

In order to determine which controls to include in the regression to mitigate selection on observable, I estimate the regression similar to equation 1; instead of having academic outcome on the dependent variable, I regress the domestic students' time-invariant background characteristics(or *Background*) on the international student ratio with time and course-professor fixed effects.

The regression is of this form:

$$Background_{\mathrm{i}} = \beta RatioInt_{ct} + \mu_t + \gamma_c + \epsilon_{\mathrm{i}ct} \tag{1.3}$$

The variable definition for each greek letter is the same as equation(2.2). I run separate regression for the following background characteristics: $ACTmath$, $ACTreading$, $highschoolGPA$, $gender$, $domesticNonresident$, $black$, $asian$, and $hispanic$. Table 1.3 shows

[10]↑I also include own-grade, and other's grades for the salary outcome. By doing so, I am not only controlling for the grades of domestic students across comparison groups, but also forcing each i's grade and her peer's grades to match. As grades are important determinants of employment (salary) in some fields, controlling for it will allow us to see if there are any other channels international peers impact domestic salary other than through impacting the domestics students' grades.

the different coefficient estimates on $RatioInt$ for each regression. The values are scaled so that it shows the change in the dependent variable for a 10 percentage point (pp) increase in $RatioInt$. If coefficients are statistically and economically significant, it may indicate that domestic students with said characteristics either select into (or out of) classes with higher $RatioInt$. For example, $ACTmath$ only changes by -0.00149 points with a 10 pp increase in $RatioInt$ which is not economically significant. On the other hand, for $gender$, there is a 1 pp increase in female for every 10 pp increase in $RatioInt$. The stronger the relationship between the depenent and $RatioInt$, the more important it is to include the variable as a control in my original benchmark regression. By doing so, I am essentially controlling for selection of domestic students based on these observable background characteristics. The results of this regression is shown in table 14 at the end of the concluding section.

1.4 Results

The result section is mainly divided in two large sections. The first section concerns the outcome on Grades while the second section is on first year Salary outcome.

1.4.1 Grade Outcome

The Grade outcome is divided into several steps. First, I show a big picture of how domestic students fare in different colleges which are Science, Engineering, Management, and Liberal arts; four of the biggest colleges in the institution. The first two colleges consists of classes that are highly technical and the latter two are less technical and generally considered non-STEM subjects. In the second step, I restrict my sample to engineering students who take the biggest portion of the students by major types. This is useful as there may be big shifts in the composition of types of domestic students taking STEM courses; if we only focus on students in one major, then we keep the environment and sample types somewhat consistent overtime. This also has the added benefit of making our environment closer to the theoretical model where one's math ability is highly predicts success and there is ample competition between the domestic and international students.

The courses in the sample are further restricted to core-science courses that all engineering students have to take in their first two years. These courses are further divided into highly technical courses and less technical courses In the last step, I further divide the courses engineering students take by either curved or non-curved courses. This is to show that classes where instructor grade on with a strict distribution is where we would see the effects of competition or crowding out of domestic students; these courses are also where the utility that comes from relative ranking is more salient. Finally, I look at heterogeneous effect by ability types of domestic students to see if the second prediction of theory holds; middle types putting least likely to put in effort compared to low and high types.

All courses

To start, in Table 1.4, we see that a 10 pp. increase in ratio of international student decreases grades by -0.027 (out of 4 point scale) for domestic students taking courses in either Science or Engineering. The negative effect is not significant for courses in Management and Liberal Arts which indicate that the lower verbal ability of international students do not necessarily harm the learning of domestic students in non-STEM courses.

Only STEM courses

In Table 1.5, I have limited the analysis just to science and engineering courses since the negative crowd-out effect is seen in these two colleges. Dividing by the level of the course, we see that 100-200 level courses experience the largest crowd-out effect into lower grade; a 10pp increase in ratio of int. causes a -0.03 decline in grades for these courses. Once the student makes it to 300-400 level courses the negative effect is less severe. This indicates that the negative effect is mostly present in the first 2 years of courses in STEM due to the more rigorous nature of these courses; many of these courses have strict curves and weed out students who are not prepared to go on their majors or programs. The reason we see less of a negative effect in later stages may be due to the domestic students' increased learning or positive spill-over effects from international students as the two groups interact more frequently in smaller class sizes. We also cannot rule out the mechanical channel of selection where students who have passed the 100-200 level courses make it into 300-400 level courses that are more advanced. For these reasons, it is difficult to parse out the portion of the effect that comes from higher competition from other peer effects in higher level courses. Hence, I focus on 100 and 200 level courses from this point on.

Core Science courses

In Table 1.6, I have limited the analysis to only engineering students. I also further limit courses to core science courses these students need to complete in order successfully declare a field within their majors. The core science courses include physics, math, biology, chemistry, and computer science; the detailed course-title can be found in table 7. Students need to do well in these core science courses in order to remain in engineering or they will have to switch to a different major. The soft criteria is that students should not receive less than a C- in any of these core courses and maintain a GPA of 2.0 across all the courses.[23].

In Table 1.6, the columns are clustered by subjects depending on how much ACTmath or ACTreading is a predictor of getting a high grade. In Table 1.7, I regress Grade on the two predictors, ACT math and ACT reading. We see that ACT math is a better predictor of success in Math and Physics as opposed to Chemistry and Biology. I refer to Math and Physics core courses as Hard STEM and the Chemistry and Biology coureses as Easy STEM to distinguish the level of technical difficulties. We see that in Table 1.6 that the Hard Stem courses show a high crowd-out effect while the effect is not present in Easy stem courses. In the third column consists of two general education courses that all incoming engineering students have to take which are communication and English composition. These two courses are non-STEM courses and emphasize one's reading and communication skills. The absence of any negative effect in these two courses corroborate the intuition that lower verbal ability of international peers do not hinder learning in college-level courses that are non-STEM in nature.

Curved courses

In this next set of results, we further narrow our scope to courses that are graded on a strict distribution (curved). This best mimics the model environment where one's relative ability is what predicts ranking (grade). In order for this to happen, instructors have to

[23]↑This criteria is soft in the sense that depending on the availability of seats in various engineering fields, the school will give flexibility on who marginally do not meet the standards

mainly consider the students' relative performance to their peers and give grades according to pre-determined distribution which is typically in the A range for the those who are in the top quartile; B for those who are in the middle two quartile; and C or below for those who are in the last quartile.

The first step is to determine whether a course-by-professor (CBP) pair is a type of class that is curved. In order to roughly determine this, I divided each CBP pairs either as grading on a "strict distribution(or curved)," or "variable distribution." Some instructors may strictly abide by a set their distribution, but rarely do instructors strictly grade by absolute scale devoid of any curves. In reality, grading scheme is not binary but falls in the continuum between a curve and an absolute scale. However, in order determine which classes are closer to grading on a strict distribution, I have used two criteria to determine if a CBP. pair is curved.[24]

1. For each CBP pair, the average grade given each term does not change significantly over time.

2. For each CBP pair, there is lack of evidence to say that the distribution of letter grades varies significantly by term.

To test the first criteria, I run a regression of grades on term indicators for each CBP pair, and get the joint significance of the coefficients on the term indicators. If I fail to reject

[24]↑

- The average grade given in each term does not change significantly over time.
  - For each course-prof. pair I regress *grade* on all the *terms* that that this course is offered and do an joint significance test to see if any term has avg. grades that significantly deviates from the rest
- The distribution of letter grades does not vary significantly across terms.
  - If the chi-square test shows that the distributions are not statistically differnet across terms, then this criteria is satisfied.

$$\chi_t^2 = \sum_t \sum_l [(\frac{(O_{lt} - E_l)^2}{E_l})]$$

  - O_{lt}= observed number of letter grade l in semester t.
  - E_l= Expected number of letter grade l in term t which is given by the ratio calculated using the sum of number of letter grades across all terms.

the null at the 10 percent level, it shows that there is lack of evidence for the average grade to change overtime. To test the second criteria, I tabulate the grade distribution of each CBP pair for each term that it is offered. I then do chi-square test to see if the distributions significantly change across the terms. If I fail to reject the null at the 10 percent level, it shows that there is lack of evidence for the distribution of grades to change across terms.

Once the courses satisfy the two criteria I separately run the same benchmark regression in equation 1 for courses that meet the criteria ("Strict Grade dist")and for those that do not("Variable Grade dist").

The assumption here is that both the instructor and the students know that the course is graded on a strict curve. Either the instructor makes that explicit in the syllabus, or the students know beforehand from external sources[25]. Figures 1.8 and 1.9 show the actual snap shot of the syllabus from one curved and one non-curved course in the data. As you can see in the syllabus that mentions the curve (in red), students are made aware that their letter grades will be determined by relative performances of their peers. In the syllabus that mentions an absolute standard (hence, no curve), we generally see a cutoff point a student has to achieve to earn a letter grade.

In Table 1.9, I have kept the regression specification from the previous tables, but further restricted by courses that either curved or didn't curve. Generally, curved courses and non-curved courses differed by type of the courses and the subject. In order to make an apples-to-apples comparison I needed to find courses where the same course was offered by at least 2 different instructor, one of which curved the course and the other did not. In the end, only courses offered in the Math department met the criteria of having the same courses that were different in the grading scheme. Comparing the two columns of Table 1.9, we see that the negative crowd-out effect is the strongest in courses that are curved.

Heterogeneity by Ability

This last part of the grade analysis shows how the crowd-out effect is felt differently across different ability spectrum of domestic students. As our model prediction shows, with the influx of higher ability international students, we would expect domestic students on the

[25]↑For example, students may get a general idea of how the professor will grade the course by other students who have taken the same course beforehand or through websites like textitRateMyProfessor.com

Grades:

Course grades will be determined from your overall total score which will be computed as follows:

Homework	100	points
Quizzes	50	points
*Two midterms @ 100 each	200*	points
*Comprehensive Final Exam	200*	points
TOTAL	550	points

There are no preset cutoffs for student grades. Instead, we will use the following system:
Each TA will be allocated a certain quantity of letter grades to award that is equal to the number of those grades earned on the *common exam totals* out of 400 points. This allocation will be *at least as generous* (may be adjusted favorably based on course-wide performance) as the following cutoffs (again, out of 400 points): 360 A+/A/A-, 320 B+/B/B-, 280 C+/C/C-, 240 D+/D.
Each TA will then award his/her allocated letter grades to individual students within his/her sections by ranking according to each individual student's overall course total out of 550 points.

Course Web Page for MA 26100: https://www.math.purdue.edu/MA261

Check this page often for important information and announcements. There is also a detailed *Daily Calendar* for the entire semester posted.

Figure 1.8. Syllabus (Curved)

COURSE GRADE

Course grades will be assigned based on the total points (out of 2000) earned in the course. The cut off total points earned for each grade will be ***no higher than*** the ones listed in the list below:

1920 or above earns A+	1840 – 1919 earns A
1760 – 1839 earns A–	1680 – 1759 earns B+
1600 – 1679 earns B	1520 – 1599 earns B–
1440 – 1519 earns C+	1360 – 1439 earns C
1280 – 1359 earns C–	1200 – 1279 earns D+
1120 – 1199 earns D	1000 – 1119 earns D–
999 or below earns F	

It is your responsibility to ensure that the grades are accurate, and report this **within 2 weeks PRIOR to when the grades are recorded,** typically the Tuesday after exam week.

How to Estimate Your Standing in the Course?

- A column in the Blackboard Learn Grade Center labeled "Non-Exam Weighted Total" is a running sum of all of the course components EXCLUDING exams weighted according to the table above. Those components comprise 1200 pts (60%) of your course grade.
  - We know from past experience, for you to succeed in this course, the average for this quantity (Lectures, Lab, Recitation, Homework and Quizzes) should be about 90%.
- Mid-Term Exams + Final Exam comprise 800 pts (40%) of your course grade.
- EXAMPLE: Suppose your...
  - 'Non-Exam Weighted Total' is 90% AND Average on Exams is 60%
  - A *conservative estimate* of your points in this class is (90% of 1200 pts) + (60% of 800 pts) = 1560 pts
  - Based on the above table, a *conservative estimate* of your final course grade is a B–.

Figure 1.9. Syllabus (Non-Curved)

higher ability spectrum to put in a lot more effort in response to heightened competition with similarly skilled international students. The middle types will probably not see much of a change in their immediate peers who are similarly skilled and may put in less effort than the higher types. The lower types may see even less competition as international students are sparse in that type, but may put in a lot of effort nonetheless as their prospect of getting zero rank (failing grade) has heightened.

In Table 1.10, I have divided the domestic engineering student sample roughly by quantiles based on their ACTmath scores; note since the scores are discrete, it is difficult to have an even number of observation across quantiles. We see that among engineering students who are taking core-science courses, the middle ability types are hit hardest by an increase in international students. This aligns with our model prediction as the those who are either high or low type put in higher effort and mitigate the negative crowd-out effect of international students. The middle types do not significantly alter their effort provision so they are mechanically pushed out to a lower grade with the influx of higher skilled international students. This result however needs to be further investigated due to the low sample size and the unsteadiness of the coefficient based on the where we make the cutoff for each quantiles.

Implications for Graduating in STEM

The data of the institution is a snapshot of all the students from years 2009 to 2015. Hence, it is difficult to precisely estimate any outcome related to graduation; one needs a longer time period to see how whether the student has persisted to eventually graduate in STEM or drop out of STEM.[26]. Added to the data issue, the estimation of persistence in STEM may be fundamentally biased if institutions somehow funnel the increased financial resources from international students to support the domestic students in STEM majors in the form of financial aid and better academic support.[27]

For these reasons, instead of directly measuring the graduation rate in STEM, I have opted to measure the predicted graduation rate in STEM based on the grade outcome. Specifically, I create a slightly different dependent variable called the "Lower than C mi-

[26]↑The major switch is not observed as the data only contain starting major and graduation major conditional on the student graduating

[27]↑International students typically pay higher tuition than their domestic counterpart; in the magnitutde of 2 or 3 times more.

nus"(L.C.m) which is a dummy that is 1 if the engineering student received a grade of C- or lower in the core science courses. According to the engineering plan of study, a grade of C- or lower in any of the core courses disqualifies one from continuing in the program.[28] Using the preferred specification from the benchmark regression, I switch out the dependent variable from Grades to L.C.m which is the dummy for a grade of C minus or lower; hence the regression becomes a linear probability model. In Table 1.11, in column 1, we see that with a 10pp. increase international students translates to 2pp. increase in the probability that a domestic earns C minus or less. This is about a 20 percent increase given that on average 11 percent of students earn grades at this level. In columns 2 and 3, I corroborate my findings in column 1 by showing that rate of repeat and rate of failure has also gone up; students are not just crowded into a lower than C grade, but many of them failing the course as well. Based on the col 1 result, a 10pp increase in the ratio of international students translates to a 2 pp decline in those who get a "passing" grade in order to continue into engineering. Note this estimates assumes that when students get at least one C minus or below, she drops out of engineering altogether. In reality the student may retake it or the program may give various lee-ways for the student to persist in Engineering despite the sub-par performance.

Robustness Check using the MIDFIELD data

In this section, I have run a similar regression to my original benchmark regression using data from other institutions; I could not control for course-by-prof fixed effects but instead used courseID fixed effects. Since the data on non-engineering majors were incomplete, I only used students who matriculated in Engineering in all of the institutions. I have also excluded small colleges, and colleges that do not have an engineering program. The time period is similar to the previous analysis. In Table 1.12, I show the results for the grade outcome with increasing $RatioInt$. Each column represents an institution. As you can see, all the statistically significant results show a strong negative effect of international students on domestic grades. I suspect that some colleges do not show any affect due to the small number of international student enrollment in their Engineering programs.

[28]↑The exact stipulation says "Minimum Grades: Earned grades must be C– or better for any course used to meet the requirements above."

1.4.2 Salary Outcome

Administrative data are rarely coupled with the actual salary information of the students. Perhaps the most interesting aspect about the admin. data I am using in this paper is that salary information disclosed. The salary is collected by the school office by individually contacting the graduates. About 1 out of 4 people in my data have responded to the survey and the response of rate of domestic students are much higher than that of the international.[29]. In Table 1.13, I test for whether or not there has been a selection of students into answering the survey based on their demographic characteristics. Based on the table, there is some selection based on demographic characteristics; however, the part that may be concerning is higher ability students responding to the survey at a higher rate as time goes by. This will bias the regression result as ratio of international students have also been increasing and we may get a selection of higher ability students reporting more frequently. When I interact the three main ability indicators with year, there seems to be no evidence that systematic over reporting of certain ability types are increasing overtime.

For the identification strategy, I have slightly modified the benchmark regression for Grade outcome. Instead of getting the share of internationals in a course-by-professor pair, I have used the share of internationals in a cohort in a given engineering field. The identification relies on the idea that the shares of international in a domestic students' cohort most accurately reflects the amount of exposure and interaction with international students. I also use the fact that the amount of increase in the ratio of internationals have differed by individual fields within engineering majors. If we look at Figure 1.10, we see that between 2009 and 2015, computer engineering has experienced the highest spike in the increase of international peers, but fields like Aerospace Engineering or Biological Engineering have not received a big influx. I use two different to get a causal estimate; the OLS, and the DID.

The (OLS) Salary regression is:

$$Salary_{\mathrm{i}cf} = \beta RatioInt_{cf} + X_f + \mu_{\mathrm{i}} + \epsilon_{\mathrm{i}cf}$$

[29]↑13,600 out of 51,300 domestic students replied to the survey whereas for the international students it was only 620 out of 6400

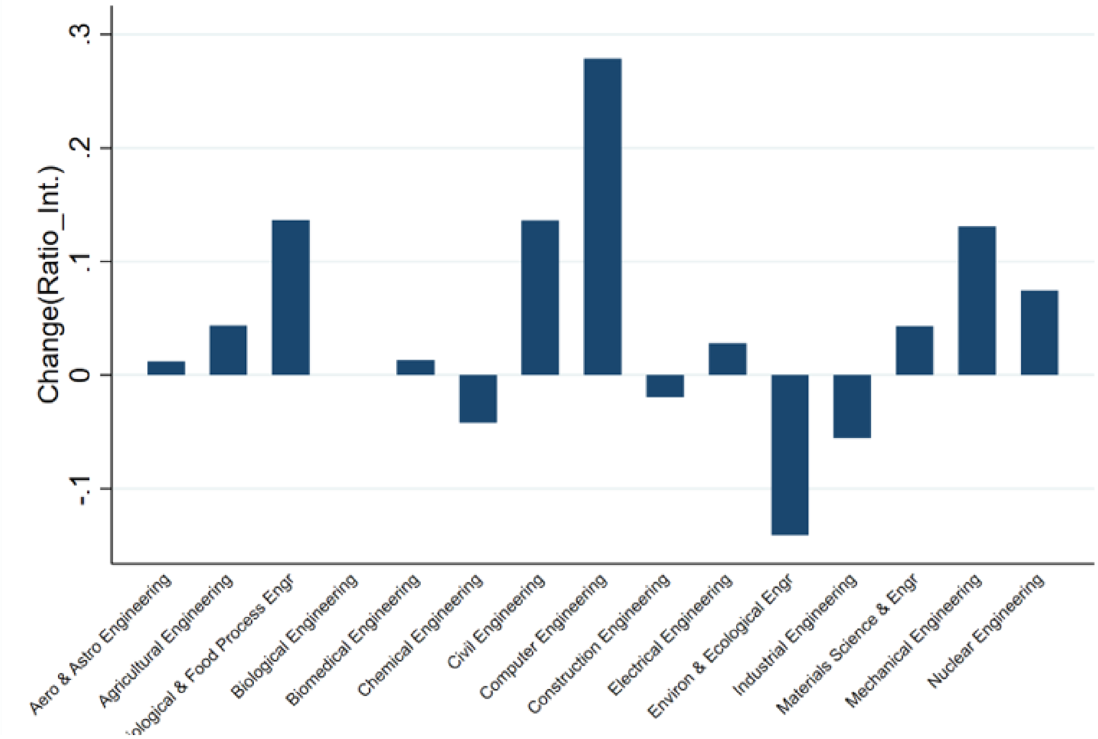

Figure 1.10. Change in (share of int.) between 2009 and 2015

Variable Definition:

- c is now cohort so $RatioInt_{cf}$ is the share of international students in one's cohort in a given field within engineering.
- X_f: controls for fields within Engineering
- μ_i : Demographic and Ability FE (as before)

This regression shows how yearly changes in the share of internationals in one's cohort in an engineering field, affects the eventual salary of the domestic student. I controlled for ability and demographic measures to ensure that I am comparing similarly skilled individuals over different cohorts. Note, I am not adding an individual fixed effect and hence do not follow the outcomes of the same individuals over time. Rather I am comparing a student in 2009 with a similar student in 2015 and having demographic and ability controls allow me to do just that.

To buttress the OLS analysis, I employ a Diff-in-Diff (DID) framework as well:

DID framework:

$$Salary_{ift} = \beta(\Delta RatioInt_f * I(2015)) + X_f + \mu_i + \gamma_t + \epsilon_{ift}$$

Variable Definition:

- $\Delta RatioInt_m$ is change in share international from 2009 to 2015.
- X_f: controls for fields within Engineering
- μ_i : Demographic and Ability FE (as before)
- γ_t : time (indicator for 2015)

The above regression we keep the identification strategy of the previous regression but take the difference outcome within an engineering field and take another difference across fields. The $\Delta RatioInt_m$ is can be considered a policy shock that is continuous.[30]

Table 1.14 shows that with the regular OLS fixed effects approach there is close to 1,300 premium that a domestic students enjoys from a 10pp increase international peers in their cohort. As heterogeneous effect by ability type is also present here as we see that higher and lower types have put in more effort in response to the increase international peers. However, with salary outcome, it is hard to parse out how much of the effect is coming from increased competition and other channels such as spill over effects in learning or more school resources. In any case, there seems to be a non-trivial effect on salary outcome for those who persist in engineering. The DID framework in the last column corroborates our results as well although it is larger in magnitude.

1.4.3 Cost and Benefit Analysis

For this exercise, I attempt to do an ex-post cost benefit analysis from having international students using the regression results we have obtained previously. There are countless factors to consider when considering the benefits (or lack thereof) of international students,

[30]↑This is similar to the famous paper by acemoglu2004women that measures the women's labor market outcome based on the rate at which men were deployed to WW2 by regions. The authors employ a continuous DID framework where the policy variable is the rate at which men were deployed.

but I limit this analysis to looking at the salary component which can be an objective measure for quantifying the returns to education. I further limit the analysis to only domestic engineering students as engineering majors have the highest returns out of all majors in this institutions and to keep the sample consistent from large compositional changes. [31] Grades are an essential component in this analysis not due to its signal of human capital acquisition nor the signal to employers of student quality, but rather it serves as an indicator for persistence in the engineering program. According to the school's website, one cannot have any core science course grade below a C in order to continue in the program. Using this criteria, I can measure a predicted attrition in a course based on the percentage of students who received a grad below the cutoff. Some additional assumptions I make in the calculations are as follows:

1. First-Year-Engineering (FYE) domestic students' grades in the first year core science courses determine whether or not the student persists in the engineering major. In specific, anyone who received a C- or below is disqualified. [32]

2. Those who fail to meet the cut-off in any of the core-courses automatically leave the engineering program to a different major where the average returns are lower or drop out altogether. [33]

3. Those who do make the cutoff continue in engineering continue in their respective engineering disciplines until they graduate.

4. The effect international students have on domestic students' Salary and Grade is linear-in-means which means that the effect is monotonic and the effect size linearly proportional to the increase in international student ratio. [34]

[31]↑ looking at the salary outcomes of all majors may be misleading if, at one point, the school dramatically increased the size of a major that has high labor market returns.

[32]↑Although in reality, the college does not strictly apply these criteria and students have the opportunity to retake courses, for the purpose of the calculating the returns to education, I will apply the most stringent measures. This will give us the upper bound of the cost of international students.

[33]↑Although engineering majors generally have higher starting salaries, this may not be true in other institutions. I assume there is no switching behavior to more higher paying major from engineering.

[34]↑ There is no quadratic effect or a flip of the sign. For more information on this method refer to manski1993identification

I attempt to do a back-of-the-envelope type calculation of the returns to an engineering degree from the perspective of a domestic student in engineering who is about to enter this institution in 2009. While having more international students decrease the probability of passing one of the core science courses needed to persist in engineering, more international peers help eventual salary outcome as we have seen in the previous section. I want to measure whether this salary premium from international students outweigh any negative effect that comes from potentially crowding out students in engineering. From table 10, we know that in the core science courses, a 10 pp. increase in international students translates into a 0.02pp. increase in probability of getting a grade that is below the cutoff. We also know from data that from 2009-2015, international population increased by about 7pp.(from 15 percent to 22 percent of student body). Hence, I compare two scenarios where 1) the first scenario is the counterfactual world where there is no increase in international student ratio since 2009, and 2) the second scenario is the real scenario where there had been a 7 pp. increase in international student ratio among first-year-engineering students.

-First Scenario (no change in ratio int.):

$E[Returns_{no}] = p(C_{above}) \times avg(Sal_{\mathrm{engr09}}) + p(C-_{below}) \times avg(sal_{other09})$

-Second scenario (7pp. increase in ratio int.):

$E[Returns_{\mathrm{int.}}] = [p(C_{above}) - (0.014^{35})] \times [avg(sal_{engr09}) + \alpha] + [p(C-_{below}) + 0.014]) \times avg(sal_{other09})$

then, to get the net expected benefit of internationals:

$\Delta Returns = E[Returns_{int}] - E[Returns_{no}]$

$= \underbrace{[p(C_{above}) - 0.014]\alpha}_{\text{Int. Student Premium}} - \underbrace{0.014[avg(Sal_{engr09} - avg(Sal_{other09})]}_{\text{Cost due to attrition}}$

[35]↑This value is given by multiplying the table 10 coefficient with the 7pp. increase in ratio int. (0.02×0.7=0.014)

In the first scenario, the returns to an engineering degree is the probability one will get a grade above the cutoff $p(C_{above})$ times the average salary of domestic engineering graduates in 2009. $p(C_{above})$ is calculated as 0.74 among 2009 FYE cohort. The average salary of engineering graduates is \$69500 among the 2009 cohort. I will make an assumption that this is the salary the graduates would have earned in the absence of the subsequent influx of internationals. In the second component, $p(C-_{below})$ is just 1 minus the probability of getting C or above and this is multiplied by the average salary of a FYE cohort in 2009 who ends up getting a different degree. The addition of the two component gives us the expected returns of an engineering degree that a domestic student can expect as she enters the engineering program among the 2009 cohort with no subsequent increase in international student ratio.

Likewise, in the second scenario I calculated the expected return with the observed increase in international students which is 7pp. of the student body. The first component is once again the expected return from finishing the engineering degree but the probability is now decreased by 0.014 due to the higher likelihood of getting a lower grade due to international students. This value is derived from table 10 where I multiply the coefficient 0.02 with the influx which is 0.7. Notice that there is α term added to the salary which is from table 12 which gives us the salary premium from having 10pp. more international peers (more on this later). $E[Returns_{int}]$ gives us what the domestic student would actually expect in 2009 if they suddenly enter in with more international peers (7pp. more).

Finally, in order to get the net benefit that the 2009 engineering cohort would have enjoyed due to their international peers, we take the difference of the two scenarios. The third equation boils down to the first component which is the premium that a domestic student can expect with more international peers due to positive effect on salary, while the second component gives the cost due to lowering of grades and eventual dropping out of engineering.

In Table 1.15, I have shown the calculation of this expected return. I have also broken down the columns by popular colleges engineering students switch into if they leave engineering. In such case, I use the average earnings of students for all majors in that specific college among the 2009 cohort for calculation of $avg(Sal_{other09})$. The $avg(Sal_{engr09})$ is fixed at $69500 across all specifications.

I also show the results using the different α values (salary premium from 7pp. increase in ratio int.) based on columns 1 and 5 from Table 1.14. As you can see across all specifications, there is always a net-positive returns to international students; the international student premium is always more than the potential harm of being kicked out of engineering due to lower grade. We see that domestic students enjoyed a return of an additional $474 due to the 7pp. increase in the ratio of international students assuming α=910. We also see that in cases where we only assume the switching majors are in Management, Liberal Arts, or Science, the returns are still positive. In the last column, I assume that those who get kicked out of engineering end up earning the market wage for college drop-outs.[36] We see that even in this case the expected return is positive.

1.5 Conclusion and Policy Implication

The results indicate that international students have a short-term negative effect on the academic outcome of domestic students in classes where math skills are important for success. This result is consistent with past literature that looks at outcomes of immigrant students on domestic students' academic outcome. However, the past literature focuses mainly on the channel of lower communication skills of international students. In this paper I have shown that in certain setting (such as highly competitive STEM programs in college), the main channel of the effect is through the discrepancy in math ability as opposed to communication difficulties. I also show that this negative effect is concentrated in early college years when courses are generally more difficult "weed out" courses, and the negative effects taper off in the later stages when the domestic student has either adjusted to the competition or have experienced positive spill-overs from their international counterpart. This is most clearly seen in the labor market outcome of Engineering students who have been exposed to more international peers.

[36]↑figure on 2009 salary of college drop-outs were obtained from: https://www.census.gov/content/dam/-Census/library/publications/2009/demo/p20-560.pdf

This study, although informative, cannot be generalized to all higher educational institutions.[37] The focal institution's Engineering and STEM programs are highly selective and attract high ability international students from all around the world. Note however that the types of institutions that higher ability international students flock to are the types of institution that are most active in educating the next generation of scientists and engineers, so this study has implications on how to structure school admission policies and course policies and even has implications on federal immigration policies as a whole.

A quick cost and benefit analysis based on the grade and salary results show that there has been a small but a net positive returns to international students in the focal institution. [38] If one takes into account the positive spillovers effects through better peers, and increased financial aid to domestic students, the positive effect far outweighs the potential crowd-out effect domestic students experience. On the national level, US higher education will benefit from immigration policies that allow US institutions to attract more foreign talents as long as there is no significant negative effect of crowding out potential domestic enrollees in selective institutions.[39] One limitation of this study is that I do not look at the potential crowding out of domestic applicants in response to higher number of international applications. More research needs to be done in this arena with availability of data in order to have a more comprehensive cost and benefit analysis.

One policy recommendation to mitigate the short term negative effect on grades and attrition is to implement tracking which is commonly practiced in primary and secondary education institutions. Tracking is where classes are segregated based on the ability of students so that there is no huge gap in achievements. Although it is somewhat difficult to enforce this in large scale college courses, it can be done through creating an honors track for those whose math ability is much higher. In a highly technical STEM major such as Engineering this can help attract higher ability students including many international

[37]↑I have run a similar regression to our benchmark regression in table 3 but using the MIDFIELD data and find inconsistent effects depending on the institution, but generally a negative relationship. Please refer to appendix for more info.

[38]↑Please refer to previous section

[39]↑shih2017internationalshows that there is no evidence of international students substituting domestic students in admission into doctoral programs. Also, according to the NAFSA data, 1 million international students generate 41 Billion dollars annually to the US economy.

students to compete among similarly skilled students in early core science courses. Once the students complete the preliminary core science courses and become established in their field or major, then those who are on the honors track can be mingled again with the regular students; this will create a positive spill over effect in the upper division coureses while mitigating the negative crowd-out effect in the lower division "weed out" courses in STEM majors.

Table 1.3. Selection Test

DV:	(1) ACTmath	(2) ACTreading	(3) hsgpa	(4) female(1)	(5) non_res	(6) black	(7) asian	(8) hispanic
Ratio_int(10%Δ)	-0.00149	-0.2049***	-0.0121***	0.0109***	0.00212	0.000324	0.00668***	0.00121*
	(0.212)	(0.491)	(0.0156)	(0.0197)	(0.0172)	(0.00595)	(0.00849)	(0.00633)
Course_prof FE	y	y	y	y	y	y	y	Y
Term FE	y	y	y	y	y	y	y	y
Mean(Y)	24.45	44.29	3.56	0.55	0.3	0.036	0.054	0.039
Observations	293,085	293,058	359,813	370,718	370,718	370,718	370,718	370,718
R-squared	0.238	0.167	0.150	0.156	0.065	0.031	0.032	0.016

Note: Sample is of all domestic students in pooled sample ofall colleges and level of students. The ratio_int is from [0,1], and hence thecoefficients I have listed here are the changes in the respective dependentvariables for a 10 percentage point change in ratio_int (aka. ratio_int(10%Δ)) for easeof interpretation.
Robust standarderrors in parentheses *** p<0.01, ** p<0.05, * p<0.

Table 1.4. Grade Outcome by College

DV: Grade (all level)	(1) SCI_ENGR	(2) MGMT	(3) LIB
ratio_int (10%$p\Delta$)	-0.0275***	-0.00861***	0.00189
	(0.0526)	(0.0966)	(0.04957)
Observations	374,235	86,984	352,493
Mean(DV)	2.88	2.96	3.27
Term FE	x	x	x
courseID-Prof FE	x	x	x
Dem_Abil_FE	x	x	x

Note:Repeated number of same students observed as they take multiple coureses. SCI ,_ENGR courses are all courses offered in the Science and Engineering dept and MGMT and LIB are management and college of liberal arts. Term FE controls for year and term of the courese (without summer), couresID-Prof FE is the couresID by instructor pair, and Dem_Abil includes the usual controls (race, non resident alien, gender) and ability measures (ACT math, ACT reading, and Hsgpa). Robust standard errors clustered at the courseID-prof level with p-value<0.01 indicated with (***), p-value<0.05 with (**), and p-value<0.1 with (*).

Table 1.5. Grade Outcome for SCI and EGNR

DV: Grade	(1) SCI_ENGR(all)	(2) SCI_ENGR(100-200)	(3) SCI_ENGR(300-400)
ratio_int (10%$p\Delta$)	-0.0275***	-0.0305***	-0.0167**
	(0.00526)	(0.00788)	(0.00703)
Observations	374,235	245,141	129,094
Mean(DV)	2.88	2.81	3.0
Term FE	x	x	x
courseID-Prof FE	x	x	x
Dem_Abil_FE	x	x	x

Note: Repeated number of same students observed as they take multiple coureses. SCI and ENGR courses are all courses offered in the Science and Engineering dept. Term FE controls for year and term of the courese (without summer), couresID-Prof FE is the couresID by instructor pair, and Dem_Abil includes the usual controls (race, non resident alien, gender) and ability measures (ACT math, ACT reading, and Hsgpa). Robust standard errors clustered at the courseID-prof level with p-value<0.01 indicated with (***), p-value<0.05 with (**), and p-value<0.1 with (*).

Table 1.6. Grade Outcome in Core Science

DV: Grade (Core)	Hard STEM (MA_PHYS)	Easy STEM (CHM_BIOL)	nonSTEM (COM_ENGL)
ratio_int (10%$p\Delta$)	**-0.0631*** **	0.0517	0.0182**
	(0.0146)	(0.0592)	(0.00888)
Observations	20,647	6,145	6,010
Mean(DV)	2.64	2.96	3.55
Term FE	x	x	x
courseID-Prof FE	x	x	x
Dem_Abil_FE	x	x	x

Note: Sample of all students whose initial major is Engineering. Repeated number of same students observed as they take multiple coureses. Columns divided by level of technical difficulty and STEM status. Term FE controls for year and term of the courese (without summer), couresID-Prof FE is the couresID by instructor pair, and Dem_Abil includes the usual controls (race, non resident alien, gender) and ability measures (ACT math, ACT reading, and Hsgpa). Robust standard errors clustered at the courseID-prof level with p-value<0.01 indicated with (***), p-value<0.05 with (**), and p-value<0.1 with (*).

Table 1.7. Predictors of Grade

DV: Grade(Core)	(1) (MA_PHYS)	(2) (CHM_BIOL)
ACT math	**0.009*****	**0.0056*****
	(0.00234)	(0.00234)
ACT reading	0.004***	0.0097***
	(0.00074)	(0.0012)
Observations	20,659	6,159
Term FE	x	x
courseID-Prof FE	x	x
Dem_Abil_FE	x	x

Note: regression of Grade on the two predictors of ability; ACTmath and ACT reading. All other specification same as Table Spirit.

Table 1.8. List of Core Science Courses

Course number	Course Title
CHM11500	General Chemistry
MA26100	Multivariate Calculus
PHYS17200	Modern Mechanics
MA16200	Pl Anly Geo Calc II
PHYS24100	Electricity Optics
BIOL11000	Fundamentals Biol I
MA16100	Pl Anly Geo Calc I
CS15900	Prog Appl For Enginrs
CHM11100	Fundamentals Biol II
MA26200	Lin Alg Diff Equats
MA16500	Anlytc Geomtry&Calc I
MA16600	Analytc Geom & Calc II

Table 1.9. Grade by Curve

	MA	
DV: Grade (MA)	curve	nocurve
ratio_int (10%$p\Delta$)	**-0.0792*****	-0.0576
	(0.0285)	(0.0415)
Observations	2,801	8,142
Mean(DV)	2.56	2.54
Term FE	x	x
courseID-Prof FE	x	x
Dem_Abil_FE	x	x

Note: Curved courses indicate coureses that meet the curved criteria within math coureses. No curve coureses do not meet the criteria. Each coureseID is present in both curve and no curve to allow for within course comparison. All other specification is the same as Table Spirit

Table 1.10. Heterogeneity in Ability (Grade)

	(1)	(2)	(3)
DV: Grade (MA+PHYS)	low	mid	high
ratio_int (10%$p\Delta$)	0.171	-0.913***	-0.285
	(0.0325)	(0.0203)	(0.0239)
Observations	3,990	11,677	4,844
Mean(DV)	2.13	2.64	2.79
Term FE	x	x	x
courseID-Prof FE	x	x	x
Dem_Abil_FE	x	x	x

Note: column 1 low are only of engineering students whose ACT math score is below 28, column2 middle are those who are in between 28 and 32, and column 3 high are those whose score is above 32. All other specification is the same as Table Spirit

Table 1.11. Prob. of Engineering Drop-out

DV (PHYS+MA)	(1) L.C.m	(2) Repeat	(3) Failed
ratio_int (10% $p\Delta$)	0.02***	0.012***	0.005**
	(0.0047)	(0.0035)	(0.0027)
Observations	20,647	20,647	20,647
Mean(DV)	0.11	0.076	0.034
Term FE	x	x	x
courseID-Prof FE	x	x	x
Dem_Abil_FE	x	x	x

Note: Col 1 has DV as prob of getting lower than C. Col2 is a indicator for Repeated, and Col3 indicates whether the student failed I the course. Sample of engineering majors in Hard STEM (PHYS+MA). All other specification the same as reference table.

Table 1.12. MIDFIELD

	(1)	(2)	(3)	(2)	(3)	(4)	(5)	(6)
DV: Grade	$school_1$	$school_2$	$school_3$	$school_4$	$school_5$	$school_6$	$school_7$	$school_8$
Ratio_int (10%Δ)	-0.028***	0.034	-0.169***	-0.014	0.001	-0.04***	0.002	0.0004
	(0.0007)	(0.031)	(0.027)	(0.01)	(0.004)	(0.01)	(0.006)	(0.0057)
Observations	929,466	38,003	77,258	67,723	323,391	155,170	217,333	157,302
R-squared	0.29	0.23	0.1834	0.2	0.19	0.16	0.18	0.19

Note: Sample is of domestic engineering students taking undergraduate courses by colleges listedin MIDFIELD. I have only chosen a subset of collegs that are large enough andhas significant observations for engineering students. Also, the period is from2008 Fall to 2018. The ratio_int is from [0,1], and hence the coefficients Ihave listed here are t he changes in the respective dependent variables for a 10percentage point change in ratio_int (aka. ratio_int(10%Δ)) for ease of interpretation. I have included Ind. Controls which are black,Hispanic, Asian, ACTmath and reading and grade. Peer Ability include avg. ACTmath and reading scores of peers in the class. All regressions includeclasssize as well. Standard errors are clustered on the courseID fixed effects.Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.

Table 1.13. Survey Response

DV:Respond to Survey	(1) math	(2) reading	(3) hsgpa
c.ACTSAT_math#c.year	1.93e-06*		
	(1.06e-06)		
c.ACTSAT_reading#c.year		1.19e-07	
		(3.57e-07)	
c.hsgpa#c.year			4.92e-05***
			(1.24e-05)
gender	0.0464***	0.0467***	0.0469***
	(0.0152)	(0.0152)	(0.0152)
non_resident_domestic	-0.00340	-0.00348	-0.00368
	(0.0135)	(0.0135)	(0.0135)
black	-0.0606	-0.0601	-0.0604
	(0.0449)	(0.0449)	(0.0449)
hispanic	-0.0457	-0.0457	-0.0458
	(0.0312)	(0.0312)	(0.0312)
asian	-0.00655	-0.00683	-0.00710
	(0.0241)	(0.0241)	(0.0241)
hsgpa	0.102***	0.102***	
	(0.0251)	(0.0251)	
Observations	4,474	4,474	4,474

Note: The dependent variable is whether the student responded to the survey.

Table 1.14. Salary Outcome

	OLS-FE				DID
DV: Salary_adjusted ($)	Total	low	mid	high	
ratio_int_cohort(10%$p\Delta$)	1,334**	2,286*	949	2,267*	
	(590)	(1,357)	(825)	(1,195)	
ratio_int_cohort*I(2015)					2560.1***
					(816.5)
Observations	1,535	239	845	448	1,146
Mean(DV)	70,405	67,625	69,327	71,923	69,361
Gradmajor FE	x	x	x	x	x
Dem_Abil_FE	x	x	x	x	x

Note: Dependent variable is adjusted first year Salary of engineering graduates. The Gradmajor FE controls for the 15 enginering fields that are listed in the previous figure. 1 low are only of engineering students whose ACT math score is below 28, middle are those who are in between 28 and 32, and high are those whose score is above 32. The DID specification only uses years 2009 and 2015 and compares across engineering fields. Dem_Abil includes the usual controls (race, non resident alien, gender) and ability measures (ACT math, ACT reading, and Hsgpa). p-value<0.01 indicated with (***), p-value<0.05 with (**), and p-value<0.1 with (*).

Table 1.15. Net Returns from more Int. Students

	All Majors	MGMT	Liberal	SCI	Dropped-out
$\Delta Return$ (α=\$910)	**474**	\$486	311	535	367
$\Delta Return$ (α =\$1750)	**1,084**	\$1,096	921	1,145	977
$avg(Sal_{other09})$	56,200	57,000	44,500	60,500	48,000
popular majors		Management, Economics	Law & Society Political Science	ComputerScience Biology	

Note: Using 2009 first year engineer cohort's average salaries. $avg(Sal_{engr09})$ is fixed at \$69,500. All in the units of US dollars. Popular majors are top 2 majors in each college. Alpha values gives by multiplying 0.7 with 1300 and similarly with 2500 which are rounded values from table 12. Salary for those who dropped out from the 2009 Census figures on college drop-outs. All salaries adjusted for inflation to match 2019 level.

2. INTERNATIONAL STUDENTS' EFFECT ON LOCAL BUSINESSES

2.1 Introduction

The United States is the greatest exporter of Higher education. In 2018, international students contributed 45 billion dollars to the US economy.[1] In addition, unlike other exports, international students who purchase this educational experience do so by coming to the US with a student visa. This allows the surrounding communities of colleges reap the benefit from added consumption by international students; money that they would have spent in their own home country had they remained. In this paper, I claim that this extra expenditure by international students (both in tuition and living expense) has had a non-trivial effect on the regional economies of college towns and attempt to quantify its effect on employment rate in these towns.

To start with, colleges play a central part in the development of the region. Indirectly, they make the region more educated which leads to innovation and creation of new industries. There is also a direct effect on the actual creation of infrastructure such as buildings, schools (for children of faculties and staff), accommodation, and public services. This is due to not only the mechanical channel of adding more people to the area but a feedback loop that brings reverberating effects in the local economy.(Drucker and H. Goldstein 2007) With more individuals there is an initial creation of more infrastructure that leads to the creation of jobs and higher tax revenues which further improves the amenities in the towns, which in turn, attract more people and students. Some examples of this positive feedback loop may be seen in the improvement of school districts with the influx of children's of highly educated faculties and students; the building of a school recreational facility that non-affiliated residents can have access to; the building of state-of-the-art medical facilities that students and residents have access to; the hiring of more staffs and faculties; increasing demand for restaurants in number and types due to varying taste; increasing demand for housing (albeit, mostly apartments), and a host of other spill-over effects that come with an influx of a young and vibrant population.

[1]↑From https://www.iie.org/en/Why-IIE

As colleges and surrounding areas primarily rely on students for its revenue and consumption, attracting more students are cruical for sustaining the economy of college towns. Unfortunately, national enrollment in higher education have been decreasing [2], and save for large flagship universities, the future trends do not seem promising, especially for many smaller colleges. On the other hand, international student enrollment have been consistently rising since the early 2000s and starting in 2008 there has been a dramatic increase as seen in Figure 2.1. The reason for this increase is two fold: 1) due to higher demand of US higher education by China and India.[3] and 2) due to colleges willing to admit more international and out-of-state students to garner higher tuition paid by these students(Li 2017)). In 2008 the OPT STEM extension has accelerated this trend to unprecedented levels. Hence, from 2004 to 2016, in a matter of about a decade, international student as a percentage of the Grand total (International + Domestic) has gone up by almost 100 percent.

In this paper, I use this sudden and dramatic increase in international students in 2008 to measure the economic effect of international students on college towns. International students are unique in that they generally have higher purchasing power than their domestic counterpart, and hence their presence in college towns may have a substantially more positive effect on the regional economy than other groups with lower spending power.[4]

Using data from IPEDS of international student enrollment from 2004 to 2016, I measure the causal effect of an increase in an extra international student on the employment in the zipcode that the school is located or the college town. I call this zipcode the school-specific zipcode. For the outcome which is employment count, I use the County Business Pattern (CBP) data from the Census that I match with the IPEDS data. A simple correlation of increase in international students between 2004 and 2016 with the increase in total employment can be heavily biased if some other factors caused the increase in employment. Hence, I employ a diff-n-diff specification where I first take the pre and post difference of the employment within the school-specific zipcode and compare that to other school-specific zipcodes

[2]↑Please refer to https://nces.ed.gov/fastfacts/display.asp?id=98

[3]↑China and India, perhaps due to their sudden economic growth are among the top origins of international students as in Figure **??**

[4]↑The higher spending power of international students is an assumption that I make based on the higher tuition they pay with little to no aid.

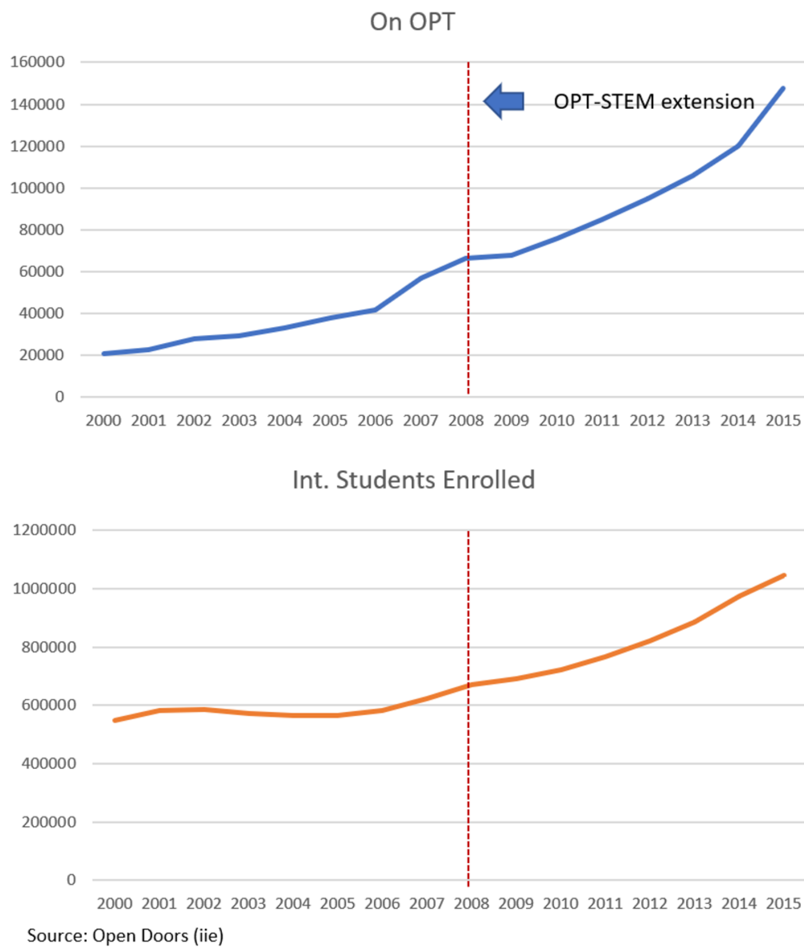

Figure 2.1. Enrollment Trend of Int. Students

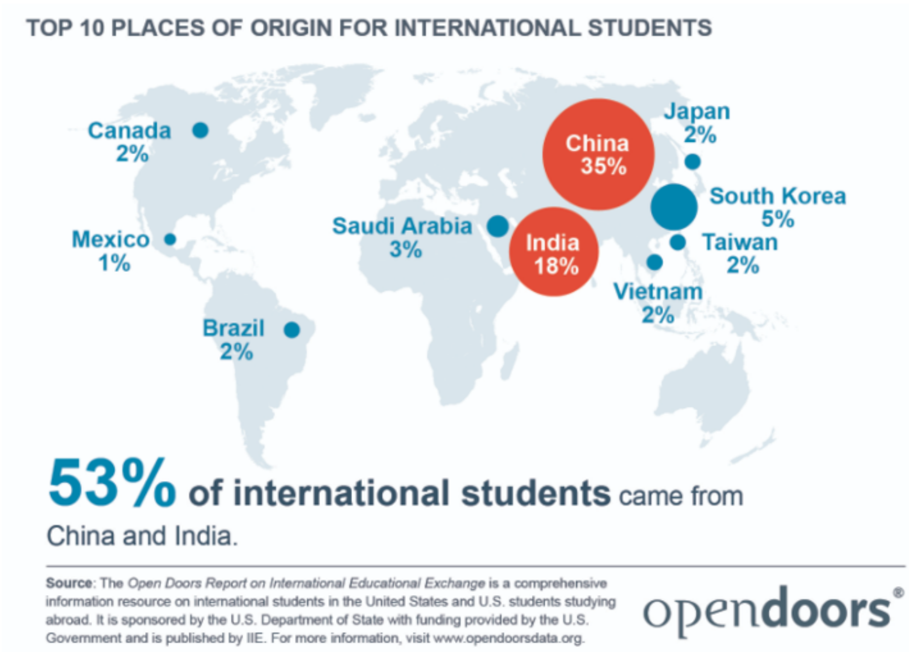

Figure 2.2. Origin Country of Int. Students

that have experienced different amounts of shocks. I find that an extra international student create 0.3 jobs. In other words, 3 extra international students support 1 job in the college town.

I show limited evidence that this is not driven by a mere increase in student body but a specific increase in international students who have higher consumption power. In addition, I perform different robustness checks to mitigate the concern of the Great Recession which took place around the same time period as my policy shock in 2008. The study is limited in that a detailed analysis by industry and sector is not feasible due to data limitations; I only show the total number of employment in a given zipcode or region. However, this study is novel in that it is the first paper that looks at the local employment effects of international students using actual employment data rather than predicting their effects through their expenditure.

2.1.1 Mechanism

This study is part of a larger branch of research that looks at the how institutions of higher education help the regional and national economic conditions. As colleges are bedrocks of knowledge-production, states and local governments increasingly capitalize on the opportunity to leverage this knowledge-based economy in their regions (Drucker and H. Goldstein 2007,Pink-Harper 2015). This research has relevant policy implications as positive returns to investing in higher education in terms of state and local development has been a goal of the government. Some of these governmental attempts include having university partner up with industries and tailor its curricula to match the skill demands (high skilled) of the local industries. An example of this could be colleges in the Seattle area heavily investing in their software engineering programs to match the demands from tech firms that are agglomerated in the city.[5] In recent times, the government has taken a proactive role in investing in public institutions with the passage of the Bayh-Dole Act that allowed universities to hold patents that result from research through governmental funding.

[5]↑One such example is shown in this article: https://durkan.seattle.gov/2020/08/mayor-durkan-announces-nearly-100-million-in-investments-in-k-12-education-for-seattle-students/

The government's role in turn has been to get a positive return to their investment in these instituttions through patents, licensings, and collaboration with industries. (Shane 2004)

However, the aforementioned knowledge-based contribution does not dramatically show up as higher employment or earnings as knowledge creation and transfer takes time. Also it is harder to quantify this contribution due to benefits extending over a long time and in unforeseen directions. According to Drucker and H. Goldstein 2007, there are other factors that universities contribute to the regional economy apart form this knowledge-based contribution. These factors are more direct in the sense that the effect is felt immediately and more measurable compared to the knowledge based effect. I will call this the direct effect following the literature. (Felsenstein 1996) This relatively short-term direct effect is what this study focuses on.

According to Felsenstein 1996, the direct effect of college students primarily shows through three channels 1)local household 2) local businesses and 3) local government/institution. Their theoretical predictions can be applied to the influx of international students and its ensuing effects on the region. To start, with increase in international student body, there is a positive effect through the local household as income of faculties and staffs and their number grows to support the growing international student body. This allows more cash to flow into the regional market in the form of demand for social/recreational facilities, accommodation, and food to name a few; this will lead to more employment. Secondly with more international students, there will be a positive effect through local businesses. This is so because more students with diverse background have different preferences for amenities. This will allow different kinds of restaurants and ethnic grocery stores to emerge creating employment. Thirdly, increasing international students will have a positive effect through the local government which leads to employment. Specifically, with more students and employees, there will be a wider tax base and higher revenue which can be funneled into creating better public services and amenities. This will further create jobs and encourage migration into the town. This also creates a positive feedback loop where the local government decides to invest more in their colleges to reap further benefits. In reality, these channels are interdependent and feed off of each other leading to higher gross output and employment in the region.

In addition, there are reasons to believe that international students can be more effective at creating these channels than domestic students. The reason for this is that they pay the full sticker price of the university tuition unlike many domestics students who receive some form of aid from the school.[6]This will directly allow universities to create facilities that are attractive to students and residents alike and can improve the attractiveness of the town.

2.1.2 Literature Review

Colleges and Regional Economies:

There is a strand of literature that looks at the effect of colleges on regional economies in terms of fiscal multipliers. In essence, they looks at how a one dollar invested by the university gets multiplied in the local output due to positive externality. Glasson 2003 looks at British schools and detailed data of expenditure to measure the school's impact on surrounding firms' output. They find that an extra dollar invested by the college creates around 0.7 to 1.2 dollar in gross local output (equivalent to a GDP but for the locality).

In the US context, Felsenstein 1996 uses data from the Northwestern university to show that the school created ten thousand jobs in the Chicago area in 1993. Other studies include Steinacker 2005 who shows that Claremont Graduate University contributed 10.5 milion dollars in its local community; H. A. Goldstein and Luger 1992 who shows data of research parks and the number of employees they support and claims that smaller non-metropolitan regions benefit from having research parks compared to more dense areas, and Huffman and Quigley 2002 who documents how Berkeley university students go on to be entrepreneurs in Silicon valley and thereby contributing to the development of that region. Finally, at a more general level, a Brookings Institute report by Jonathan Rothwell[7] uses a representative data from the Consumer Expenditure Survey to show spending behaviors of highly educated individuals and estimate how much value college students and graduates will add to the college towns in which they reside. Some methodological limitation of these impact studies is that studying a narrow region does not fully capture the benefit of colleges and their spill-over

[6]↑According to a 2019 Open Doors report, 62 percent of international students receive most of their funding through their family or government from their home country:https://www.iie.org/Research-and-Insights/Open-Doors/Economic-Impact-of-International-Students

[7]↑https://www.brookings.edu/research/what-colleges-do-for-local-economies-a-direct-measure-based-on-consumption/

effects into the larger economy and perhaps the world.

International Students' Effect on Regional Economies:

In the past, international students were only small percentage of the total student body, and because of this not much attention has been given to their regional economic impact. One of the oldest papers that attempts to measure their impact does so by measuring their per-capita expenditure. The paper uses data from a Michigan school to estimate the expenditure and find that international students contribute roughly $\$11,000$ per-capita (1986 dollar value) to the regional economy.(Gale 1988)

There is one other analysis from NAFSA that attempts to quantify the economic effecst of international students on the region and it uses the most up to date from Open Doors and IPEDS.[8] It also examines the same outcome variable as this study which is employment and hence closest in spirit to this paper. The results are shown as an interactive map on the website of NAFSA which is a think tank dedicated to studying international students around the world.[9]

According to the complementary manual on the methodology, the way they calculated the predicted employment effect is by first getting the total economic value of international students which is just the addition of various expenses that a typical international student incurs such as tuition, and predicted living expenses. Assuming that these expenses are actual contribution to the local economy, international students contributed 28.4 billion dollars in 2020-2021 and this has led to the creation of about 300,000 jobs which is given by dividing the total contribution by the average export amount to support one job. In another words for every 3 international student, 1 job is created.

This analysis is the first to use recent information on international student consumption patterns to estimate their overall benefit to the local economy in the US. However it has limitations in that it makes a strong assumption that whatever cost is incurred by the

[8]↑The detailed analysis can be found in this link: https://www.nafsa.org/sites/default/files/media/document/NAFSA_Methodology_Economic_Value_2021_Final.pdf

[9]↑please refer to the online tool: https://www.nafsa.org/policy-and-advocacy/policy-resources/nafsa-international-student-economic-value-tool-v2

international student is directly contributed to the local economy. Also, instead of using actual data on employment it shows an estimated effect on employment based on the aforementioned assumption. **Hence, in this study, I complement this earlier analysis by using actual regional employment data from the Census(CBP) coupled with the IPEDS data of international students. Using actual employment data shows more credible evidence of the effect international students have had on their local economy.**

2.2 Data & Identification

2.2.1 Data

I use IPEDS data of total number of degree-seeking students by nativity from 2004-2016; I primarily use the change in enrollment and employment between year 2004 and 2016. I chose this range as 2004 is sufficiently far from the policy year so that there is no announcement effects, and 2016 is when the influx of international students reached its peak. I mainly focus on doctoral research institutions (R1, R2, Doctoral/prof) classified by the Carnegie Classification. I limit my analysis to these research institutions because 1) these institution are sufficiently large to lead the local town's economy and 2) due to the fact that most international students seek education in these large research institutions that are in many cases flagship universities. Large research institutions also tend to be public and slightly cheaper than smaller liberal arts schools which may appeal to international students who usually pay the full sticker price. In Figure 2.3, I show that most of the increases in international students have come from R1 institutions. R1 schools are flagship institutions of very high research activity, R2 research schools of high research activity, and Doctoral research institutions consist of schools that have moderately high research activity compared to the first two classification. We see that most of the increase in international student enrollment came from R1 schools but also from other research institutions.

For the outcome which is employment count, I use the County Business Pattern (CBP) data from the Census that I match with the IPEDS data. The CBP data is an annual data from the Census that records employment and payroll information by industry and zipcode.

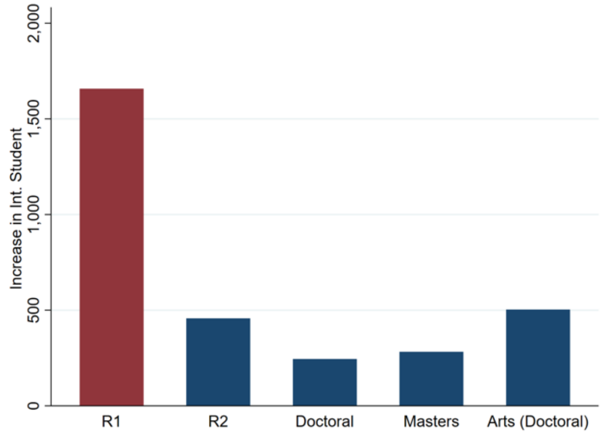

Figure 2.3. Changes between 2004 and 2016

Note: Graph of the top 5 Carnegie classification in terms of number of international students. R1, R2, and Doctoral are research institutions. Masters category are school where the highest degree is a masters, and Arts(Doctoral) are research institutions for the arts.

The industry is coded using the North American Industry Classification System(NAICS) and I use the first two digits when I analyze the effect of excluding certain sectors or industries.

The IPEDS data also includes the zipcodes of the institutions which allow the data to be matched with the Census data on employment. I use zipcode level employment data as zipcodes that the schools are located in will most directly capture any spill-over economic benefits of the extra international student enrollment in those schools. The census data breaks down employment by sectors but I focus on the total number of employment as employment by sector/industry can be too small to find meaningful correlations overtime. In Figure 2.4, we see that international student enrollment have gone up by almost a 100 percent between the two years whereas the Grand total enrollment and the total employment in the school-specific zipcode have not changed significantly. In Figure 2.5, I show a side-by-side comparison of the heat maps of the change in international student count and the change in total employment in the same CBSA. There appears to be some correlation between the two overtime, although not strikingly clear.

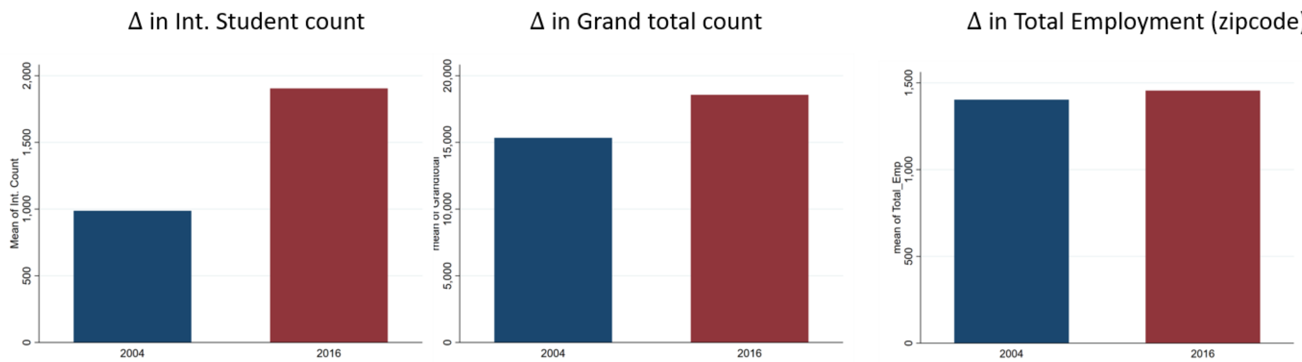

Figure 2.4. Changes between 2004 and 2016

Note: Using only doctoral research institutions. These three graphs show descriptive statistics of the key variables this study uses. Note, each unit is a school-specific zipcode.

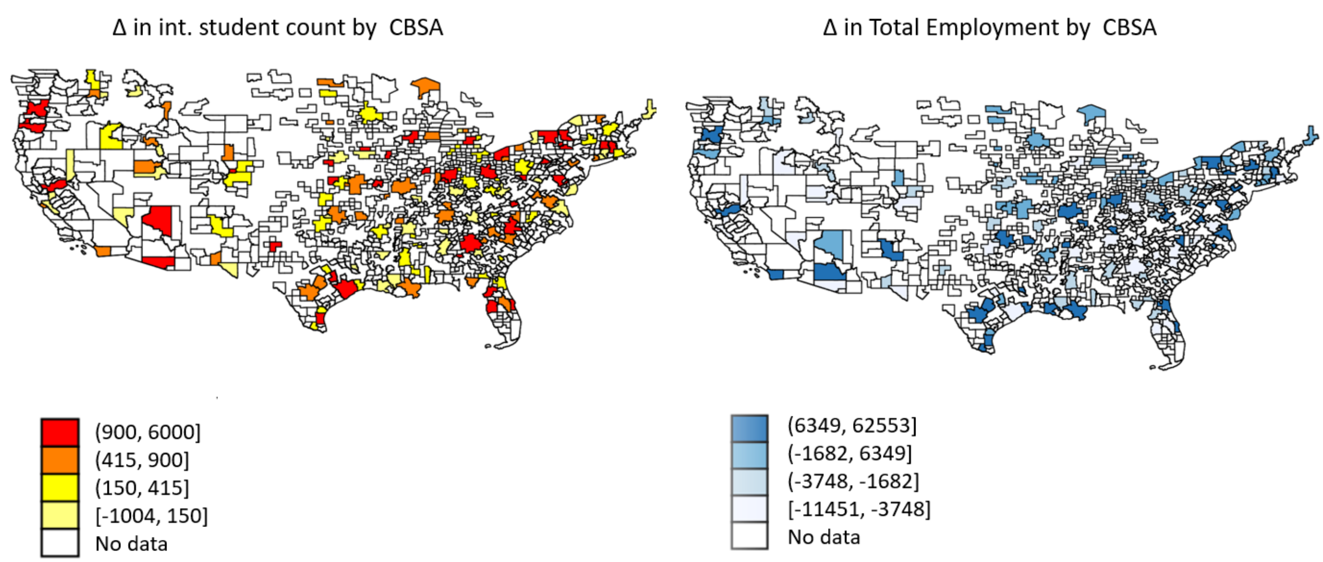

Figure 2.5. Changes between 2004 and 2016

Note: The maps show descriptive evidence of the correlation between change in int. student inflow and change in employment by CBSA. Some CBSAs are blank due to no presence of research institutions.

2.2.2 Identification (OPT Shock)

Please feel free to skip this section if you have read my first chapter since it uses the same exact identification.

Optional Practical Training(hereby OPT) is a program by the Dept. of Homeland Security that allows US educated foreigners to work in a US firm with their student visas for up to 12 months. Typically, foreigners need to secure a working visa such as (h1b) in order to work full time but the OPT obviates the need to go through the somewhat labyrinthine process of getting a working visa. [10]. OPT has been in existence since the early 1990s, but lobbyists from large tech firms have tried to convince the congress to increase the duration of it to be able to retrain foreign talent for a longer period and attract foreign workers to pursue a US degree in related fields. These corporations were mainly concerned about retaining talents in STEM fields as the demand for technical expertise grew larger than the supply of eligible native candidates. In 2008, the efforts by tech lobbyists paid off and the duration of OPT was extended for an additional 24 months, totaling 3years for international students graduating in STEM fields in the US. I will call this extension the OPT STEM extension, and this is the policy shock that I am utilizing in my paper.

The OPT STEM-extension was a powerful incentive mechanism for foreigners who were on the margin of pursuing a US college education. As most foreigners who pursue a US college education want experience working in the US, the policy change has dramatically increased foreigners who wanted to pursue a US education primarily in STEM fields. The stipulation of the OPT policy says that only full time students who are on a F-1 Visa are eligible for OPT. J-1 visa holders are also eligible to work in the US through a separate job training program called the Academic Training(AT) that allows work for up to 18months. While the OPT was extended to 3 years in 2008, AT has not experienced such extension and hence we see a dramatic increase in the take up of F-1 visas as opposed to J-1 after 2008. The distinct policy effect on the issuance of F-1 visas as opposed to J-1 visas is shown in Figure 2.6. This gives strong evidence that the OPT-STEM extension has had a labor market incentive for foreigners considering an education in the US. In this paper I use this

[10]↑typically, applicants compete through a lottery from a limited number of yearly allotment

OPT Shock as an shock that brought an exogenous increase in the number of internationals students in US colleges.

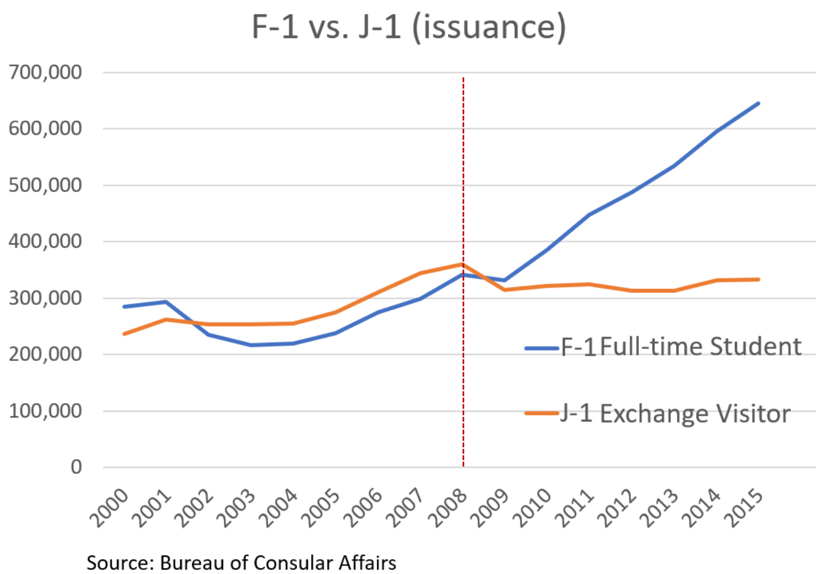

Figure 2.6. F-1 vs. J-1

In Figure 2.7, I show trends of treated schools overlaid with control schools that received little to no treatment. The treatment variable I use in later regressions is a continuous variable of the increase in international students. However, in order visualize the employment trends of the treatment and control group, I redefine treatment to be a dichotomous for the purpose of creating these graphs. Specifically, I divide the schools into 3 categories based on the institution size; Large Size, Middle Size, and Small Size. For each size category I get detailed summary statistics of the increase in international students between 2004 and 2016. Then, I rank order these schools based on the size of the increase. If the increase is in the top 50 percent they are in the low intensity treatment group. If the increase is in the top 25 percent they are in the high intensity treatment group. The control group consists of schools on the bottom 25 percent of the increase(or rank).

One key take away from these graphs is that comparing with the trend in the low treatment group, the trend of the high treatment group tends to show more of a divergence after 2008 with the control group. This is most pronounced in comparing the right panel to the

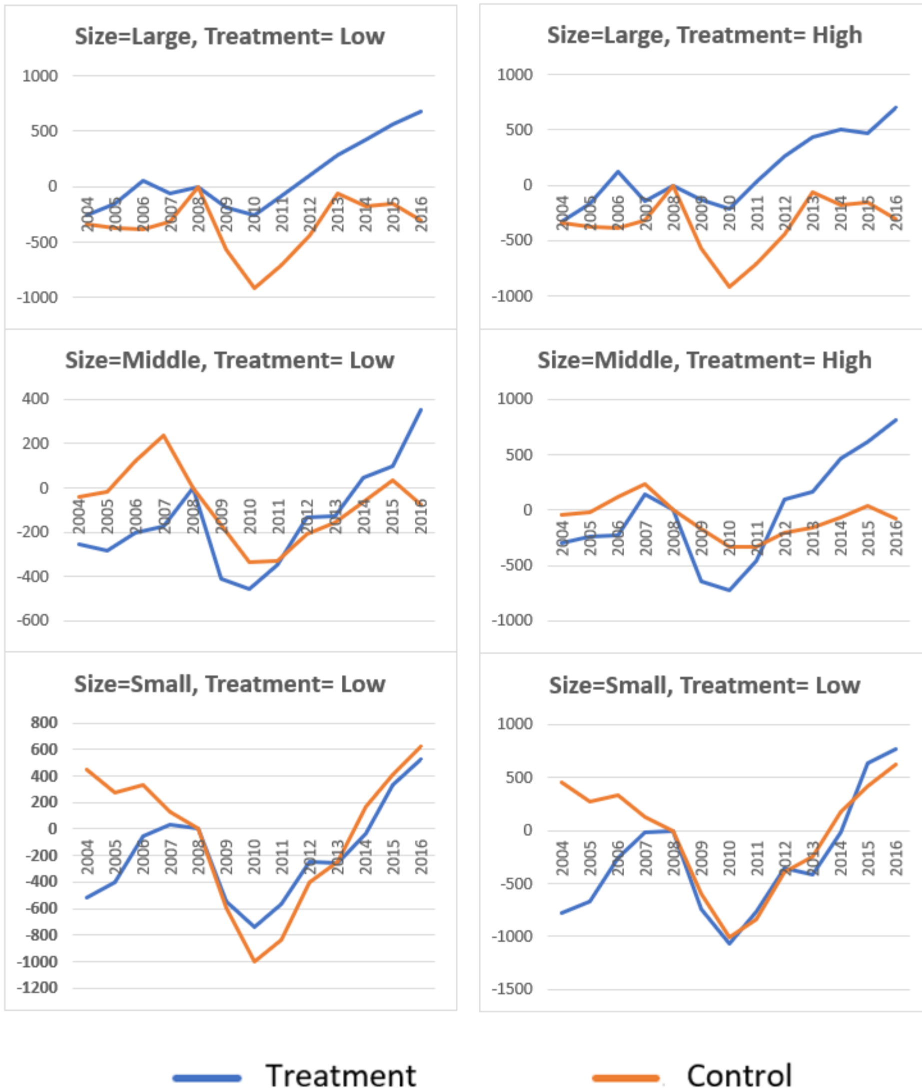

Figure 2.7. Trendline of Employment (by size and treatment)

Note: The figure shows the total change in employment (with 2008 employment level as reference). The top panel consist of research schools that are large in size typically 20,000 more more students. The middle panel is those that are typically 10,000 to 20,000 and the bottom panel consist of schools that are smaller than 10,000. The control group schools show increase in magnitude of international students that fall in the bottom 25 percent in the respective size categories. The treatment group has low and high intensity group. The low intensity groups are schools whose magnitude of the increase falls in the top 50 percent and the high intensity falls in the top 25 percent within the size category.

left panel in both the large size and middle size schools; the gap between the blue series and the orange series gets larger after 2008 for high intensity treatment groups. This indicates that controlling for the size of schools, schools that had relatively more influx of international students have a slight advantage in the increase in the number of local employment after the 2008 OPT shock.

2.3 Methods and Results

2.3.1 Ordinary Least Squares

In order to capture the simple change in employment in response to the inflow of international student, I first run an OLS linear model with employment in a particular zipcode that a school s is located in as my dependent variable, Then I regress this DV on the yearly change in the number of international student in the same school s. This will show how the total employment changes year by year from 2004 to 2016 with the changes in international student enrollment. Note, I use all years in this one. Conveniently, each school in the data (total of 320 research institutions) is matched one-to-one with a zipcode[11].
The OLS regression is then :

$$TotalEmp_{st} = \beta(TotalInt._{st}) + SchoolFE_s + Year_t + \mathrm{e}_{st} \tag{2.1}$$

I add school and year fixed effects so that the relationship is not driven by school-specific trends or macroeconomic trends. Table 2.1, Column 1 shows the result without weight and column 2 shows the result weighted by the 2004-level of international student count to roughly take account of the size of institution based on its size of their international student body. We see that the coefficient on $TotalInt$ is about 0.2 which translates to 1 additional international student creating 0.2 jobs. A more tractable interpretation will be that for every 5 additional international student, 1 extra job gets created in the region. In column 3, I have added two lags of the independent variable. We see that there is a 2 year lag before the

[11]↑Some school campuses span more than a single zipcode in actuality but IPEDS list the single most relevant zipcode in its data

Table 2.1. OLS Regression

	(1) OLS	(2) OLS weight	(3) OLS_lag
TotalInt	0.208***	0.246***	0.0463
	(0.0328)	(0.0230)	(0.174)
TotalInt _lag1			-0.114
			(0.250)
TotalInt _lag2			0.322*
			(0.195)
Observations	4,132	4,090	4,089

Note: Universe of 320 schools classified as research institutions by the Carnegie Classification. The regression includes year and school fixed effects. Col 2 & 3 are weighted with 2004 level internatonal student count. (*) represent significance.

effect is fully realized. This can be thought of as the adjustment period that businesses need to catch up to the increasing demand created by international students.

2.3.2 Using the OPT Shock (DID)

A simple OLS may not tell the whole story as there may be reverse causation; international students may be attracted to the amenities that college towns have to offer rather than international students causing the towns to have better amenities. To mitigate this channel, I utilize the 2008 OPT STEM extension(OPT Shock) which acts as a shock to the inflow of international students. For this specification, I only use two periods which are the years 2004 and 2016. The dependent variable is once again the total employment, but the independent variable is now the change in international student enrollment between 2004 and 2016 which is then interacted with the indicator for the post-policy year, 2016. This regression will be essentially comparing the employment differences within a school and compares this difference across those of other schools to see how the degree of exposure (influx of international students) affect changes in total employment.

The DID regression is then :

$$TotalEmp_{st} = \beta(\Delta TotalInt_{st} \times I(post08)_{st}) + SchoolFE_s + Year_t + \mathrm{e}_{st} \tag{2.2}$$

As before I have included the school and year fixed effects. In Table 2.2, column 1 row 1, we see that an extra international student creates about 0.4 jobs, so 2.5 international students create 1 job in the region, roughly speaking. Column 2 replaces our main independent variable with the same interaction term but using the change in Grand total number of students instead of just international students. This is to show that this increase in employment has not been driven by overall increase in college enrollment but specifically by the increase international students. In equation (3), I include both interactions in the same regression and hence the regression specification looks like so:

$$TotalEmp_{st} = \beta_1(\Delta TotalInt_{st} \times I(post08)_{st}) + \beta_2(\Delta Grand_{st} \times I(post08)_{st}) + SchoolFE_s + Year_t + \mathrm{e}_{st} \tag{2.3}$$

The result of equation 3 is in Table 2.2, column 3. We see that the coefficient on the main independent variable does not change with the inclusion of another policy variable. This shows evidence that international students play a distinct role in increasing employment and have been mainly driving this increase. As I have discussed in the mechanism section, this is due to their higher consumption power. However, one thing to note is that the domestic enrollment has more or less stagnated and hence the bulk of the increase in the Grand total enrollment has been driven by international students. The insignificance of the coefficient on Grand total interaction term may not necessarily mean that domestic students do not spend more compared to international students but could merely be a data problem where we do not see enough variations across time.

2.4 Robustness Check 1

2.4.1 Recessionary Effect: Using adjacent zipcodes

Since 2008 coincides with the recession, the results we previously saw may be driven by a contemporaneous economic shock that affect total employment in areas that have shown high enrollments of international students. This can be so if there are certain characteristics of college towns that attract international students, and at the same time for unrelated reasons, make the town recession-proof or more prone to rebound after the initial dip in employment compared to places that have received little international student inflow. These is no obvious characteristics of these college towns that might cause a differential effect from the recession, but one way to mitigate this bias is to compare the employment rate with the zipcodes adjacent to the school-specific zipcodes. Specifically, I compare the changes in the total employment in the school-specific zipcodes to the average of the changes in the surrounding zipcodes that share the same first 3 digits. By doing so I am getting the increase in employment due to international student in the school-specific zipcode net of the common

Table 2.2. DID Specification

	(1) Int.(raw)	(2) Grand(raw)	(3) Both	(4) Int.(%)	(5) Grand(%)
$\boldsymbol{\Delta TotalInt \times I(post08)}$	**0.399*** (0.0779)**		**0.382*** (0.0107)**		
$\Delta Grand \times I(post08)$		0.0367 (0.0291)	-0.006 (0.0334)		
$\Delta\% TotalInt \times I(post08)$				1.043*** (0.387)	
$\Delta\% Grand \times I(post08)$					13.85*** (4.447)
post_2008	82.37 (191.1)	604.1*** (187.7)	-95.49 (158.28)	531.6*** (153.1)	415.3** (165.8)
Observations	630	630	630	552	554

Note: Universe of 320 schools classified as research institutions by the Carnegie Classification. The regression includes year and school fixed effects. Only years 2004 and 2016 are included. Post 2008 indicator is the year 2016. 2008 OPT shock is used as a policy variable. Columns represent the indepdent variable. The first three are in actual raw number and the latter two are in percentage terms. Column three includes both policy variables in the same regression. All regressions weighted by 2004 level International student count. (*) represent significance.

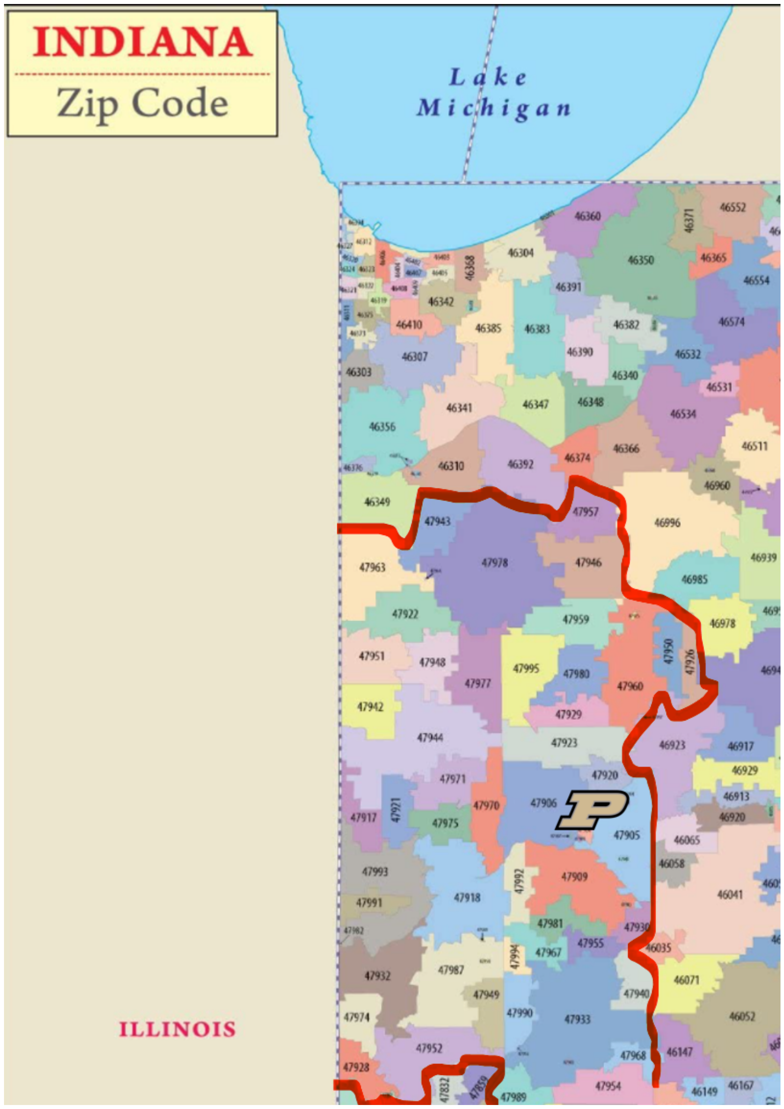

Figure 2.8. Zipcodes around Purdue Univ.

Map of Indiana with Purdue Univ. The red line indicates all the zipcodes with the same 3 headings (479xx). Source: www.randymajors.org

recessionary effect that the school-specific zipcode is subjected to along with the surrounding area zipcodes.[12]

To illustrate this lets take for example Purdue University since it is ranked high in terms of research and number of international student enrollment. If you look at figure 2.8, Purdue

[12]↑ This method relies on the implicit assumption that zipcodes that have the same first 3 digits have similar recessionary shocks which may not be true. For example, zipcodes with similar headings may not share borders or economic activity as zipcodes were defined to share the same central post office instead of a region that shares the same economy.

Table 2.3. DID Specification(Adjacent Zip)

	(1) Int. Only	(3) Both
$\boldsymbol{\Delta TotalInt \times I(post08)}$	0.353***	0.382***
	(0.0589)	(0.0641)
$\Delta Grand \times I(post08)$		-0.0258
		(0.0231)
post_2008	-369.1**	-309.5**
	(144.8)	(154.2)
Observations	630	630

Note: Universe of 320 schools classified as research institutions by the Carnegie Classification. The regression includes year and school fixed effects. Only years 2004 and 2016 are included. Post 2008 indicator is the year 2016. 2008 OPT shock is used as a policy variable. Column 1 uses only the policy variable for international students and column 2 includes both policy variables. DV is the total employment in a zipcode net of surrounding zipcodes's average employment. All regressions weighted by 2004 level International student count. (*) represents significance.

is located in zipcode 47907. Hence, I will be comparing the total employment change at 47907 where Purdue is located to the average of the employment changes in the surrounding zipcodes with the same 3 headings which are shown by the redline.[13]

The modified DID regression is of this form:

$$(TotalEmp_{st} - Avg(EmpZip3)_{st}) = \beta(\Delta TotalInt_{st} \times I(post08)_{st}) + SchoolFE_s + Year_t + \mathrm{e}_{st} \tag{2.4}$$

Here, the only thing that changed is the dependent variable where now it is the total employment minus the average of the total employment in surrounding zipcodes that share the 3 first headings of the zipcodes. In Table 2.3, we see that in the first column the coefficient is 0.35 which is similar to what we have obtained in Table 2.2, which shows that this result is robust. Also, in column 2 I have added the interaction term for Grand total, and as before, it does not show any significance.

[13]↑Indiana University-Bloomington which is a comparable flagship school in the same state will be compared to its own surroudnig zipcodes which start with 474xx.

2.4.2 Recessionary Effect: Using CBSA

As I have mentioned in the previous section, zipcodes as a geographical unit is not a great definition of shared economy as they are delineated by proxmity to central post offices. Using Core-based Statistical Area (CBSA) as the geographical unit is a more reliable way of delineating areas that share the same economy. The classification was defined by the Office of Management and Budget (OMB) to comprise several counties that are tied socioeconomically and have at least 10,000 people. I have used the crosswalk between zipcodes and CBSA to create a new measure of adjacent economies. To illusrate, going back to the example of Purdue University, I have indicated the CBSA of Purdue and Indiana University in figure 9 to show which CBSAs these institutions will be compared to. Note, the geographical boundaries of the adjacent economy that the school-specific zipcode belongs is now much smaller than using the first 3 zipcode headings. In short, in this exercise, I run a regression similar to equation (4) but now I compare the total employment in a school-specific zipcode to the average employment of the zipcodes that belong to the same CBSA of the school-specific zipcode. By doing so, I limit the comparison to regions that better reflect a tied economy that shares the spillovers from international students. The regression is therefore:

$$(TotalEmp_{st} - Avg(CBSA)_{st}) = \beta(\Delta TotalInt_{st} \times I(post08)_{st}) + SchoolFE_s + Year_t + \mathrm{e}_{st} \tag{2.5}$$

Looking at Table 2.4, we see that the coefficient on the policy variable increases sligtly to 0.43. This means that almost 2 international students support 1 job in the local economy. This slight increase from 0.3 may be evidence that spillover effects are more pronounced within a given CBSA than in a adjacent zipcodes that shares the first 3 heading.

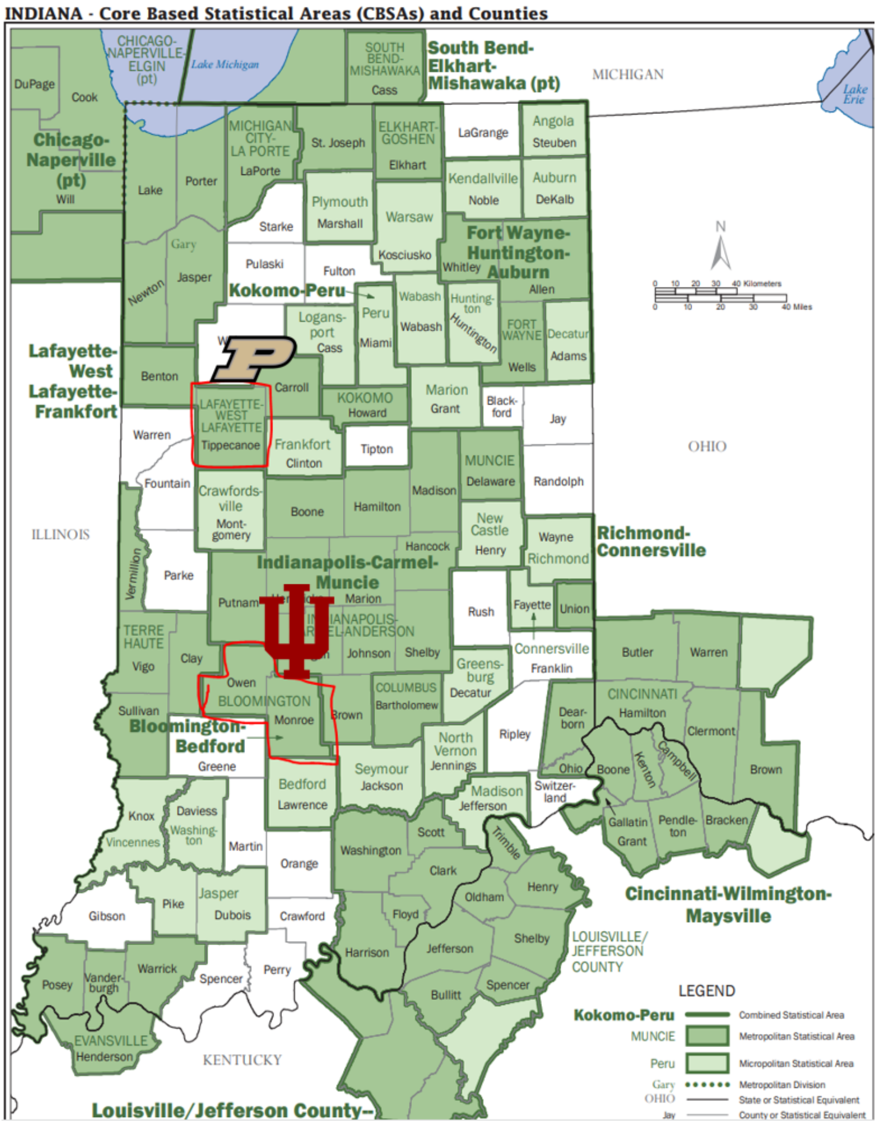

Figure 2.9. CBSA of Purdue Univ.

Map of Indiana with Purdue Univ. and Indiana University. The red line indicates delineates the CBSA that these two schools belong to. Source: www.census.gov

Table 2.4. DID Specification(CBSA)

	(1) Int. Only	(3) Both
$\boldsymbol{\Delta TotalInt} \times \boldsymbol{I(post08)}$	0.425***	0.418***
	(0.0984)	(0.106)
$\Delta Grand \times I(post08)$		0.00552
		(0.0321)
post_2008	-216.8	-226.1
	(178.4)	(186.7)
Observations	630	630

Note: Universe of 320 schools classified as research institutions by the Carnegie Classification. The regression includes year and school fixed effects. Only years 2004 and 2016 are included. Post 2008 indicator is the year 2016. 2008 OPT shock is used as a policy variable. Column 1 uses only the policy variable for international students and column 2 includes both policy variables. DV is the total employment in a zipcode net of average employment in the zipcodes within the same CBSA. All regressions weighted by 2004 level International student count. (*) represents significance.

2.5 Robustness Check 2

In this section, I performed a robustness check by separating the level of internatioanal students by undergraduate and graduate students. This distinction may be important especially as the two groups are differentiated by their consumption power, age, backgrounds, and employment by the school. One particular aspect of graduate students is that they may be counted towards local employment if they are employed as TAs or RAs by the graduate school.

2.5.1 General Result using Graduate School

For the data, I redownloaded all the education related dataset from IPEDS but instead of choosing all students, I have divided by undergraduate and graduate full time students. This was to alleviate the concern that perhaps graduate students who are counted towards the regional employment is driving the effect. After running the same analysis separately by groups, I found out that graduate students are indeed responsible for the employment. After controlling for both undergraduate and graduate students in col3 of Table 2.5, we see that the coefficient on the graduate student term is only significant. This may be due to the fact that among international students graduate enrollment in research institution (masters and phd) are slightly larger than undergraduate enrollment. Hence, the larger group is responsible for the consumption effect. I initially assumed undergraduate international students to have a much higher purchasing power than graduate international students due to higher tuition payment. However, given that graduate students are a bit more older and potentially have dependents, they may have more fixed costs on car, housing, and food. I do not think that the employment effect is primarily being driven by the graduate students being counted towards the education sector's employment. First, there is no evidence that this is happening at a large scale as graduate students are mostly employed part-time, and secondly, as Table 2.6 shows, the exclusion of the education sector barely changes the coefficient. This indicates that the mechanical increase in head count of education employment through graduate students is probably not the main channel.

Table 2.5. Graduate and Undergraduate

	(1) Graduate	(2) Undergrad	(3) Both
$\boldsymbol{\Delta Grad.Int \times I(post08)}$	0.964***		1.107***
	(0.187)		(0.207)
$\Delta Under.Int \times I(post08)$		0.0925	-0.285*
		(0.157)	(0.166)
post 2008	247.7*	565.0***	354.9**
	(142.1)	(154.3)	(153.0)
Observations	630	630	630

Note: Graduate and Undergrad as defined by IPEDs. Interaction term with post period indicator is created for both groups for each school. All other specification is the same as before.

2.5.2 Trendline of Employment

As we have seen in the previous section, only Graduate enrollment is significant. In this section, I recreated the trendline using just international graduate student enrollment. Figure 2.10 shows the employment effect of the treated groups which are college towns that have received more international students overlaid with control groups which are towns that received less than zero. The pre-trends seem more or less parallel up until 2008 and gets disrupted probably due to the recession, but starting 2010, you see a clear upward trend of treated towns. The Grey line represents towns that have increased more than 1200 in international student enrollment between 2004 and 2016 and you see that the divergence in starker than it is for the Blue line that received a bit less. Nevertheless, both the Blue and Grey lines (treated towns) seem to show an increasingly diverging upward trend of employment compared to that of the Orange line (control). In Figure 2.11, I show a similar graph with just the undergraduate enrollment, and we do not observe a clean divergence depending on the inflow of international students.

I have also investigated if the regional economies' size relative to the size of the school may perhaps impact employment. For example, UCLA which is at an already large metro area may not respond much with the influx of international students compared to a smaller college town where the local employment heavily relies on the school. To get a consistent and universal measure of the ratio of school size to the local economy, I have calculated the share of the total enrollment over the total employment in the zip-code for each school using year 2008 ($Share = \frac{totalEnroll_s}{totalEmp_s}$).

Figure 2.12 shows the trend for varying levels of this share. The orange line is the control groups as before. We can see that schools whose size is a relatively smaller share of the town's employment has a much bigger effect (Grey and Green). Once the share becomes large, the effect goes away. This results is somewhat counter-intuitive in that I expected smaller towns (relative to the school size) would have a stronger effect. This may however indicate that the employment in zipcodes of larger schools do not have many businesses due to the larger presence of campus buildings and facilities. In a later response, I extend my

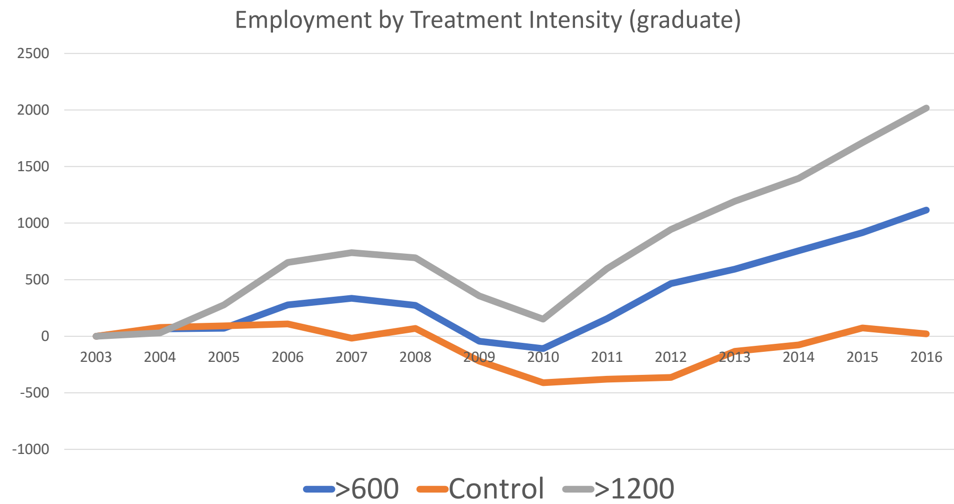

Figure 2.10. Employment by Treatment Intensity (graduate)

Only using Graduate students as defined by IPEDS. Treatment intensity is the change in enrollment of international student from 2004 to 2016. Greyline is more than 1200 and Blue line is more than 600. Control line are towns that received 0 or less international students.

definition of a college town to include the cities, counties, and the CBSA that the colleges belong to. The effect is still present up until the county-level but not throughout the CBSA.

As a caveat, these are only qualitative evidence as I could not get statistical evidence of the parallel trends of treated and control groups. I have added an extra pre-period, and experimented with varying restriction on pre-periods and treatment intensity. However, results show that the divergence in trend started taking place before the policy; albeit, the difference in the post-periods is more statistically significant than that of the pre-periods. This may indicate that college towns that later received more international students have been economically growing compared to towns that do not; however, the difference in their growth diverged even more after the influx of international students. More work has to be done on this end to show clear statistical evidence.

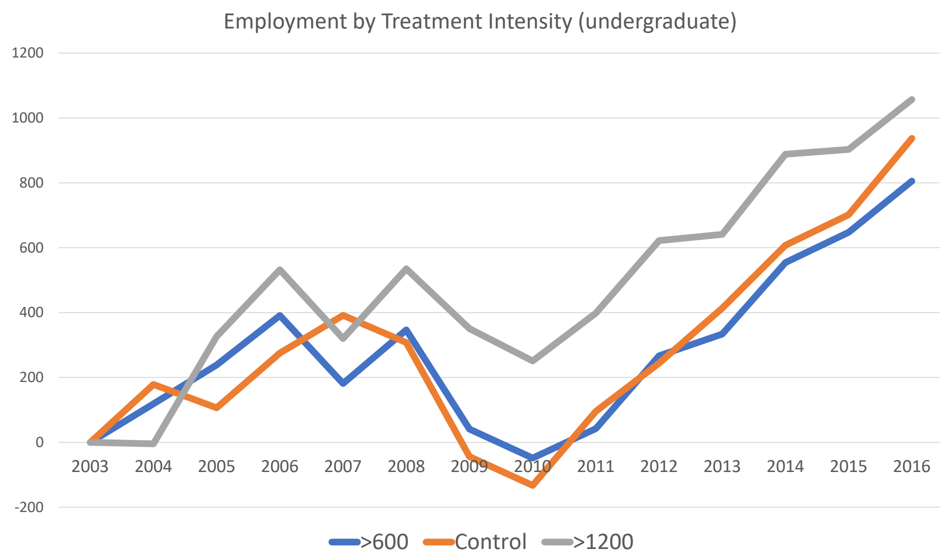

Figure 2.11. Employment by Treatment Intensity (Undergraduate)

Only using Undergraduate students as defined by IPEDS. Treatment intensity is the change in enrollment of international student from 2004 to 2016. Greyline is more than 1200 and Blue line is more than 600. Control line are towns that received 0 or less international students.

2.5.3 Varying Units of Region

In this section, I have varied the unit of anlaysis of my dependent variable to see if there is a trickling down effect from graduate international students to areas surrounding the college town zipcodes. Table 2.6 shows varying levels of units I used for the dependent variable $TotalEmployment$. I have summed all the employment count in each respective regional units. The crosswalk I generated between the zipcode and city, county, and CBSA were obtained from the United States Department of Housing and Urban Development (HUD) website. I could not get a reliable crosswalk between zipcodes and commuting zones so I used CBSA instead which are collection of counties that are in the same economic region. I have also only focused on graduate students as they are mainly leading the economics growth.

We see that the effect of international students trickle down to surrounding zipcodes in the same city and counties as the significance in the interaction term of international students

Table 2.6. Changing Regional Units

DV unit	(1) Original(zip)	(2) City	(3) County	(4) CBSA
$\boldsymbol{\Delta Grad.Int} \times \boldsymbol{I(post08)}$	0.964***	0.467***	0.422***	0.0912*
	(0.187)	(0.143)	(0.142)	(0.0505)
post_2008	247.7*	434.3***	448.7***	445.6***
	(142.1)	(108.6)	(107.5)	(40.79)
Observations	630	630	630	630

Note: Using only graduate students as defined by IPEDS. Each column is a different regional unit and it increases with the column. Used the HUD data to get zip code and city,county,cbsa crosswalk files. Results are null for the interaction term for Grandtotal. All other specification same as before.

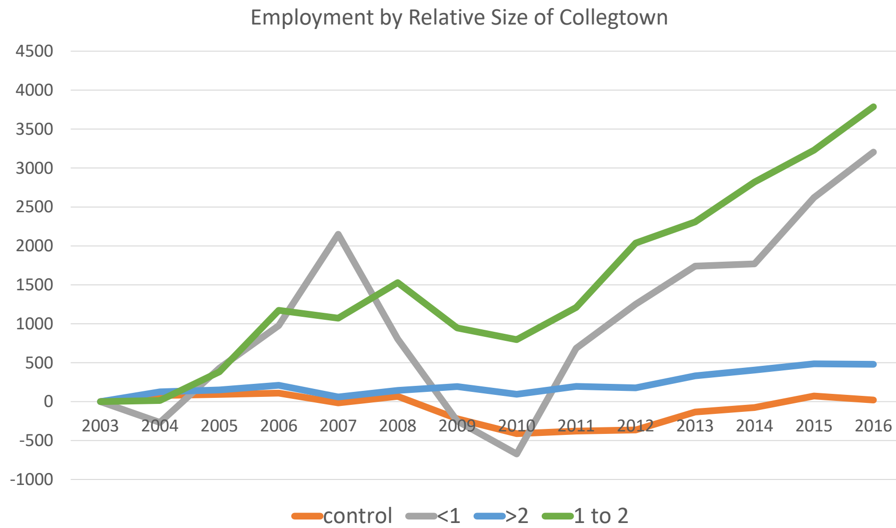

Figure 2.12. Employment by Relative Size of Collegtown

Shares are calculated as total enrollment in 2008 over total emp in the zipcode of the school in 2008. All other same as before.

show. The effect slowly dissipates as we increase the size of the unit which makes sense as the effect should be strongest near the campus. Also, this effect more or less disappears or dramatically dissipates once we choose CBSA as the unit of analysis; CBSAs generally are too big for international students to have a significant employment effect throughout.

2.5.4 Heterogeneity By Industry

In Table 2.7, for each column,I have excluded the labeled industries from the total employment count. I have started with excluding the education sector which theoretically will most likely be affected by the influx of international students. While the NAICS manual does not explicitly have information on whether or not graduate students are counted towards employment, it does include primary and secondary education industries which may be diluting some of the effect of international students. Comparing with the original column we

Table 2.7. Sector-Industry Level Analysis

Excluded Sector	(1) Original	(2) Educ.	(3) Rec.	(4) Service.	(5) Retail	(6) Finance
$\Delta Grad.Int \times I(post08)$	0.964***	0.954***	0.795***	0.962***	0.988***	0.887***
	(0.187)	(0.237)	(0.182)	(0.198)	(0.216)	(0.192)
post_2008	247.7*	314.7	109.8	259.8	353.2**	319.3**
	(142.1)	(203.5)	(140.6)	(159.8)	(168.0)	(155.6)
Observations	630	490	595	572	530	576

Note: Using only graduate students as defined by IPEDS. Each column represents the sector/industry excluded in calculuating the total emp. Sector/Industry as defined by NAICS. Column2 excludes 61; Col3 excludes 71 and 72; Col4 excludes 62, 81, 92, 23, 22; Col 5 excludes 42,44 and 45; Col 6 excludes 52, 53 ,54, 55, and 56.

still see a slight decrease (from 0.96 to 0.95) in the coefficient when excluding the education sector.

In the next column I have excluded Arts, Recreation, and Accomodation which are NAICS code headings 71 and 72. I lumped these two since these industries will directly capture the extra spending from international students in the form of amenities for entertainment and housing. We see that the coefficient decreases dramatically from 0.96 to 0.79 which indicates that these industries are responsible for the lion's share of the growth resulting from international students. This makes sense in that international students will have particular proclivity for different kinds of recreation and food. They will also have dire need of housing due to lack of established family ties near the area. In the next column, I have excluded general services provided by the city such as health care, construction, and government administration. We see that this sector is not much responsible for the trend. Next, I have excluded retail, and finally in the last column I have excluded finance, insurance, and management firms. These last set of industries are somewhat responsible for the growth as the coefficient has decreased more than other exclusions. This may be due to increase in various forms of insurance and services required by international students as they buy cars and housing. Regarding using larger geographic units, the results were generally null and did not tell a clear story.

In sum, the regional employment growth due to international students do not primarily take place in the actual host institutions but in the small restaurant and housing businesses outside the school.

2.6 Conclusion and Policy Recommendation

So far we have seen that international students have had a positive effect on the employment outcomes of surrounding areas. A conservative estimate shows that 3 additional international student enrollment creates 1 additional job in the zipcode that the school belongs to. The effect is driven primarily by graduate international students as opposed to undergraduate students. This value is consistent with the estimates of the NAFSA study which is also 3 to 1. However, one caveat is that the regressions are meant to only show the short term benefits in the immediate surroundings. The spill-over effect is probably larger if we include surrounding areas and take a more dynamic approach. Also, more data and analysis is needed to quantify other positive externalities that have far-reaching outcomes in terms of knowledge-based contributions.[14]

There are some policy recommendations based on these set of results. For one, this shows the benefit experiencing college in-resident as opposed to remote. The channels that create infrastructure, businesses, and eventually more jobs are possible when students are present in campus. This has implications in today's world where the expectation of wide scale lockdowns due to COVID can prevent and deter international students from physically coming to the US if a remote option is available. Such COVID related immigration restrictions may altogether deter foreigners from coming to the US in the first place.

The results also have implications on how local governments can interact with the schools in their region to maximize the returns to investing in colleges to attract and retain more students. Investment in public services and amenities to attract more students to local college campuses may prove to be more profitable than we have thought in terms of creation

[14]↑For example, Chellaraj, Maskus, and Mattoo 2008 attempt to show how international students help generate more patents in the US.

of jobs. In a nutshell, international students create more jobs in the college towns they reside in.

3. IMMIGRANTS REDUCE UNIONIZATION IN THE UNITED STATES

3.1 Introduction

The rise of unionization from the early to mid-20th century and its subsequent decline marked one of the most dramatic changes in the U.S. labor market over its history H. S. Farber and Western 2001 (H. S. Farber and Western 2001). In 1900, about 3 percent of the employed workforce was unionized. As shown by Figure 3.1, union density rose to 26 percent in 1960 on the eve of immigration liberalization, and has steadily fallen since to about 11 percent today (Nowrasteh and Powell 2020).

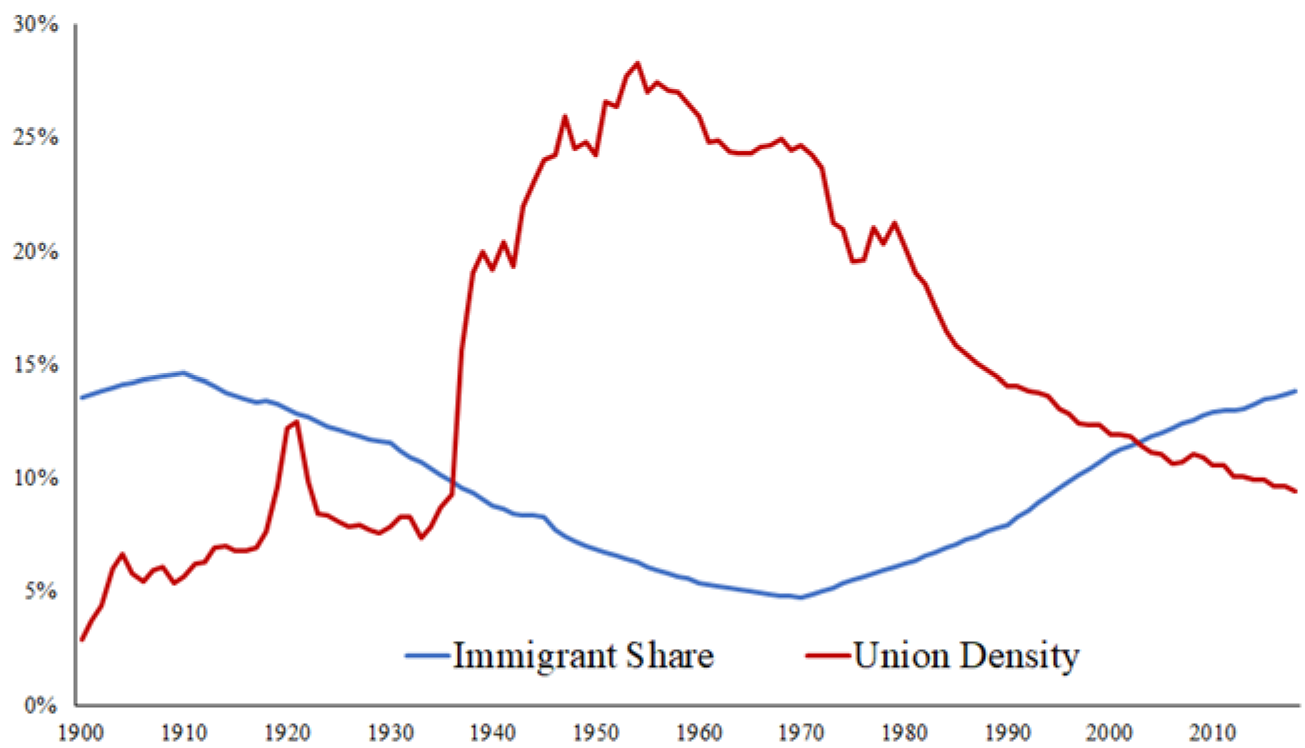

Figure 3.1. Union Density v. Immigrant Share

Source: Nowrasteh and Powell 2021, 208.

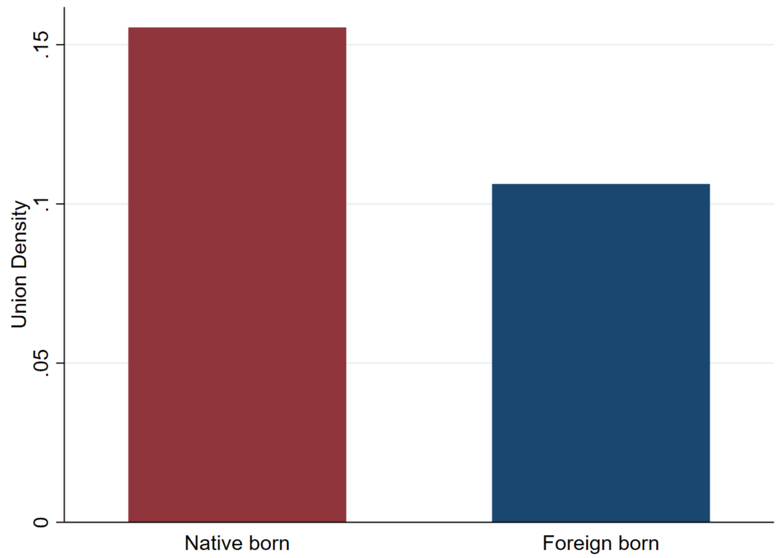

Figure 3.2. Preferences for Unionization by Nativity

Generated using CPS-ASEC 1994-2020. This figure shows the share of natives and immigrants who are part of a union averaged over 1994-2020. Used sampling weights.

This trend alludes to a negative relationship between immigration and unionization, which bears substantial implications for the United States labor market. Economists have studied this relationship in many parts of the world, including Norway (Finseraas, Røed, and Schøne 2020), Austria (Antón, Böheim, and Winter-Ebmer 2016), and across OECD countries more broadly (Lee 2005). In this paper, we seek to bridge the literature on unions and the labor market impact of immigrants to examine how immigrants affected unionization by increasing the ethnic and racial diversity of the American workforce that, in turn, diminished worker solidarity. Our first step is identifying and modifying a theoretical model of union formation that includes variables of how diversity affects solidarity.

We adapt a model of union formation developed by Naylor and Cripps 1993 to explain how immigration affects unionization through its effects on the solidarity between union members and potential union members. In this model, we allow workers to be heterogeneous in their individual solidarity from social customs and examine the extent to which group solidarity changes with immigration. To measure diversity, we adopt a fractionalization index that gauges the cultural differences of the workforce (Alesina and La Ferrara 2000). Specifically, we measure immigrant-induced fractionalization by measuring the degree of concentration of various foreign-born nationality groups and native racial groups. A perfectly fractionalized country is one where every resident has a different ethnic or racial background.

To empirically estimate the effect of increased immigration and diversity on unionization, we employ the national skill-cell method developed by Harvard economist George J. Borjas (Borjas 2003). This method requires the creation of different skill categories based on education level and years of experience in the labor market. The national skill-cell approach assumes that workers are mobile within the United States, seek out the highest wages, are perfect substitutes with other workers who have the same levels of education and experience, and imperfect substitutes with workers in other skill-cells. Grouping individuals by education and work experience allows us to more accurately describe the environment in which workers make labor market decisions.

Our paper is unique in three ways. First, we adapt the Naylor and Cripps 1993 model to study how immigration affects union formation through its impact on worker solidarity. Second, our paper is the first to apply the national skill-cell method to measure how immigrants affect union density. The national skill-cell method is appropriate for this analysis because it groups workers that are substitutes and better explains unionization behavior than the spatial approach.[1] Third, we incorporate commonly accepted measures of fractionalization to study union formation.

In our baseline analysis of the effect of immigrants on union density, we find that a 10 percentage point increase in immigrant share corresponds to a roughly 5 percentage point decline in union density. The immigration-induced diversification of the workforce that, in turn, lowers worker solidarity, is the main channel through which union membership declines. In our robustness checks, we find that a mere increase in labor supply due to immigrants is not responsible for the fall in unionization. We also find qualitatively similar results when

[1] ↑More on this in in later Section

using a modified immigrant share to account for contemporaneous native supply shocks with immigrant shocks. The rest of this paper is outlined as follows. Section 2 describes the background for this analysis and delves into the relevant literature. Section 3 gives the theoretical basis. Section 4 explains the empirical methods and data. Section 5 shows the empirical results. Section 6 shows the robustness checks. Finally, Section 7 concludes.

3.2 Background

American unions largely opposed immigration in the early 20$^{\text{th}}$ century because they viewed immigrants as labor substitutes for members of their unions (Briggs 2018; Briggs Jr 2010; Critzer 2003; Watts 2002; Burgoon et al. 2010). Thus, unions thought that immigrants would weaken their power to bargain with employers that would result in lower wages and contribute to the demise of organized labor (Sinyai 2006). The American Federation of Labor (AFL), the largest union in the United States, supported immigration restrictions like the literacy test and national origin quotas to reduce labor competition between their members and immigrants in order to raise wages (LeMay 2006). Later, union organizers like Cesar Chavez complained bitterly about illegal immigrants and lawful migrant workers competing with his unionized workforce and asked the federal government to step up deportations (Briggs Jr 2010). But anti-immigration opinion was not uniform across all labor unions and many attempted to extend union membership to immigrants through sustained organizing efforts, especially after many accepted the inevitability of relatively pro-immigration public policy after the immigration liberalization of 1965 (Critzer 2003; Watts 2002; Burgoon et al. 2010). Beginning in the mid-20$^{\text{th}}$ century, the newly formed AFL-CIO started supporting more liberal legal immigration policies while opposing illegal immigration. In 2000, the AFL-CIO dropped its support for increasing enforcement against illegal immigrants, supported an amnesty for them, and tentatively endorsed increasing legal immigration (Briggs 2018).

Unions were likely wrong about immigrants reducing worker wages. A massive empirical literature finds that immigrants have a relatively small effect on the wages of native-born American workers that is often positive, especially in the long run (National Academies of Sciences, Medicine, et al. 2017, p. 201). The most important strand of research in the literature that examines how immigrants affect wages uses Borjas' skill-cell method, which estimates the relative wage impact of immigrants on native-born workers by regressing cell-specific labor market outcomes on the immigrant share in the respective education-experience group (aka. skill-cell) (Borjas 2003).

Adding a further wrinkle, union membership has been largely divided along racial and ethnic lines because diversity reduces solidarity among members (A Thomas Lane, A. Lane, and A. Lane 1987; Mink 2019; Ferguson 2016). In fact, according to the survey results of Putnam 2007, people in ethnically and racially diverse communities tend to withdraw and trust others less in the short run. This applies to people of both the same and different racial or ethnic backgrounds. In the words of Putnam 2007, "Diversity does not produce 'bad race relations' or ethnically-defined group hostility, our findings suggest. Rather, inhabitants of diverse communities tend to withdraw from collective life, to distrust their neighbours, regardless of the colour of their skin ..." Putnam's findings are controversial, but we suspect that diversity will make union formation more costly by raising transaction costs across a diverse population (Olson 2012). In recent decades, immigrants have dramatically increased the diversity of the labor force. Hence, immigrants could affect union formation by increasing ethnic and racial diversity.

We consider how immigrants affect union formation by following in the footsteps of several economists who have tested the social customs model of unionization. Visser 2002 uses European population and survey data to see whether social customs affect an individual's decision to join or leave a union, finding that an individual is less likely to leave a union if their parent(s) were union members and that a person's perception of how others view union membership significantly impacts their probability of joining a union. Finseraas, Røed, and Schøne 2020 find that immigrants have no effect on union density in Norway's construction sector. The most relevant empirical literature in the American context is a paper by Ferguson 2016 that examines how diversity increases transaction costs and influences peer effects in the various stages of union formation that reduce union density. His work, however, only examines diversity overall and not whether immigration-induced diversity makes the U.S. labor force less likely to unionize.

Other papers also examine the relationship between immigration and unionization within specific contexts. For instance, a cross-country analysis by Brady 2007 finds that immigrants positively impact unionization, but the results are not robust because they did not hold up to a sensitivity check.[2] Antón, Böheim, and Winter-Ebmer 2016 looks at the relationship between immigration and unionization rates in Austria and find that higher shares of foreign workers decrease union density among natives. This pattern is not due to native workers leaving unions, but to the different separation rates and hiring practices of firms which appear to have adjusted their demand to the increased supply of foreign workers. Lee 2005 analyzes the relationship between international migration and unionization across 16 affluent OECD countries and finds a negative relationship between international migration and union density between 1962 and 1997.

Additionally, Burgoon et al. 2010 examine how immigration affects union density in the United States using a time series analysis. They find that immigration does not affect union density. However, this paper is different from our paper in several ways. First, our analysis groups individuals by their educational attainment and level of experience across time. This more accurately represents how workers affect each other in the labor market than a time series analysis that is only indexed by time. Additionally, we introduce several restrictions on our sample that Burgoon et al. 2010 does not. These include restrictions by gender, age, and labor force characteristics. By implementing these restrictions, we more precisely identify how immigrants could affect unionization.

[2]↑In fact, Brady 2007 mentions "... a careful sensitivity analysis of the models suggests that these results are sensitive to including the other country-level variables." Brady 2007 also points out that the descriptive statistics show a null relationship between immigration and unionization. Therefore, although their results show a positive relationship between immigration and unionization, a closer look at the robustness of their models and their descriptive statistics points to an insignificant relationship between these variables.

3.3 Theory

3.3.1 Overview of Social Customs Theory in Union Formation

The theoretical literature on how immigration may potentially affect union density is relatively small and relies primarily on what is known as the Social Customs Theory. Akerlof 1980 defines a social custom as “an act whose utility to the agent performing it in some way depends on the beliefs or actions of other members of the community.” In the context of unionization, Social Customs Theory refers to the idea that individuals decide whether to join a union based on how others decide to unionize and what beliefs others hold about unionization. Social Customs Theory is important when analyzing how immigrants affect unionization behavior because immigrants are different from natives in their proclivity towards unionization. Therefore, when the share of immigrants in the population changes, so will the diversity of beliefs and actions pertaining to unionization. According to Social Customs Theory, these differences in the population will drive changes in unionization behavior. Booth (1985) develops a social customs model that shows unions can form without compulsory membership, even in the presence of the free rider problem, if reputation is included in each individual’s utility function and if all individuals are assumed to be identical. Overcoming the free rider problem is important for unions to survive. If, for instance, all workers free rode on unionization efforts by not paying dues while they received the benefits of unionization, then nobody would pay dues, the unions would disband or fail to form in the first place, and those benefits would not exist. Booth 1985 is a major breakthrough in the theoretical literature on union formation because it addresses the free rider problem, but the conclusion that union membership will only exist at a density of 0 percent or 100 percent does not match empirical reality. The advantage of the Naylor and Cripps 1993 model is that workers are allowed to be heterogeneous and predicts union density that is between the two extremes.

Here, we will describe the mechanism by which immigrants affect union density and unionization behavior using the Naylor and Cripps 1993 social customs model. To start, we will define union density as follows:

$$u = \frac{M}{L}$$

where M is the number of union members and L is the total number of employed individuals. Here, union density will change when either M or L change.

With that, there are two ways immigrants can influence union density. The first is through their effects on the labor supply. Since L is a combination of both native and immigrant workers, if the number of working immigrants increases, then L will also increase, *ceteris paribus*. This will cause the denominator of u to increase, which means u itself will decrease. Note that this will only occur if immigrants unionize less frequently than natives. In the United States, the percentage of immigrants who are unionized is less than the percentage of natives that are unionized, which holds across time. Figure 3.2 shows that immigrants are 33 percent less likely to unionize than natives in the representative sample of labor force participants from the 1994-2020 CPS-ASEC. Mechanically, we would expect union density will fall as immigration increases for this reason alone.

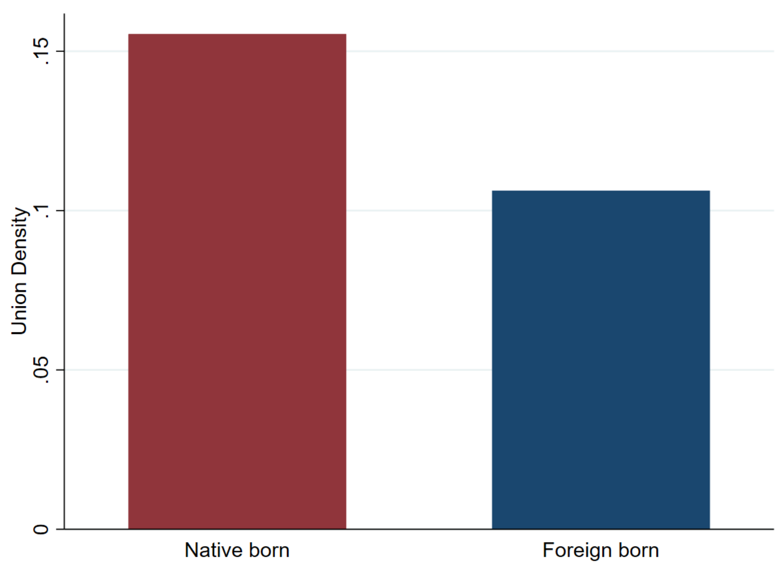

Figure 3.3. Preferences for Unionization by Nativity

Generated using CPS-ASEC 1994-2020. This figure shows the share of natives and immigrants who are part of a union averaged over 1994-2020. Used sampling weights.

The second way immigrants change union density is through their effects on union behavior. In the presence of free riding, the theoretical literature on union formation and social customs states that there are two reasons why an individual may decide to join a union (Booth 1985; Naylor and Cripps 1993; Akerlof 1980). The first is the direct benefits that workers receive from joining a union. These direct benefits include higher wages and benefits, better working conditions, and better protection against employer misconduct. The second reason workers join unions is because of social customs. When workers join unions, they derive benefits from conforming to group social customs that are produced by the union. For instance, according to the results of Van de Vall and Vall 1970: *"Many workers join the union in order to occupy a psychologically safe position among the members of their group, i.e. in order not to be isolated or despised as a 'parasite'. Evidence of this is that 82 percent of blue-collar and 81 percent of white-collar workers mentioned persons in their immediate environment who had influenced their decision to join. Since 32 percent and 38 percent, respectively, gave such influence as their basic motive, it may be concluded that at least one-third join mainly on account of the convictions of others."* Additionally, workers can derive disutility from transaction costs associated with group heterogeneity. When workers are heterogeneous, individual workers will have different demands, thus making collective action more difficult (Olson 2012).

With that, we will define the utility functions for union membership as follows:

$$U^J = U(w - d) + \alpha V(u, \epsilon) \tag{3.1}$$

$$U^{NJ} = U(w) + \alpha V(1 - u, \epsilon) \tag{3.2}$$

where ϵ represents the individual benefit of conforming to the group, α represents individual sensitivity to social custom, w represents the wages and benefits of the worker, d represents the net pecuniary cost of joining a union, and u is union density. Notice that ϵ considers both individual benefit from peer effects and individual disutility from transaction costs (associated with group conformity). U^J is the utility of joining a union and U^{NJ} is the utility of not joining a union. In this case, $U(\cdot)$ accounts for the utility a worker receives from pecuniary factors and $V(\cdot)$ accounts for the utility a worker receives from social factors. This is consistent with the theoretical literature in that it takes into account the two main reasons why people join unions. With that, we will define $u(\epsilon, \alpha, d, w)$ to be the expression of u that satisfies the following equation:

$$Z = U^J - U^{NJ} = 0$$

When $Z = 0$, a given worker is indifferent between joining and not joining a union. Here, we will assume that workers are individually heterogeneous in their utility derived from solidarity effects. Therefore, we will define a twice continuously differentiable distribution function $F(\epsilon, \theta)$, where θ represents the group's propensity to abide by social customs. In this case, θ will shift the distribution of ϵ. For any given union density, union members will have ϵ values higher than non-members. For instance, if union density is 25 percent, then the union members will have ϵ values in the highest quartile.

Workers will alter their decisions to join when the number of people that have incentive to join the union does not equal the number of people in the union. To illustrate this concept, we will use Figure 3.3. At point M, people who are currently in a union at union density u_a have $\epsilon_a \leq \epsilon \leq \epsilon_0$. However, the number of people who have incentive to join a union at union density u_a have $\epsilon > \epsilon'_a$. Since more people would like to join the union than are in the union, union membership will increase from point M over time. This applies for any $u \in (u_1^*, u_2^*)$. If, however, $u > u_1^*$ or $u < u_2^*$, then for any given union density, the number of people who have incentive to be union members is less than the number of people who are currently union members. In these cases, union density will fall over time.

Since equilibrium will fall to (ϵ_1^*, u_1^*) for $u > u_1^*$ and rise to (ϵ_1^*, u_1^*) for $u_2^* < u < u_1^*$, we will call this equilibrium point the solidarity equilibrium. Also, since union density will fall to 0 for $u < u_2^*$, we will call (ϵ_2^*, u_2^*) the threshold equilibrium. With that, the equilibrium points at which members and non-members will not change their decisions can be expressed as follows:

$$1 - F(\epsilon^*, \theta) = u(\epsilon^*, \alpha, d, w) = u^* \tag{3.3}$$

where (ϵ^*, u^*) are the equilibrium values of ϵ and u. Given our assumptions about the concavity of $u(\epsilon, \alpha, d, w)$ and $F(\epsilon, \theta)$, there can be, at most, two equilibrium solutions to (3).

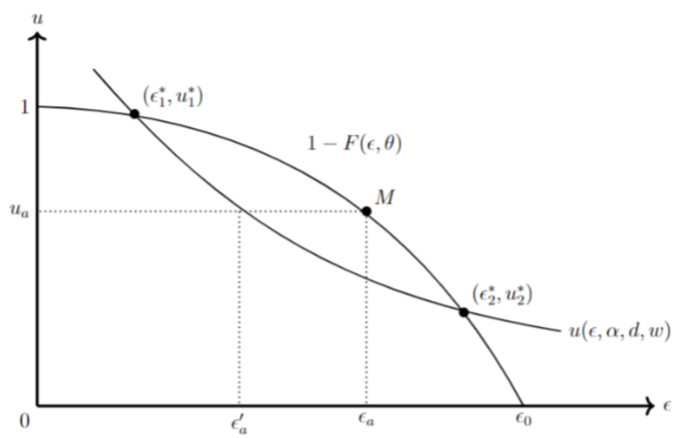

Figure 3.4. Union Density and Individual Solidarity Distributions

When considering how increases in the share of immigrants affect the solidarity equilibrium, we will examine how the group's solidarity value changes with immigration and how that affects the equilibrium union density. By property (1c) in (Naylor and Cripps 1993), $\frac{\partial u^*}{\partial \theta}$ is positive at the equilibrium level of union membership and negative at the threshold level of union membership.[3] Graphically, this can be represented by a shift in the distribution from $1 - F(\epsilon, \theta_1)$ to $1 - F(\epsilon, \theta_2)$, where $\theta_1 > \theta_2$ (as shown in Figure 3.4). When θ_1 decreases to θ_2, the solidarity equilibrium will shift from point P to point P', and the threshold equilibrium will shift from point Q to point Q'.

The group's value of solidarity will affect the utility individuals derive from abiding by a social norm. For instance, when a group becomes more homogeneous, the utility an individual derives from solidarity effects will increase. Likewise, when a group becomes less homoge-

[3]↑This proof can be found in the appendix of (Naylor and Cripps 1993).

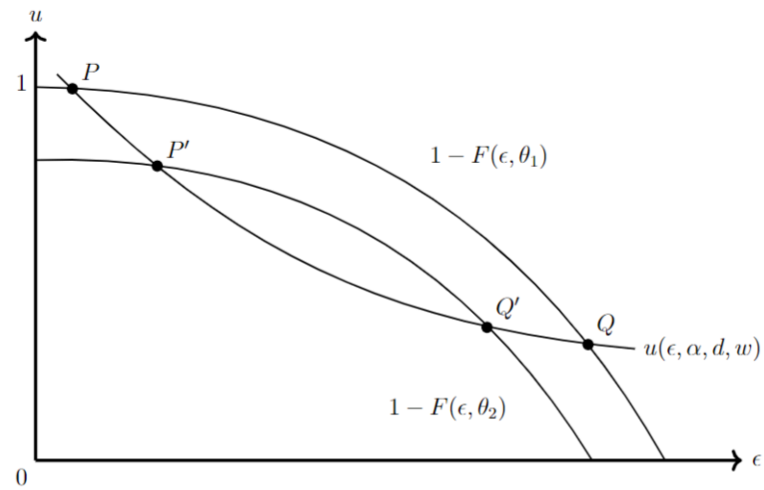

Figure 3.5. Shift in ϵ Distribution from an Increase in θ

neous, the utility an individual derives from solidarity effects decreases. Since we observe that immigrants exhibit unionization behavior that differs from natives (i.e. immigrants are less likely to unionize than natives), we can define group solidarity effects as a function of cultural heterogeneity (Ottaviano and Peri 2006; Ager and Brückner 2013). We will describe cultural heterogeneity as follows:

$$\theta = \sum_{\mathrm{i}=1}^{N} \pi_{\mathrm{ie}xt}^{2}$$

where π is the share of cultural group i in education group e and experience group x for time t and N is the total number of cultural groups in the population. Conceptually, θ represents the probability of selecting two individuals from the same cultural group. Therefore, as the share of immigrants in the population increases, group solidarity effects will decrease and, as a result, cause union density to fall.

3.3.2 Free Choice Assumption

In the Naylor and Cripps (1993) model, we assume that each worker has free choice in whether to join or not join a union. However, in reality, this is not always the case. For instance, in states that do not have Right-to-Work laws, workers can be required to join a union as a condition of employment. In the cases where workers are not able to freely decide on their union membership status, equation (3) will not hold. Without loss of generality, in the case where workers are not allowed to freely leave unions, the number of workers that join a union will be greater than the number of workers with incentive to join a union. Figure 3.5 shows this phenomenon in relation to the two curves in Figure 3.3. Here, the solidarity equilibrium will shift to u_{seq} and the threshold equilibrium will shift to u_{teq}, outside of the intersection points.

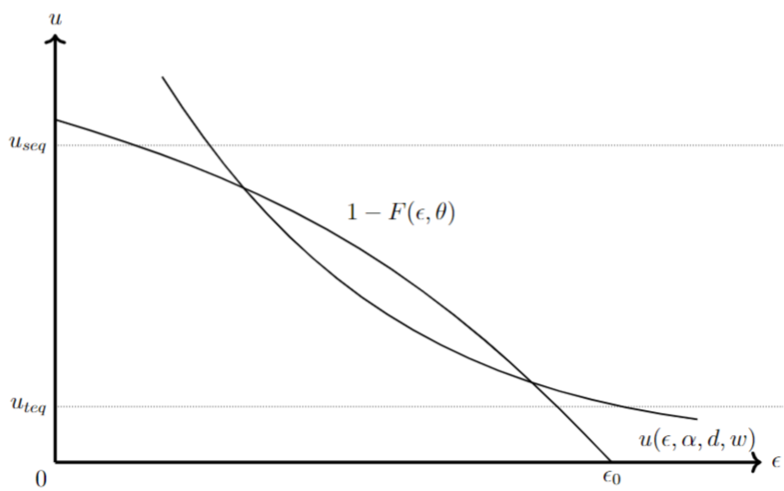

Figure 3.6. Equilibria When Free Choice Assumption Does Not Hold

3.4 Data and Methodology

This section explains the data and methods used to test how immigrant-induced workforce diversity affects unionization in the United States.

3.4.1 Data Overview

Given that data on union membership and immigration cannot be aggregated from the same source for our time period (1980-2020), we used several different data sets. We used data from the Decennial Census (1980-2000) and the American Community Survey (ACS,

2010) to measure immigrant shares of the population from 1980 - 2010.[4] For the year 2020, we used immigration data from the Current Population Survey Annual Social and Economic Supplement (CPS-ASEC). Union membership data from 1990-2020 was also retrieved from the CPS-ASEC.(Flood et al. n.d.) Finally, union membership data for 1980 was retrieved from the CPS May Extract on the NBER Website.(Gary and Staigler n.d.) The main analysis is restricted to males between the ages of 18-64 who are employed in a civilian wage/salary job. From here on, we will refer to the combination of all data as the Final Data Set (1980-2020). We later relax the sex restriction in the results section and when looking at public sector unionization.

We define an immigrant to be anyone who is born outside of the United States (and its territories) that is also either a naturalized citizen or a non-citizen. We structure the data so that we are looking at immigrants and natives with the same level of education and work experience. In this paper, we use share of immigrants in particular education and experience groups rather than geographic regions as we obtain more reliable estimates of immigrants on union density using the national skill-cell group approach.[5] Immigration share is therefore defined as follows:

$$I_{\mathrm{e}xt} = \frac{imm_{\mathrm{e}xt}}{imm_{\mathrm{e}xt} + native_{\mathrm{e}xt}}$$

Here, the subscript e denotes the highest education level that are divided into four large categories: 1 (less than high school), 2 (high school graduates), 3 (some college), and 4 (college and more). The subscript x denotes experience levels and has 8 categories: 1 (1-5 years), 2 (6-10 years),...,8 (36-40 years). The combination of e and x constitutes a skill-cell, and these cells are repeatedly observed for time t. None of our data sets show the years of work experience, so we followed Borjas 2003 method of subtracting the assumed age at completion of highest degree from the current age. These skill-cells will be the unit of analysis as immigrant shares differ across these cell groups and across years.

[4]↑Each year of the Decennial Census used 5% and the ACS used 1% of the population.

[5]↑Section 3.2 explains in detail how the national skill-cell approach is more appropriate than using regional variation of immigrant populations.

We divided the observations into skill-cells to clearly see the direct effect of incoming immigrants on labor market outcomes of similarly skilled workers. If immigrants do affect existing workers' propensity to unionize, the effect will be strongest among workers with levels of education and work experience identical to those of the incoming immigrant workers. For example, a Vietnamese immigrant with a high school degree employed as a construction worker will not have a direct impact on the labor market outcomes of workers with a college degree who work in finance. Similarly, the same immigrant with 0 years of work experience will have little effect on a worker with 30 years of experience even if they had the same level of schooling.

Sampling weights are used in all calculations and regressions. In some cases, different sampling weights may be used for different years/variables. For instance, the Decennial Census and ACS from 1990-2010 use person-level weights.[6] The immigrant share variable (from the CPS-ASEC) for the year 2020 used a person-level weight that was adjusted to account for nonrandom nonresponses from the COVID-19 pandemic. The union membership variable (for the years 1990-2020) uses an Earner Study weight that is different from the person-level CPS-ASEC weight. Finally, for the union membership variable for 1980, we used the CPS May Extract weight. In addition to using weights in our variable calculations, we weighed each observation in our final data set by the size of each skill-cell. Given that we have different weights from different surveys, we chose to use the weight that corresponds to our dependent variable.[7]

Our main outcome variable is union density. It is based on the same skill-cell division as we have used for immigrant share. Union density is therefore defined as follows:

$$u_{\text{ext}} = \frac{M_{ext}}{L_{ext}}$$

[6]↑The year 1980 was a flat sample, so all individuals had the same weight here

[7]↑We conducted the analysis with the weights used to create the immigrant share variable and found no statistically significant difference in our results.

where M is the number of union members and L is the total number of employed individuals per skill-cell ex for time t. We look at all workers, both immigrants and natives. For this reason, we are looking at how immigrants impact the overall tendency for unionization rather than just the impact on native's propensity to unionize. In fact, one of the channels through which union density is affected by immigrants is the lowering of $\frac{M_{ext}}{L_{ext}}$, as immigrants are less prone to unionize.

In order to measure diversity, we use the country of origin and race to develop an index of cultural diversity based on a method developed by Ottaviano and Peri 2006 and Ager and Brückner 2013. We call this the index of "fractionalization" following the literature. The equation is given as follows:

$$frac_{\mathrm{ext}} = 1 - \sum_{\mathrm{i}=1}^{N} \pi^2_{\mathrm{i}ext} = 1 - \theta$$

where $\pi^2_{\mathrm{i}ext}$ is the squared value of the share of the population in cultural group i belonging to education and experience group e and x at time t. Since we wanted to consider both diversity in culture and ethnicity, we combined the method employed by Ottaviano and Peri 2006 and Ager and Brückner 2013 in classifying the cultural group. To be specific, Ottaviano and Peri 2006 uses immigrant nationality groups and Ager and Brückner 2013 adds various racial groups who are U.S. born.

Table 3.1 lists the cultural groups we used in calculating our fractionalization index that account for the largest proportion of our sample.[8] We follow the literature by limiting nationality groups to those that make up more than 0.5 percent of the foreign-born population within a given year. For the native-born, we have divided the population by four main racial categories of white, black, Hispanic, and other. As the fractionalization index approaches zero, one group's share dominates the population and hence there is little diversity. When it approaches one, it indicates that there is a balance in the cultural groups where each group has equal share and hence diversity is high. The fractionalization index is just the solidarity

[8]↑In the appendix, we provide the full list of countries used to construct the fractionalization index.

parameter θ in the model subtracted from 1; the more heterogeneous cultural groups are, the lower the θ, and in turn, this decreases the fractionalization index.

3.4.2 Strength of the skill-cell Approach Compared to Other Methods

Most research that examines the impact of immigrants on labor market outcomes exploits some exogenous variation of immigrant influx across geographic regions, occupation groups, industries, or skill-cells. Peri, Shih, and Sparber 2015 use regional variation, Orrenius and Zavodny 2007 use occupational variation, and Finseraas, Røed, and Schøne 2020 exploits industry level differences in immigration shocks. In contrast to the standard way of looking at regional variation in immigration, we have taken the same approach as Borjas 2003 and Borjas 2014 as we look at the differing influx of immigrants across skill-cells defined by education and experience. This method is appropriate for the following reasons:

1. The biggest reason for our choice to use skill-cells as opposed to regional variation is that workers move across states regularly. For example, in Figure 3.6, we have plotted the percentage of people that have changed their state of residence from the previous year. This movement is problematic because it may influence union density, but cannot be explained by our variables. In Table 3.2, we run estimates for the effect of immigrants on unionization using spatial grouping of workers and find that 1) the explanatory power of the model weakens,[9] and 2) the coefficient estimates become increasingly insignificant when workers are aggregated by smaller geographic units. This suggests either measurement error and/or selection is responsible for the weakening of the model using smaller spatial units.[10]

2. According to a U.S. Census Bureau article by Schmidley and Robinson 1998, *"[t]he CPS sample frame and stratification levels are based on geography and socioeconomic data from the latest census. Groups such as the foreign born who are not represented in the sample strata and non-randomly distributed across the United States."* Hence,

[9]↑The adjusted R-squared becomes smaller with smaller geographic units

[10]↑Please refer to Table 4.2 of Borjas 2014 for more information on the reasons that Borjas lays out for avoiding spatial variation.

Table 3.1. List of Largest Cultural Groups

Nativity	Cultural Groups (1980)	Percentage	Nativity	Cultural Groups (1990)	Percentage
Native	White	79.42	Native	White	75.58
Native	Black	8.71	Native	Black	8.58
Native	Hispanic	3.84	Native	Hispanic	4.31
Native	Other Race	1.09	Native	Other Race	1.28
Immigrant	Mexico	1.53	Immigrant	Mexico	2.94
Immigrant	Cuba	0.34	Immigrant	Philippines	0.45
Immigrant	Canada	0.32	Immigrant	Cuba	0.35
Immigrant	Italy	0.32	Immigrant	India	0.33
Immigrant	Germany	0.32	Immigrant	El Salvador	0.30
Immigrant	Philippines	0.25	Immigrant	Vietnam	0.28
Nativity	Cultural Groups (2000)	Percentage	Nativity	Cultural Groups (2010)	Percentage
Native	White	69.96	Native	White	62.93
Native	Black	8.28	Native	Black	8.28
Native	Hispanic	5.03	Native	Hispanic	7.11
Native	Other Race	2.38	Native	Other Race	2.84
Immigrant	Mexico	4.95	Immigrant	Mexico	6.90
Immigrant	India	0.63	Immigrant	India	1.06
Immigrant	Philippines	0.55	Immigrant	El Salvador	0.73
Immigrant	Vietnam	0.47	Immigrant	Philippines	0.69
Immigrant	El Salvador	0.44	Immigrant	China	0.60
Immigrant	China	0.42	Immigrant	Guatemala	0.55
Nativity	Cultural Groups (2020)	Percentage			
Native	White	57.90			
Native	Hispanic	10.27			
Native	Black	8.55			
Native	Other Race	4.49			
Immigrant	Mexico	5.55			
Immigrant	India	1.97			
Immigrant	El Salvador	0.75			
Immigrant	China	0.66			
Immigrant	Guatemala	0.60			
Immigrant	Philippines	0.55			

Generated using the final data set (1980-2020).Following Ottaviano and Peri (2006), we include immigrant nationality groups that make up more than 0.5% of the foreign-born population and classify all other immigrant nationality groups into "miscellaneous." For native groups, we divide the sample by non-white Hispanic, black, Hispanic, and all other races that include mixed races and other lesser represented minorities. Given that Germany and Korea are classified differently across time, we treated East/West Germany as Germany and North/South Korea as Korea. All categories are mutually exclusive.

using variation in either regional, education, work experience, or other socioeconomic variables may not perfectly capture a nationally representative change in immigrant

Table 3.2. Regional Analysis

	(1) metarea	(2) statefip	(3) region
log_imm	-0.0602**	-0.121***	-0.250***
	(0.0235)	(0.0387)	(0.0706)
Observations	4,114	1,372	243
R-squared	0.629	0.802	0.937

Generated using CPS-ASEC 1994-2020. Regression of Log of union denstiy on log of immigrants share with year and region fixed effects. The regional unit varies by column. The effect is dramatically different for level-level and this is due to the presence of heteroscedasticity (tested it using the Breusch-Pagan test). The log transformation resolves this issue. Used Earner Study weight for union density and the CPS-ASEC weight for immigrant share. $(***p < 0.01, **p < 0.05, *p < 0.1)$

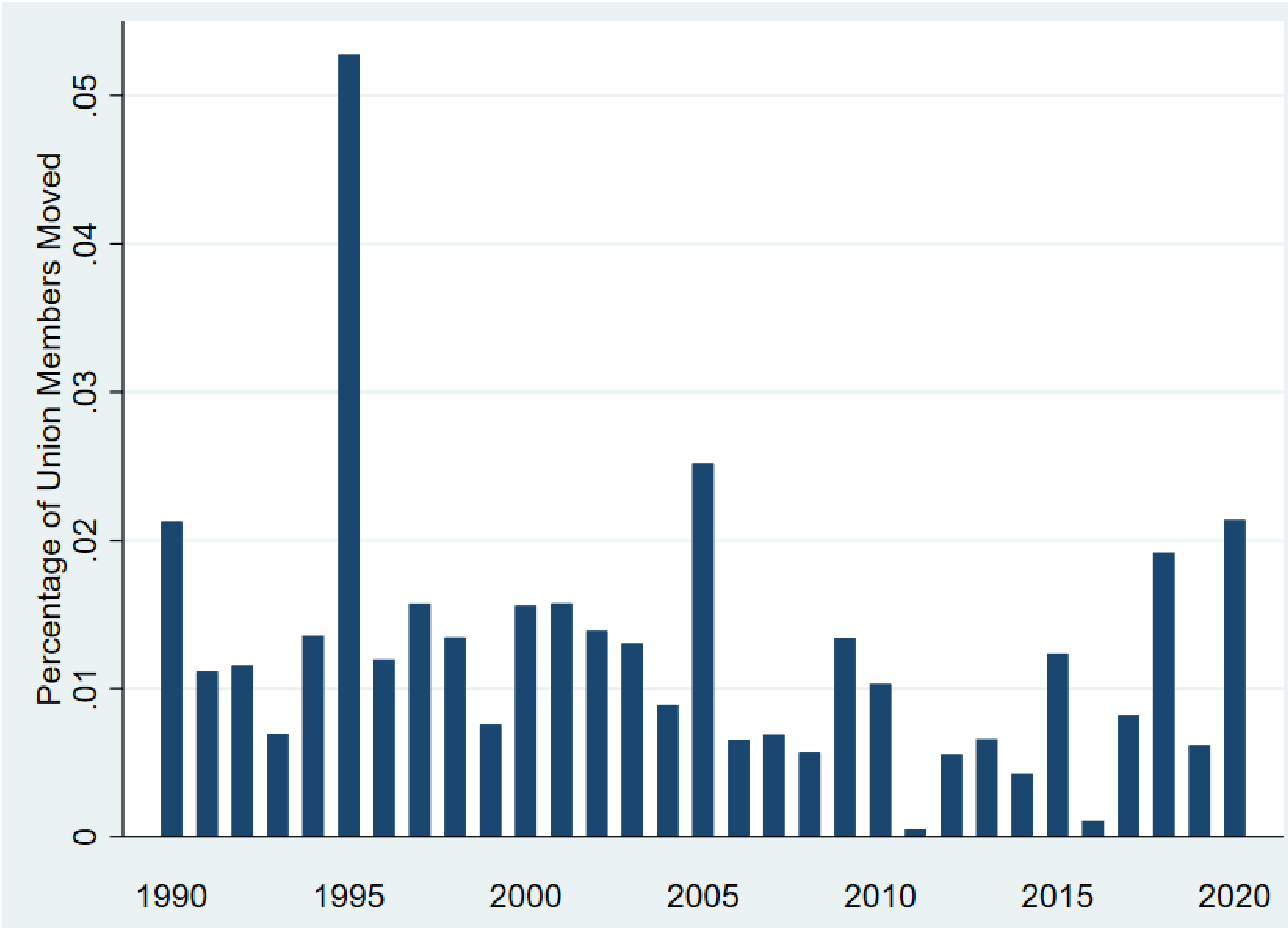

Figure 3.7. Interstate Migration for Workers

Generated using CPS-ASEC 1990-2020. Sample of employed, working-age males. This figure shows the percentage of people that moved to another state from the previous year. The IPUMS recommends using caution when interpreting migration data from 1995.

share due to small sample sizes in some units. However, using educational-experience as opposed to regional variation has a slight advantage in that there are a fewer number of skill-cells than states or metropolitan areas that vary overtime which allows more samples in each varying unit [11] Also, using the national skill-cell as the unit allows us to estimate the fractionalization index; there are severe data limitations in slicing

[11]↑Some states such as Alabama, Indiana, Iowa, Kentucky, Main, Mississippi, Missouri, Montana, North Dakota, South Carolina, South Dakota, Tennessee, West Virginia, Wyoming has less than 10 immigrants in the CPS-ASEC sample in some years.

the data by nationality groups when we use states as the varying units. The same argument goes with doing any heterogeneity analysis using occupations or industry.[12]

3. borjas2014immigration criticizes the use of regional variation in immigrant shocks to identify the causal effect of immigrants on the labor market. Immigrants and natives self-select to migrate to certain localities due to underlying labor market characteristics that will bias the result due to underlying omitted variables. For this reason, we have also decided against using the shift-share instrument that utilizes MSA-level or state-level variation in immigrant populations by nationality group. Apart from the data restrictions of using CPS to further slice by U.S. regions and nationality groups, Borjas 2014 argues that the initial economic conditions that attracted immigrants to certain localities is not random and correlated with the economic outcomes of natives.[13]

4. To show that our panel specification is valid, we have tested for both serial correlation and the unit-root. Serial correlation will not necessarily bias our results but it will affect our standard errors to be underestimated. This is resolved by clustering the standard errors by the panel ID which in our case is the education and experience level(Cameron and Trivedi 2010). Unit-root test ensures that our dependent variable (log(union density)) and independent variable (log(immigrant share)) is stationary which indicates that an effect of an event that happened at time 't' is not being amplified at a later time. Using the Levin–Lin–Chu test, we accept the alternative hypothesis that all panels are stationary(Levin, Lin, and Chu 2002).

With the national skill-cell method, we may still have selection of immigrants into certain education or experience cells. However, as we aggregate these measures across all U.S. re-

[12]↑Further dividing the data by industry sectors is also something we have considered but have not been able to fully develop as the data become severely limited in certain industries and so preclude a robust analysis. In general however, there is no single industrial sector that is solely driving the effect that we find later in the results section.

[13]↑In other words, national level shift-share instruments do not satisfy the exclusion restriction, which will produce an inconsistent estimator (Goldsmith-Pinkham, Sorkin, and Swift 2020). Additionally, Borusyak, Hull, and Jaravel 2018 point out that, if the unobserved shocks affect the outcome variable via the exposure shares, then the shift share estimator will violate the share exogeneity assumption, even if the observed and unobserved shocks are uncorrelated. For instance, Borusyak, Hull, and Jaravel 2018 use an example where, if the share used is local employment share (with the shock being new import tariffs), then changes in foreign migration (a shock) may be dependent on other industry factors, which is problematic in this context. A skill-cell method on the national level obviates this concern on the regional geographic level.

gions, we are able to use the disproportionate and sometimes erratic influx of immigrants who vary by education and experience over time. Table 3.3 shows the percentage change in union density and immigration between 1980 and 2020 by education level. Where immigrant share generally increased, union density had a proportional decrease. Table 3.4 shows a similar, albeit, less-correlated trend for experience levels. These are suggestive descriptive evidence that there might be a relationship between immigrant shares and union density in each skill-cell. The following sections of the paper will estimate the relationship using the skill-cell method.

Table 3.3. Changes in Union Density and Immigrant Share by Education

Education		(1) Immigrant Share	(2) Union Density
< HS			
	1980	0.116	0.345
	2020	0.500	0.030
	%Δ	331.03	-91.30
HS			
	1980	0.042	0.377
	2020	0.168	0.118
	%Δ	300.00	-68.70
Some College			
	1980	0.056	0.270
	2020	0.116	0.123
	%Δ	107.14	-54.44
College			
	1980	0.075	0.168
	2020	0.189	0.110
	%Δ	152.00	-34.52

Generated using the final data set (1980-2020). This Table shows the percentage change in Union Density and Immigrant Share between 1980 and 2020 by education levels of all employed, working-age civilian males.

Table 3.4. Changes in Union Density and Immigrant Share by Experience

Years of Experience		(1) Immigrant Share	(2) Union Density
1-5 Years			
	1980	0.054	0.203
	2020	0.129	0.057
	%Δ	138.89	-71.92
6-10 years			
	1980	0.068	0.287
	2020	0.147	0.109
	%Δ	116.18	-62.02
11-15 Years			
	1980	0.078	0.330
	2020	0.190	0.105
	%Δ	143.59	-68.18
16-20 years			
	1980	0.079	0.318
	2020	0.207	0.127
	%Δ	162.03	-60.06
21-25 Years			
	1980	0.077	0.332
	2020	0.219	0.132
	%Δ	184.42	-60.24
26-30 Years			
	1980	0.073	0.358
	2020	0.225	0.135
	%Δ	208.22	-62.29
31-35 Years			
	1980	0.068	0.348
	2020	0.220	0.100
	%Δ	223.53	-71.26
36-40 Years			
	1980	0.069	0.358
	2020	0.193	0.125
	%Δ	179.71	-65.08

Generated using the final data set (1980-2020). This Table shows the percentage change in Union Density and Immigrant Share between 1980 and 2020 by experience levels of all employed, working-age civilian males.

3.5 Results

3.5.1 Immigrants and Union Density

This section explains our baseline regression model and results. The first relationship we explore is how immigration affects the union density of the existing labor force. We are interested in the outcome variable u_{ext}, which is the ratio of workers in a union to all workers in the relevant skill-cell ex as defined as the combination of education and experience. The data are collapsed by the national skill-cells for each year and the variable values are averages in each cell. The regression specification is as follows:

$$u_{ext} = \beta(I_{ext}) + s_{\mathrm{e}} + \sigma_x + \boldsymbol{\pi}_t + \phi_{\mathrm{e}x} + \mu_{\mathrm{e}t} + \delta_{xt} + \mathrm{e}_{ext} \tag{3.4}$$

where I is the immigration share defined as the ratio of immigrants over the total labor force in a skill-cell, s_{e} is a vector of fixed effects indicating the group's educational attainment, σ_x is a vector of fixed effects indicating the group's work experience, and $\boldsymbol{\pi}_t$ is a vector of fixed effects indicating year. These first three fixed effects control the different rates of unionization across education, experience, and over time. We also control for how, over time, there are structural changes in how education or experience impact union density. The interaction term $\mu_{\mathrm{e}t}$ accounts for the impact of education groups changing over time such as how having an extra year of schooling may affect union density differently 20 years ago compared to today. Similarly, experience groups δ_{xt} account for how an extra year of experience has had a different effect on union density over time. Finally, $\phi_{\mathrm{e}x}$ accounts for how an extra year of experience has a different effect on union density compared to an extra year of education. Table 3.5 presents the results for regression (1). Column 1 values are in levels and the standard deviation of union density and immigrant share are in the bottom rows. The coefficient is -0.479 which means that a 10 percentage point increase in immigrant share translates to a 4.8 percentage point decrease in immigrant share. Given that the overall immigrant share of the workforce increased from 6.9 percent in 1980 to 18.8 percent in 2020, this translates to immigrants causing a 5.7 percentage point decrease in union density during the same period. Given that union density went from 30.2 percent to 11 percent during the period, immigrants were responsible for 29.7 percent of the decline in union density from 1980 to 2020.

Table 3.5. Immigrants and Union Density

	(1) Levels
Immigrant Share (Level)	-0.479***
	(0.083)
Observations	160
SD(imm)	0.144
SD(u)	0.107
Mean(u)	0.181

Generated using the final data set (1980-2020). The dependent variable is union density (col1). The regression includes education, experience and year fixed effects, and their combinations. Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. There are 4 education, 8 experience, and 5 different years amounting to 160 cells. Regression weighted using sample size for each collapsed bin (education-experience-year combo). Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

3.5.2 Heterogeneity

By Schooling and Experience

Table 3.3 shows that the largest increase in immigrant shares has been in the less-than-high-school and high-school education categories, which are also where the largest decreases in union densities have occurred. To test whether the negative relationship between union density and immigrant share is mostly driven by changes in the lower educated skill-cells, we run the benchmark regression where we omit one educational category starting with the less-than-high-school level. This allows us to keep our identifying strategy of using the skill-cell method and to still infer how much each education category contributes to the overall effect.

Column 1 of Table 3.6 contains our original results from Table 3.5. With the omission of all individuals who did not finish high school, we see that the coefficient on the immigrant share variable becomes insignificant, which indicates that the biggest decrease in union density is coming from those who have not graduated high school. All other columns remain significant when omitting a given education group. One caution in interpreting the coefficients is that the less economically or statistically significant the coefficient becomes with the omission of an education sub-category, the bigger the share the particular sub-category has in driving the overall effect.

In Table 3.7, we have similarly omitted each experience level from the benchmark regression. We find that the biggest driver of the effect is coming from those with the lowest experience of 0 to 10 years. This is consistent with other findings that younger workers are much less likely to be unionized than older workers (Milkman 2020).

By Sector and Sex

So far, we have restricted the sample of analysis to employed, working-age civilian males and have not distinguished private and public sector union members. In this section, we show how union density is affected by the addition of female workers and the separation of private and public sector union membership. Our data does not explicitly have variables for public or private sector unions. For this reason, we have categorized union members who are employed in local, state, or the federal government as belonging to public sector unions, and all other union members as belonging to private sector unions. We combine the heterogeneity analysis of public vs. private sector union membership and sex into one section as the two are closely related because females tend to work in public unions at higher rates than males.

To start, females are often omitted when studying how immigrants affect wages (Borjas 2003), because their labor market dynamics are slightly different than for males; they are underrepresented in union membership (Finseraas, Røed, and Schøne 2020), and frequently change union membership (Haile 2016). Figures 3.7 and 3.8 show evidence of this disproportionately by sex. To be specific, public sector union density is high for both sexes compared to the private sector, but females are much less likely to work in a private sector labor union

(Figure 3.7). Despite low private sector union density, the number of union members in the private sector is larger than the public sector, and males dominate in private sector union membership in total count and density. Figure 3.8 shows that females who are highly educated have higher union density, because they are more likely to be unionized school teachers and work in other skilled government occupations that are unionized, while less educated males tend to have higher union density. Given that the influx of immigrants happened primarily in the less-than-high-school or high-school educated cells, immigrants would have had a much larger effect on male union members and less of an effect on female union members.

To see if the addition of females changes our main results, we run our benchmark regression separately for male-only, male and female combined, and female-only workers. In addition, we also split between private and public sectors since males and females tend to have higher membership in private sector unions and public sector unions, respectively. Tables 3.8, 3.9, and 3.10 show the differences in results between male/female samples in the public/private sector.(You can ignore the "frac" columns until we define it in the next section.). In the private sector, the male union density is more affected by immigration than the female union density. However, in the public sector, union density is unaffected by immigration for both males and females.

We chose not to focus our analysis on just the private sector, despite the concentration of male workers, since the addition of the public sector members adds statistical power and richness to the data in terms of education, experience levels, and nationality groups in the calculation of the fractionalization index.

3.5.3 Diversity and Union Density

The decrease in union density that is correlated with a rise in immigration can be partly explained by the mechanical channel of adding more workers to the labor force who are less prone to unionize. However, we hypothesize that the main channel is through how immigrants affect whether workers choose to unionize. The immigration-induced diversification

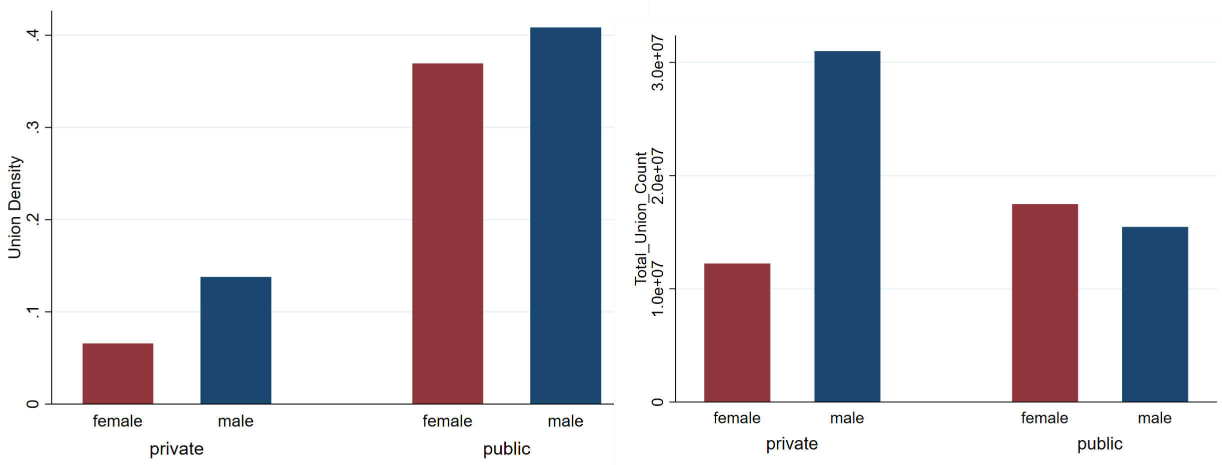

Figure 3.8. Union Density and Count by Sex and Sector

Generated using the final data set (1980-2020). This figure compares union density by sector and sex between 1980 and 2020 by education levels of all employed, working-age adults.

of the work force is the mechanism by which immigration diminishes worker support for unionization. As we have seen in the theory section, the (Naylor and Cripps 1993) model includes the θ parameter, which represents the propensity to abide by social customs; we will also call it the solidarity parameter. As the model suggests, at the solidarity equilibrium level of union membership, the relationship between θ and union membership is negative. In other words, unionism is more likely when people have the same social customs.

Our hypothesis is that the influx of immigrants increases diversity and weakens the solidarity of workers. Solidarity is weakened as cultures, languages, and demands for different work-place amenities differ between cultural groups. Collective action is more costly when there are high transaction costs due to communication difficulties and homophily, especially when it comes to unionization and their role in the work place (Alesina and La Ferrara 2000; Bacharach and Bamberger 2004; Bond, Giuntella, and Lonsky 2020). As an example show-

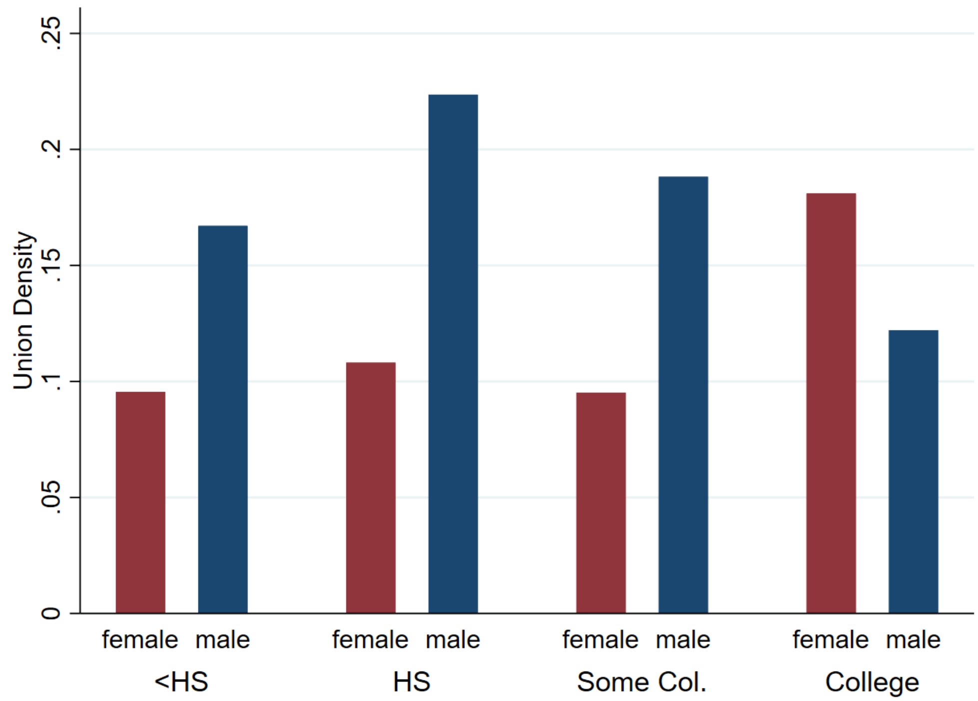

Figure 3.9. Union Density by Sex and Education

Generated using the final data set (1980-2020). This figure compares union density by education and sex between 1980 and 2020 by education levels of all employed, working-age adults.

ing demands for different workplace amenities, Bond et. al., (2020) find that immigrants prefer night shifts relative to natives while unions tend to support regular working hours for all workers. Since immigrants have different preferences for their work environments relative to other groups of people, more immigrant workers will further weaken the motivation for diverse groups to unionize together.

Labor unions in the United States faced similar barriers to expanding union membership at the beginning of the 20^{th} century. In order to overcome the free rider problem that bedeviled union formation, unions tried to entice members to join by supplying local excludable goods like insurance (Olson 2012). Importantly, supplying excludable goods was less costly when the workers were culturally and ethnically homogeneous as they were more likely to demand similar goods like accident insurance or Christmas parties. Local unions were also more likely to be homogeneous than nationwide unions and membership was correlated with meaningful social and recreational commonalities (Olson 2012). Overcoming the free-rider problem is difficult even when all of the workers are homogeneous and have essentially identical demands, but it becomes even more difficult when they can't even agree on those demands – such as which holidays deserve vacation time, which sabbath should be honored by employers, and what kind of insurance is appropriate (Olson 2012; Nowrasteh and Powell 2020).

For these myriad reasons, immigration-induced diversity creates an environment that disincentivizes various demographic groups to come together to unionize. Here, we use the fractionalization index as our measure of diversity, which is 1 minus the solidarity parameter θ. The equation is given as follows:

$$frac_{\mathrm{e}xt} = 1 - \sum_{\mathrm{i}=1}^{N} \boldsymbol{\pi}^2_{\mathrm{ie}xt} = 1 - \theta$$

where $\boldsymbol{\pi}^2_{\mathrm{ie}xt}$ is the squared value of the share of the population in cultural group i belonging to education and experience group e and x at time t. Since we wanted to consider both diversity in culture and ethnicity, we combined the method employed by (Ottaviano and Peri 2006) and (Ager and Brückner 2013) in classifying the cultural group. Note, (Ottaviano and Peri 2006) use immigrant nationality groups and Ager and Brückner 2013 adds various racial groups who are U.S. born. We measure diversity of the workforce using an immigrant-induced fractionalization that measures the degree of concentration of various foreign-born nationality groups and native racial groups. A perfectly fractionalized country is one where every resident has a different ethnic or racial background.

We run a regression with the specification that uses the fractionalization index:

$$u_{\mathrm{e}xt} = \beta(frac_{\mathrm{e}xt}) + s_{\mathrm{e}} + \sigma_x + \boldsymbol{\pi}_t + \phi_{\mathrm{e}x} + \mu_{\mathrm{e}t} + \delta_{xt} + \mathrm{e}_{\mathrm{e}xt} \tag{3.5}$$

Table 3.11 shows the relationship between increasing fractionalization and unionization. We used the same regression specification as in Table 3.5 but used the fractionalization index as the explanatory variable rather than the immigrant share. Immigration affects union density, but fractionalization has a slightly smaller effect. We believe that both the effects from immigration and diversity (fractionalization) are one and the same. In other words, immigration increases diversity and this lowers the solidarity of workers to unionize. This would not necessarily be the case if an influx of immigrants do not increase diversity, i.e., only a single immigrant nationality group comprises the majority of a skill-cell. However, we believe such instances are rare, and that a given skill-cell comprise of diverse groups of immigrants. The variables ”imm_share” and ”fraction_index” have a correlation coefficient of 0.78 which indicates that high immigrant share in a skill cell generally means high diversity as well. In sum, influx of immigrants increase diversity, and in turn, lessens solidarity among workers that contributes to the demise of unions.

3.6 Robustness Checks

3.6.1 Are Immigrants Just Diluting the Labor Force?

In this section, we want to abstract away from viewing immigrants and natives as different groups and see if the effect on unionization is driven by a sudden increase in the supply of workers in a particular skill-cell rather than an increase in diversity. A sudden influx of workers, be it immigrants or natives, may create some short-term frictional cost on the incoming workers' ability to join unions. We assume that these short-term frictional costs are not driving the decrease in union density, but if our assumption is wrong, we would see an increase in the supply of immigrant workers in a skill-cell have the same qualitative effect as a similar increase in the supply of native workers in the same skill-cell.

To explore whether a sheer increase in the number of workers can explain the decline in union density, we looked to see whether the marginal effect of an additional immigrant on unionization is different from the marginal effect of an additional native-born worker. If immigrants are merely increasing the supply of potential union workers and thereby diluting union density, then the impact of an extra immigrant worker will be similar to that of an additional native-born worker.

To precisely show this channel, we had to use a subset of our main data: the CPS-ASEC (1994-2020) in 1 year increments. We could only modify the dependent variable union density to our preferred specification using the CPS-ASEC because the 1980 survey does not allow us to identify immigrants or natives with their union membership status. Thus, we modify our dependent variable to measure the union density of just natives since we are interested in comparing the marginal effect of immigrants on native union density to the marginal effect of natives on the same native union density. The dependent variables we use then is the log of:

$$u^N_{ext} = \frac{M^N_{ext}}{L^N_{ext}}$$

where M^N is the number of union members who are native-born and L^N is the total number of employed individuals who are native-born per skill-cell ex for time t. We also introduce a slight change to the main independent variable in columns 1 and 2 in Table 3.12; instead of the usual immigrant share we merely look at the raw count of immigrants for each skill-cell, which we label as "raw imm" in Table 3.12. Since we are comparing units that are scaled very differently we standardized both the dependent and the independent variable into logs. The interpretation of the coefficient is then that of an elasticity between immigrants and unions; if we change immigrants by one percent, we'd expect union density to change by β_1 percent.

Columns 1 of Table 3.12 shows that adding an extra immigrant to the existing pool of workers has a negative effect on unionization of -0.255. The coefficient's interpretation is that a 10 percent increase in the raw number of immigrant workers, as opposed to immigrant share, corresponds to a 2.5 percent decrease in union density. Compare this to column 2 result that a 10 percent increase in the raw number of natives increases union density by 4.2 percent. Comparing columns 1 and 2 clearly shows that immigrants and natives differently affect union density, which supports our hypothesis that immigrants reduce union density because they increase cultural diversity.

Decline in unionization could also be driven by a pure increase in the number of immigrants rather than their impact on fractionalization. We have previously discussed two channels through which immigrants affect union density. The first channel is through immigrants diluting the union density due to their lower propensity to unionize, and the second channel is through weakening the solidarity of all workers. Using only natives in calculating the union density has the added benefit of seeing whether the effect is still present after taking away the first channel: immigrants' lower propensity to unionize.

Our prior is that the negative relationship between immigration and unionization is mainly driven by the second channel that weakens worker solidarity, but the first channel could still be driving a substantial part of the effect. In Table 3.11, we show that the second channel, the indirect effect on worker solidarity, is the main channel. Column 3 of Table 3.12 shows that even after considering only natives in calculating union density, we still see a big negative effect of immigrants on natives' propensity to unionize. This result is contrasted with column 4 where the effect of an increase in native shares on natives' union density. This shows that the decrease in union density is not a result of a mechanical decrease due to inclusion of immigrants but due to immigrants having an effect on natives.

[Insert Table 3.12 about here]

3.6.2 Lagged Immigrant Share

Card and Peri 2016 claim that the Borjas 2014 method of calculating the immigrant share is biased as changes in the supply of natives are confounded with the immigrant supply shock in ways that may bias the outcome variable, which in our case is union density. For example, a troublesome correlation can arise if changes in the number of workers in a particular skill-cell is positively correlated with other labor market outcomes such as wages. Although our outcome variable is the share of union membership, the same mechanism that may bias wages may also bias union membership. In essence, Card and Peri 2016 argue that immigrant shock to a particular skill-cell is not exogenous if such correlations arise. [14]

Card and Peri 2016 propose a slight modification to the usual immigrant share that Borjas 2003 calculated. Basically, they use the lagged size of the labor force as the base when calculating the current immigrant shock. Hence, with the modification, the changes in immigrant share from $t-\mathrm{j}$ to j is now:

$$\Delta p'_{\mathrm{i}t} = \frac{\mathrm{i}mm_{\mathrm{it}} - \mathrm{i}mm_{\mathrm{i}t-\mathrm{j}}}{native_{\mathrm{i}t-\mathrm{j}} - \mathrm{i}mm_{\mathrm{i}t-\mathrm{j}}} = \frac{\Delta \mathrm{i}mm_{\mathrm{it}}}{native_{\mathrm{i}t-\mathrm{j}} - \mathrm{i}mm_{\mathrm{i}t-\mathrm{j}}}$$

The authors use $\mathrm{j} = 10$ due to Borjas's original use of the decennial census that is ten years apart. However, in our framework j can be a smaller passage of time. Here since we are using the previous period's count of natives in the denominator of $\Delta p'_{\mathrm{i}t}$, we do not have to worry about confounding the effect of changes with current changes in native labor supply. In

[14]↑To show this formally, let's go back to how we defined immigrant share.

In Borjas 2014(and ours), the immigrant share $p_{\mathrm{i}t}$ is simply the current period's count of immigrants in skill-cell i at time t over the size of the labor force of skill-cell i at time t:

$$p_{\mathrm{it}} = \frac{\mathrm{i}mm_{\mathrm{e}xt}}{\mathrm{i}mm_{\mathrm{e}xt} + native_{\mathrm{e}xt}}$$

To see how the outcome variable y changes with the immigrant share we specified, for outcome y of natives in skill-cell i at time t:

$$\Delta y_{\mathrm{it}} = \text{fixed effects} + \beta^p \Delta p_{\mathrm{it}} + \Delta v_{\mathrm{it}}$$

This equation is the simplified version of our benchmark regression with first-differencing. The fixed effects here include time, education, experience, and the combinations of the three fixed effects (some of which are accounted for with the first-differencing). According to Card and Peri (2016), the coefficient β^p is biased as we do not know how much of the effect is 1) coming from an exogenous change in immigrant population at time t and 2) how much of it is coming from changes in the base supply of natives in the same time period. They show this conundrum through estimating the first-order approximation for $\Delta p_{\mathrm{i}t}$:

$$\Delta p_{\mathrm{it}} \approx (1 - p_{\mathrm{i}t-\mathrm{j}}) \frac{\Delta \mathrm{i}mm_{\mathrm{it}}}{\mathrm{i}mm_{\mathrm{i}t-\mathrm{j}} + native_{\mathrm{i}t-\mathrm{j}}} - p_{\mathrm{i}t-\mathrm{j}} \frac{\Delta native_{\mathrm{it}}}{\mathrm{i}mm_{\mathrm{i}t-\mathrm{j}} + native_{\mathrm{i}t-\mathrm{j}}}$$

This first term is the weighted average of the immigrant-driven supply shock $\frac{\Delta \mathrm{i}mm_{\mathrm{i}t}}{\mathrm{i}mm_{\mathrm{i}t-\mathrm{j}} + native_{\mathrm{i}t-\mathrm{j}}}$ and the second term is the weighted average of the change in the number of native workers in skill-cell i divided by the lagged size of the skill-cell: $\frac{\Delta native_{\mathrm{i}t}}{\mathrm{i}mm_{\mathrm{i}t-\mathrm{j}} + native_{\mathrm{i}t-\mathrm{j}}}$. The takeaway from this equation is that when we are looking at the change in the native outcome Δy_{it}, it is important not to confound the effect coming from the 1) supply shock of immigrants which is the first term and 2) the native supply changes which is the second term.

short, this correction allows the immigrant shock to be more exogenous than in equation (4).

In Table 3.13, we incorporate the lagged immigrant share to the CPS-ASEC (1994-2020); as in the previous section, we use the log transformation for ease of interpretation. We vary the number of lags to see how sensitive the outcomes are to the choice of lags. Column 1 is our original result with no lag to the labor force. Each subsequent column represents one additional year of lag. In general, with the longer lags, the effect size is smaller, and the effect size is no longer significant around $t - 5$. In column 7, we have used the our final data set from 1980 to see how it compares to the CPS-ASEC; with the 10 year lagged base, we see that the coefficient on the lagged immigrant share is not significant. These results indicate that when we bias-correct the immigrant share variable using the size of the labor force in the previous years, similar negative effects persist. In addition, once we go too far back for our base year, the effect size tapers off as the composition and size of the labor force in the distant past is not reflective of today's labor force.

[Insert Table 3.13 about here]

3.7 Conclusion

Even with the decline of unions, few researchers have examined how immigrants affect unionization and most tend to attribute their decline to changes in labor law, deregulation, structural economic changes, or other issues (Kleiner 2001; Fisk and Malamud 2008; H. Farber 2005; Greenhouse 2020; Nunn, O'Donnell, and Shambaugh 2019; Milkman 2020). Most research on how immigrants affect the U.S. labor market focuses on wage and employment effects. Unions, despite being on the wane in the United States, wield sizable influence on wages and employment in different sectors. Government policies are also affected by union density. Furthermore, many politicians today want to increase legal immigration and unionization – two goals that could be in conflict.[15] Thus, examining how immigrants affect union density is important insofar as how unions are important in affecting wages, employment,

[15]↑While unions have historically been on the decline, recently, there has been an increased effort by the Biden Administration to make America a pro-union state(Greenhouse 2021)

and government policies.

We find that immigration explains a sizable portion of the decline in unionization in the United States. Overall, we find that a 1 percentage point increase in the immigrant share corresponds to a 0.479 percentage point decrease in the union density. Immigration reduced union density by 5.7 percentage points between 1980 and 2020, which accounts for 29.7 percent of the overall decline in union density during that period.

Across education and experience groups, we find that the effect of immigrants on unionization is most pronounced for high school dropouts and people with 1-10 years of experience. Across all sectors, this effect is most substantial for males; however, in the private sector, this effect is significant for both males and females. Immigrants do not have an effect on public sector unionization. Replacing immigrant share with the fractionalization index does not affect the direction or significance of the results compared to the main regression. To see whether immigrants reduced union density through an increase in the labor supply, we compared regressions where the main independent variable was the native population share or the immigrant population share. Here, we found that immigrants and natives both affect unionization differently, which suggests that immigrants decreased union density through the diversification of the population. Finally, we changed our definition of immigrant share to match that of Card and Peri 2016 and found results similar to our original results.

Although we have found sizable and significant negative relationships between the share of the workforce that is foreign-born and union density, the data show only the final union membership of individuals, and hence, it is difficult to sift out how much of the effect is coming from peoples' changing preferences for unionization behavior or high external costs to joining a union. Ferguson 2016 claims that minorities are more prone to unionize but face harsher hurdles from employers and hence end up having lower unionization rates. In this paper, we have assumed that less union membership indicate that individuals choose to not join unions or organizers have a harder time organizing more diverse people. More research and data are required to examine the employer-side. Regardless, from policy viewpoint, our results indicate that there is a clear trade-off between pro-immigration policies and pro-union policies.

Table 3.6. Heterogeneity by Education

	Omitted Categories				
	(1) Original	(2) < HS	(3) HS	(4) Some College	(5) College
imm_share	-0.479***	-0.684	-0.440***	-0.504***	-0.420***
	(0.083)	(0.424)	(0.093)	(0.106)	(0.085)
Observations	160	120	120	120	120
Adjusted R-Squared	0.8642	0.8635	0.8076	0.8924	0.8606

Generated using the final data set (1980-2020). Running the benchmark regression but omitting each education category. All other specification is the same as Table 1. The regression includes education, experience and year fixed effects, and their combinations. Each column starting with column 2, omits the education level in the column heading. Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. Due to the omission of certain education levels, the observations are less than 160 which is the original number of cells. Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 3.7. Heterogeneity by Experience

	Ommited Categories				
	(1) Original	(2) 1-10	(3) 11-20	(4) 21-30	(5) 31-40
imm_share	-0.479***	-0.311*	-0.493***	-0.558***	-0.432***
	(0.083)	(0.164)	(0.074)	(0.092)	(0.114)
Observations	160	120	120	120	120
Adjusted R-squared	0.8642	0.8854	0.8452	0.8822	0.8519

Generated using the final data set (1980-2020). Running the benchmark regression but omitting each experience category. All other specification is the same as Table 1. The regression includes, education, experience and year fixed effects, and their combinations. Each columns starting with column 2, omits the experience level in the column heading (i.e. col 2 excludes those who have 1 to 10 years of experience). Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 3.8. Heterogeneity Analysis (All Sectors)

Public and Private	Male imm	Male frac	M&F imm	M&F frac	Female imm	Female frac
imm_share	-0.479***		-0.363***		-0.142	
	(0.083)		(0.075)		(0.115)	
fraction_index		-0.409***		-0.404**		-0.162
		(0.149)		(0.150)		(0.212)
Observations	160	160	160	160	160	160
Adjusted R-squared	0.8642	0.8518	0.8815	0.8715	0.7723	0.7706

Generated using the final data set (1980-2020). Running the benchmark regression for imm_share and fraction_index separately for all sectors. Run separately by males only, males and females, and female only. The regression includes education, experience, year fixed effects, and their combinations. Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. There are 4 education, 8 experience, and 5 different years, amounting to 160 cells. Regression weighted using sample size for each collapsed bin (education-experience-year combo). Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 3.9. Heterogeneity Analysis (Private)

Private	Male imm	Male frac	M&F imm	M&F frac	Female imm	Female frac
imm_share	-0.466***		-0.414***		-0.276***	
	(0.080)		(0.064)		(0.083)	
fraction_index		-0.409**		-0.452***		-0.269**
		(0.154)		(0.130)		(0.129)
Observations	160	160	160	160	160	160
Adjusted R-squared	0.8856	0.8748	0.9162	0.9021	0.6976	0.6696

Generated using the final data set (1980-2020). Running the benchmark regression for imm_share and fraction_index separately for the Private sector. Run separately by males only, males and females, and female only. The regression includes education, experience, year fixed effects, and their combinations. Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. There are 4 education, 8 experience, and 5 different years, amounting to 160 cells. Regression weighted using sample size for each collapsed bin (education-experience-year combo). Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 3.10. Heterogeneity Analysis (Public)

Public	Male imm	Male frac	M&F imm	M&F frac	Female imm	Female frac
imm_share	-0.892		0.184		0.250	
	(1.325)		(0.450)		(0.416)	
fraction_index		0.196		0.107		0.246
		(0.581)		(0.474)		(0.384)
Observations	156	156	157	157	155	155
Adjusted R-squared	0.2783	0.2704	0.3974	0.3972	0.5729	0.5739

Generated using the final data set (1980-2020). Running the benchmark regression for imm_share and fraction_share separately for the Public sector. Run separately by males only, males and females, and female only. The regression includes education, experience, year fixed effects, and their combinations. Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. There are normally 4 education, 8 experience, and 5 different years, amounting to 160 cells. However, given the small size of the public sector, some categories did not have any workers in them. This explains why these regressions have less than 160 observations. Regression weighted using sample size for each collapsed bin (education-experience-year combo). Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 3.11. Fractionalization and Unionization

	(1) Frac.	(2) Imm.
fraction_index	-0.409**	
	(0.149)	
imm_share		-0.479***
		(0.083)
Observations	160	160

Generated using the final data set (1980-2020). The Fractionalization index is created using immigrant nationality groups and 4 broad categorizations of native-born: whites, blacks, Hispanics, other minorities. All columns include education, experience, year fixed effects, and their combinations. Col 1 only includes frac. Index, Col2 only uses Immigrant share (I) which is the same as that of Table 1. Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. There are 4 education, 8 experience, and 5 different years amounting to 160 cells. Regression weighted using sample size for each collapsed bin (education-experience-year combo). Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 3.12. Raw Count of Immigrants and Natives

	(1) Immigrant Raw	(2) Native Raw	(3) Immigrant (Share)	(4) Native (Share)
log(raw imm)	-0.255*			
	(0.147)			
log(raw nat)		0.424**		
		(0.197)		
log(ImmShare)			-0.311***	
			(0.197)	
log(NativeShare)				1.089*
				(0.621)
Observations	848	848	848	848

Columns 1 and 2 have the log of raw number of immigrant and natives as the main independent variable. Columns 3 and 4 have the log of shares of immigrants and natives. Dependent variable is union density of just natives as opposed both natives and immigrants. The regression includes education, experience and year fixed effects, and their combinations. Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. There are 4 education, 8 experience, and 27 years amounting to 864 cells. When using logs, zero union densities are dropped. Regression weighted using sample size for each collapsed bin (education-experience-year combo). Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 3.13. Using Immigrant Share with Lagged-size of Labor Force

	CPS-ASEC (1994-2020)						(1980-2020)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged Base	t	t-1	t-2	t-3	t-4	t-5	t-10
log(I)	-0.311***						
	(0.109)						
log(I-1)		-0.256**					
		(0.101)					
log(I-2)			-0.321***				
			(0.0968)				
log(I-3)				-0.196*			
				(0.111)			
log(I-4)					-0.249*		
					(0.137)		
log(I-5)						-0.215	
						(0.152)	
log(I-10)							-0.052*
							(0.027)
Observations	848	816	721	753	721	753	128

CPS-ASEC (1994-2020) is used for col1 to col6, each column represents an additional lag to the base labor supply of the main explanatory variable, log of immigrant share. Column 1 is the original result from Table 1, and column 6 is using the modified immigrant share where the base labor supply is lagged 5 periods. Column 7 is uses the final data set (1980-2020) as the main results section and the lag is 10 years. Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

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