Exporting Education or Importing Labor? The Labor Market Impacts of International Students*

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Abstract

In 2018, U.S. educational service exports totaled $50 billion, with over one million international students enrolled. This paper measures U.S. local exports in higher education services using student enrollment and expenditures and examines their impact on local labor market outcomes. Exploiting exogenous shifts in international student enrollment in other high-income countries, I find that regions experiencing larger positive demand shocks see relative employment gains compared to less affected regions. These gains are primarily concentrated in low-skill service sectors, university-related jobs, and among U.S. native workers. To assess the aggregate effects, I build and estimate a spatial general equilibrium model featuring trade in goods and export services. My findings indicate that U.S. educational service exports support nearly one million U.S. jobs. Amid ongoing debates on restricting student visas in developed countries, these results suggest that such policies could suppress local employment and economic activity in host countries.

JEL Codes: E24, F14, F16, L60, R12.

Key Words: Exporting Educational Service, US jobs, Spending Multiplier

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1 Introduction

Trade in services has expanded significantly over the past several decades, now accounting for roughly a quarter to a third of total international trade (Eaton and Kortum, 2018). The top sectors of service exports include tourism, financial services, innovation, and education. Among these, higher education services have seen substantial growth over the past three decades: until 2018, 5.3 million students pursued degrees abroad, with 58% studying in the US, Canada, Australia, and the UK (UNESCO Institute for Statistics, 2021). The United States alone hosts over one million international students—more than twice the number recorded in 2000 (Institute of International Education, 2024). Other destinations, such as Australia, Canada, and the UK, have experienced even more rapid growth in international student enrollment (see Table 1).

The surge in international student enrollment has raised growing concerns among host countries. Post-COVID-19, there has been a spike in visa applications in several major host countries, leading to proposed policies aimed at regulating student enrollment.[1] Very recently, the United States has proposed a bill to ban student visas for Chinese nationals, citing national security concerns related to intellectual property. While international students may raise certain concerns in host countries, they also serve as a crucial revenue stream for universities (Bound, Braga, Khanna and Turner, 2020). According to the U.S. Department of Commerce's Bureau of Economic Analysis (BEA), U.S. exports in educational services grew from $9 billion in 2000 to $50.2 billion in 2023, making educational services the seventh-largest service export industry today. While existing literature has extensively examined the impact of international student enrollment from multiple perspectives (see page 5 for the literature review), the effects of exporting educational services on local economies remain relatively understudied.

In this paper, I compile a rich dataset to estimate both the local and aggregate labor market consequences of U.S. exports in higher education services. My analysis proceeds in two steps. First, I provide reduced-form estimates of how local demand shocks from exploring educational services affect local labor market outcomes between 2000 and 2018, leveraging variation across U.S. commuting zones (CZs). I construct a shift-share instrument that assigns changes in international student enrollment in other high-income countries to U.S. CZs based on immigrant enclaves and universities' openness to international students. Second, to quantify the aggregate impact, I build

[1]For example, in January 2024, the Canadian government implemented a cap expected to limit study permit approvals to approximately 360,000—a 35% decrease from 2023 (Immigration, Refugees and Citizenship Canada (IRCC), 2024). Since August 2024, the Australian government has also been actively discussing a potential cap on international student enrollment, proposing a limit of 270,000 for 2025. In the UK, effective January 1, 2024, international students not enrolled in postgraduate research programs are no longer permitted to bring family members to the UK (UK Government Report, 2024).

a spatial general equilibrium model that features trade in goods and exported services. I structurally estimate model parameters to match the differential impacts implied by the reduced-form estimates. Using this model, I assess the effects of exporting educational services on U.S. employment and highlight the underlying mechanisms.

Since trade is often recorded at the national rather than the regional level, shift-share design, which maps aggregate shocks to local economies based on regional exposure to industrial shocks, is a commonly used tool for estimating the labor market consequences of aggregate trade shocks (Topalova, 2010, Kovak, 2013, Autor, Dorn and Hanson, 2013, Adao, Arkolakis and Esposito, 2023). One key distinction in mine is that I measure local exports in educational services using university-level data on international student enrollment, tuition and fees, and expected living expenses. This is made possible by leveraging the Integrated Postsecondary Education Data System (IPEDS), which provides comprehensive data on U.S. universities including full-time enrollment by degree type, enrollment by domestic student counts and nonresident, as well as tuition fees and estimated living expenses (such as rent, food, and other necessities). These expense estimates are provided by universities to help prospective students evaluate the cost of education and living.

The key variable in my empirical analysis is the local expenditure shock due to international students, which is computed as the change in total expenditures by international students (including both tuition and living expenses), relative to the CZ's gross consumption of goods and services in the initial year (2000). This variable captures the percentage change in local expenditure if the only thing changing since the initial year was the arrival of international students and their expenses.[2] I refer to this as the "local demand shock".

The arrival of international students had notable and systematic uneven effects on local demand across CZs since 2000. Among the 722 commuting zones, international students led to an average 0.18% increase in local expenditure (inflation-adjusted), with a standard deviation of 0.21%. The effects are large for small college towns and for CZs that are home to many universities, ranging from -0.47 to 2.50%. The most affected CZs are Campbellsville, Kentucky, home to Campbellsville University (2.50%); and State College, Pennsylvania, home to Pennsylvania State University (2.46%). To understand the plausibility of these local demand measures, I also find the temporary population shock from changes in international student enrollment relative to CZ's population in 2000 are in similar magnitude, which has an average of 0.20 %and a standard deviation of 0.22 %.[3]

[2]Local gross consumption of goods and services is estimated using data from the Bureau of Economic Analysis and the Consumer Expenditure Survey. See Section 2.3 for details.

[3]On average, international students (including both tuition and living expenses) spend a similar

During this period, the rise in international student enrollments was also observed in many other developed countries that serve as host nations. The primary source countries were developing economies, and the expansion of international student mobility was driven by broader economic transitions (Bound et al., 2021), rising secondary school attainment, and increasing post-secondary enrollment (Bird and Turner, 2014). Additionally, the limited capacity of high-quality universities in many developing countries made foreign education more attractive. At the same time, destination countries such as the UK, Canada, and Australia implemented student-friendly visa policies in the early 2000s to attract international students. These policies streamlined visa application processes and introduced immigration pathways that facilitated long-term employment opportunities for graduates.

Given these external drivers of international student flows, I construct a shift-share instrument that leverages changes in enrollment from the top 30 source countries to Australia, Canada, and the United Kingdom combined, allocating them to U.S. CZs based on immigrant enclaves and universities' openness to international students. I begin by estimating how university employment responds to local demand shocks using cross-CZ variation. Using the instrument, I estimate that a 1% increase in the local demand shock (driven by exports) led to a 1.57 percentage point (p.p.) increase in the CZ's university employment-to-population (working-age) ratio. CZs at the 75th percentile of demand shocks experienced a 0.15 p.p. higher university employment-to-population ratio compared to those at the 25th percentile.

The employment effects extend beyond the university sector. Local non-tradable industries—such as retail, construction, restaurants, wholesale, and hotels—experienced notable employment gains in CZs that were more positively affected. The estimated effects are meaningful: again, comparing CZs at 75th and 25th percentiles, the former saw relative growth in employment-to-population of 10.4% in university, 1.78% in wholesale, 1.27% in retail, 4.42% in hotel, 1.12% in restaurant and drinking places. These (relative) employment gain reflects both the local spending patterns of international students and the role of these industries as key intermediate inputs in university production. I also find that employment gains stem from increased labor force participation and a decline in unemployment. All these conclusions hold both under the state-level clustered standard errors and the confidence interval recently developed in Adao, Kolesár and Morales (2019).

I take rigorous steps to address potential threats to identification. First, I demonstrate that the estimated causal effects remain stable when controlling for changes in domestic student enrollment, which accounts for potential crowding out of native

amount per capita as U.S. households.

enrollment (Borjas, 2007), as well as changes in university appropriations and other revenue sources that often fluctuate with business cycles (Bound et al., 2020). Second, the large influx of international students analyzed in this study coincided with a period of systematic transformation in the U.S. local labor market. To assess the sensitivity of my estimates, I control for CZ's differential exposure to Chinese import penetration, recession, automation adoption, technological change, as well as CZ-level labor supply proxies. While these factors influence employment outcomes with expected signs, their inclusion modestly affects the magnitude of my point estimates. Third, I conduct a falsification test by examining employment changes in the past, from 1990 to 2000. The estimated effects are close to zero and become imprecisely estimated. The stable estimates and the placebo test results further strengthen the credibility of my causal estimates.

In the long run, international students could contribute to local labor supply shocks if they remain in the U.S. labor market after graduation. I show the estimated employment gain is not a result of increasing labor supply from "former" international students. Specifically, I estimate the reduced-form regression separately for native workers and for workers who are unlikely to be former international students on student visas.[4] I find that much of the employment gains are realized among US natives and immigrant workers who are not former international students.

Since university students tend to live and spend near their campuses, employment responses may vary by industry and by geographic proximity to universities. To investigate the intra-CZ geography of employment responses, I use County Business Patterns (CBP) data, measuring local outcomes, demand shocks, and the instrument all at the county level. Estimating the model with CZ fixed effects, I find that employment responses strongly depend on the geographic extent of an industry's products. In restaurants, drinking places, and retail, where proximity to university campuses is crucial for serving growing student demand, employment growth is stronger in university counties compared to other counties within the same CZ. In contrast, in construction, transportation, and wholesale, where employees can commute to deliver goods and services, employment growth is relatively higher in non-university counties within CZ.

Finally, I build a spatial general equilibrium model incorporating exports in both goods and educational services. In the model, U.S. CZs trade manufactured goods and educational services with each other and with the rest of the world (ROW), following a standard spatial model of trade (Allen and Arkolakis, 2014). Educational services are modeled as a composite consumption bundle of two industries: university ser-

[4]Using the American Community Survey, I identify likely former-international-student workers based on characteristics (Peri and Basso, 2016). See Section 5 for details.

vices and local non-tradable. Workers are perfectly mobile across industries and decide whether to work. Exports of educational services affect local non-tradable industries through two channels: (1) student consumptions; (2) university production relies on non-tradable as intermediate inputs (Caliendo and Parro, 2015). I calibrate the model to match 2018 U.S. data and estimate the structural parameters using indirect inference, where the model implied differential effects across counties aligning with that in the reduced-form estimates.

Using the estimated model, I simulate a counterfactual scenario in which educational service exports are reduced to zero. Since this counterfactual differs from reality only in the absence of educational service exports, the estimated employment effect speaks to that of education exports alone. I find that U.S. educational service exports generate 948,000 jobs in aggregate.

I compute two model predictions to study the plausibility of this large employment gain I find. First, the model implies a spending multiplier of 1.96, which operates through rising income and consumption among local residents. Second, I compute the model-implied cost per job. Both measures are similar to previous literature estimates (Chodorow-Reich, 2019), thus bolstering the credibility of my findings.

The economic literature has examined international students from multiple perspectives. Early work follows closely to the immigration literature. One major focus is on the determinants and selectivity of international student flows. Rosenzweig (2006) proposes a theory suggesting that limited educational opportunities in home countries and the high labor market returns in destination countries are two key drivers of student mobility. Empirically, factors such as the scarcity of high-quality educational resources in home countries (Bound, Turner and Walsh, 2009), a country's GDP per capita, and the size of the college-aged population (Bird and Turner, 2014) are strong predictors of international student enrollment. Another important strand of research examines whether international students crowd in or crowd out domestic students in educational institutions. Borjas (2007) finds evidence of crowding out in graduate programs, particularly among white native men. In contrast, more recent studies suggest that revenue generated from international students cross-subsidizes domestic students (Shih, 2017) and compensates for state budget cuts faced by public research universities (Bound, Braga, Khanna and Turner, 2020). See Bound, Braga, Khanna and Turner (2021) for a review.[5] More recently, Khanna, Shih, Weinberger, Xu and Yu (2023) argue that the rise in Chinese international student enrollment in the U.S., driven by China's rapid economic growth and its integration into the world economy, has generated a no-

[5]For discussions on the selectivity of foreign-born doctoral students in the U.S., see Grogger and Hanson (2013); for their location choices after graduation, see Grogger and Hanson (2015).

table surplus in service trade. My work differs from the existing literature in both its methodology and its focus on the labor market effects on the exporting country.

My instrumental strategy leverages international student enrollment growth in other developed countries, inspired by Autor, Dorn and Hanson (2013). Recently, Monras (2020) exploits the unanticipated Mexican Peso crisis to study the local wage responses to the inflow of low-skilled migrants from Mexico. In his case, the push factors also contribute to exogenous variation for identification. Burchardi, Chaney and Hassan (2019) investigates time-series variations in origin-specific push factors and destination-specific pull factors over a century to allocate immigrants across U.S. counties by origin.[6] Both approaches combine exogenous supply and demand factors to improve identification over the classical instrument in Card (2001), which relies solely on exogenous shares (Goldsmith-Pinkham, Sorkin and Swift, 2020). Complementing those papers, my approach leverages exogenous shifts that are unlikely to be driven by unobserved demand shifts and demographic changes in US regions (Borusyak, Hull and Jaravel, 2022, Adao, Kolesár and Morales, 2019).[7]

My paper also relates to the growing literature that uses quantitative spatial equilibrium models to analyze the consequences of aggregate or local shocks Monte et al. (2018), Albert and Monras (2022), Adao et al. (2023). I build on the framework developed in Allen and Arkolakis (2014), Redding (2016), and Redding and Rossi-Hansberg (2017) to incorporate exports in educational services, a new element in this class of quantitative frameworks. My focus on exporting services is also closely related to Faber and Gaubert (2019), who studies how exporting tourism services drives the long-run development in Mexico. My overall approach—using reduced-form estimates to assess differential impacts across regions and employing a general equilibrium model to evaluate the aggregate impact—is similar to that of Kline and Moretti (2014) and Donaldson and Hornbeck (2016).

2 Data and Empirical Approach

This section discusses empirical specification and the data source. My empirical estimation focuses on the period between 2000 and 2018, which is chosen because of the surge of international student enrollment at this time, and data availability.[8]

[6] Burchardi et al. (2019) use time-series variations in origin-specific push factors and destination-specific pull factors over a century to allocate immigrants across U.S. counties by origin. This time-series variation is absent in my instrument.

[7] For valid inference, the asymptotic consistency requires none of the source countries dominate in the initial period. In Section 3.2, I show the effective sample size is relatively high.

[8] Data on university tuition and expected living expenses were published for only a small set of universities before 2000.

2.1 Data Source

The choice of geographic units involves a tradeoff: while larger units, such as commuting zones (CZ), might dilute the intensity of the shock as the geographic boundary expands, they are conventionally used in the recent literature in better capturing the spillover of demand shocks. In contrast, since there are substantial differences across US counties in the share of employees who live in nearby counties (Monte, Redding and Rossi-Hansberg, 2018), I use CZ in my baseline analysis. Results using cross-county variation will be discussed in Section 5.2 and Appendix B. Below, I briefly describe the data sources, with further details provided in Appendix A.

Integrated Postsecondary Education Data System (IPEDS). IPEDS provides comprehensive information on all U.S. postsecondary institutions. It includes university-level information on full-time enrollment by degree type, by domestic students and nonresident aliens, university employees, and financial information. Importantly, IPEDS provides information on in-state and out-of-state tuition fees, as well as costs associated with housing, books, rentals, food, and other living expenses. See Appendix Table C.2 for several examples. These information often are collected to inform prospective students about expected college-related expenses.

I classify international students as "nonresident aliens" in IPEDS—students who are not U.S. citizens, hold temporary visas, and do not have the legal right to remain in the country indefinitely. I focus on full-time international students enrolled in bachelor's, master's, and associate degree programs, excluding Ph.D. students, as most receive scholarships and stipends. To measure local exports in educational services, I use full-time enrollment and tuition fees, aggregating the data to the CZ level. Throughout this paper, university sector employment refers to full-time university employees from IPEDS, aggregated to either the CZ or county level.

Labor Market Variables. Labor market variables, including employment, labor force participation, and income, are obtained from the Census Integrated Public Use Microdata Samples (IPUMS) (Ruggles et al., 2024) for the years 1990 and 2000, as well as from the American Community Survey (ACS) (2015–2019), which I use to represent 2018. I restrict the sample to the working-age population (16–65 years old), and all variables are aggregated to 722 CZs. Employees are those whose employment status is "employed" and earn a positive salary.

Consumption in Goods and Services. To my knowledge, the CZ level consumption in goods and services is not directly available in any existing data source. I combine three data sources to construct this measure. First, I extract state-level consumption in

goods and services from the Bureau of Economic Analysis (BEA). I then use Consumer Expenditure Survey and American Community Survey (ACS) to allocate state-level consumption to CZs (see Appendix A.2 for details).

UNESCO Institute for Statistics. I use data from the UNESCO Institute for Statistics to measure the number of international students from the 30 largest source countries studying in three major English-speaking destinations: Australia, Canada, and the United Kingdom.[9] These variables are used to construct the shift-share instrument.

2.2 Empirical Specification

The arrival of international students boosts local consumption in certain industries and could potentially lead to an increase in local labor demand and wages. I estimate the following equation which links changes in employment-to-population ratio in industry k to expenditure shocks as follows

$$\Delta \frac{\text{Emp}_{rk}}{\text{Pop}_r} = \beta_k \cdot \hat{\mathcal{X}}_r^f + \hat{\mathcal{G}}_{rk} + \hat{\mathcal{U}}_{rk}. \tag{1}$$

The outcome variable is defined as: $\Delta \frac{\text{Emp}_{rk}}{\text{Pop}_r} = \frac{\text{Emp}_{rkt}}{\text{Pop}_{rt}} - \frac{\text{Emp}_{rkt-1}}{\text{Pop}_{rt-1}}$. The choice of employment-to-population ratio as dependent variable aligns with several recent studies (Autor et al., 2013, Acemoglu and Restrepo, 2020).

The main regressor is local expenditure shock, $\hat{\mathcal{X}}_r^f$, and is defined as

$$\hat{\mathcal{X}}_r^f = \frac{\Delta \mathcal{X}_r^f}{\mathcal{X}_{rt-1}}. \tag{2}$$

The numerator, $\Delta \mathcal{X}_r^f = \mathcal{X}_{rt}^f - \mathcal{X}_{rt-1}^f$, is the change in r's gross consumption (aggregating all industries) from international students between time $t-1$ and t. The denominator, $\mathcal{X}_{rt-1}$, is CZ gross consumption in the initial year. The interpretation of $\hat{\mathcal{X}}_r^f$ is intuitive: it captures the percentage change in local expenditure if the only factor changing since 2000 is the arrival of international students and their spending.

The coefficient β_k captures the reduced-form effect of a local expenditure shock on k-industry employment. In Appendix F, I present a simple general equilibrium model to motivate the reduced-form estimating equation in (1), demonstrating that β_k is determined by several factors. First, it depends on labor supply elasticity. Second, it

[9] The source countries include China, Japan, Korea, India, Canada, Thailand, Indonesia, Malaysia, Mexico, Germany, Turkey, Hong Kong, Brazil, United Kingdom, Russia, France, Pakistan, Venezuela, Colombia, Saudi Arabia, Spain, Bangladesh, Italy, Kuwait, Nigeria, Australia, Nepal, Iran, Vietnam, and Oman. The data are available under the Sustainable Development Goals (SDG) theme of education, specifically under international student mobility statistics.

is influenced by the expenditure share of international students in industry k. Third, input-output linkages play a role, particularly the extent to which k-industry serves as key intermediate inputs in university production.

The regression residual consists of two components: other unobserved local labor demand shocks occurred contemporaneously, denoted as $\hat{\mathcal{G}}_{rk}$, and an unobserved labor supply shock, $\hat{\mathcal{U}}_{rk}$.

2.3 Measuring Local Demand Shocks

The measurement of $\hat{\mathcal{X}}_r^f$ requires two sets of information. First, $\Delta\mathcal{X}_r^f$ is the change in total expenditure of international students (also r's exports in educational service). It is estimated as:

$$\Delta\mathcal{X}_r^f = \sum_{\omega\in\Omega_r}\Big(\textbf{Exper}_{rt}^f(\omega)\textbf{Enrl}_{rt}^f(\omega) - \textbf{Exper}_{rt-1}^f(\omega)\textbf{Enrl}_{rt-1}^f(\omega)\Big). \tag{3}$$

Here, $\text{Enrl}_{rt}^f(\omega)$ is the number of full-time international student enrollment in university ω in year t. Ω_r denotes the collection of universities in CZ r. $\text{Exper}_{rt}^f(\omega)$ denotes the average expense per full-time international student, which includes tuition fees as well as living expenses. While IPEDS reports tuition and fees separately for in-state and out-of-state students for public institutions, they do not explicitly separate tuition and fees for international students. In practice, international students might be charged the same or additional fees compared to out-of-state students. However, such information is not available. I measure $\text{Exper}_{rt}^f(\omega)$ using the sum of three components: out-of-state tuition and fees, on-campus rent, and other living expenses. Expenses are inflation-adjusted in 2000 dollars.

Although $\text{Exper}_{rt}^f(\omega)$ may not perfectly capture actual expenditures, they serve as a good proxy for the aggregate students' spending on the local community. According to IPEDS, the total expense from full-time international students grew from 8.9 billion in 2000 to 30.8 billion in 2018.[10]

The denominator, $\mathcal{X}_{rt-1}$, is the gross consumption of goods and services in year 2000. To the best of my knowledge, such data is not directly available. I adopt two ways to measure the denominator. My baseline measure is based on personal consumption of goods and services. I extract data on the state-level personal consumption of goods and services available at the BEA. After that, I project household consumption on a rich set of household characteristics using Consumer Expenditure (CE) Survey, to allocate

[10]Note that this value is lower than the BEA report, which also includes revenue from other education programs such as summer schools, short-term exchange programs, language immersion programs, professional training or certification courses, and other temporary academic programs where students reside in the U.S.

state-level consumption to CZ-level taking into account variation in CZ's household characteristics (See Appendix A.2).

Appendix Table C.1 compares the average expenses of international students, domestic students, and U.S. households per capita. In both 2000 and 2018, international students' expenses were more than twice those of domestic students. International student per capita expenses are similar to U.S. household per capita expenses.

My alternative measure incorporates government spending in the denominator.[11] Here, the only difference from the baseline measure is that $\mathcal{X}_{rt-1}$ equals the sum of the (imputed) CZ's personal consumption and government spending. Again, data on government spending are available at the state level from the US census. I allocate state-level government spending to CZ using population shares. The two measures exhibit a correlation of 0.98 and the choice has little impact on the estimated results (see Section 4.4).

International students had notable and systematic uneven effects on local demand across CZs. The left panel of Figure 1 maps the changes in international student expense relative to the initial year total local expenditure. Darker color denotes regions with more positive demand shock. Among the 722 commuting zones, 521 has at least one university. On average, international students led to 0.18% increase in local consumption (inflation-adjusted), with a standard deviation of 0.21%.

The right panel lists the most affected CZs in terms of $\hat{\mathcal{X}}_r^f$, as well as the major university hosted. The effects are large for small college towns and for counties that are home to many universities, and the magnitudes are as large as 2.50% in Campbellsville, Kentucky, and 2.46% in State College, Pennsylvania. Cities that are home to major state universities, such as Champaign, Illinois, Bloomington, Indiana, Pullman, Washington, Auburn, Alabama, and Lansing, Michigan, are on the lists. In contrast, regions without a university receive zero demand shocks.

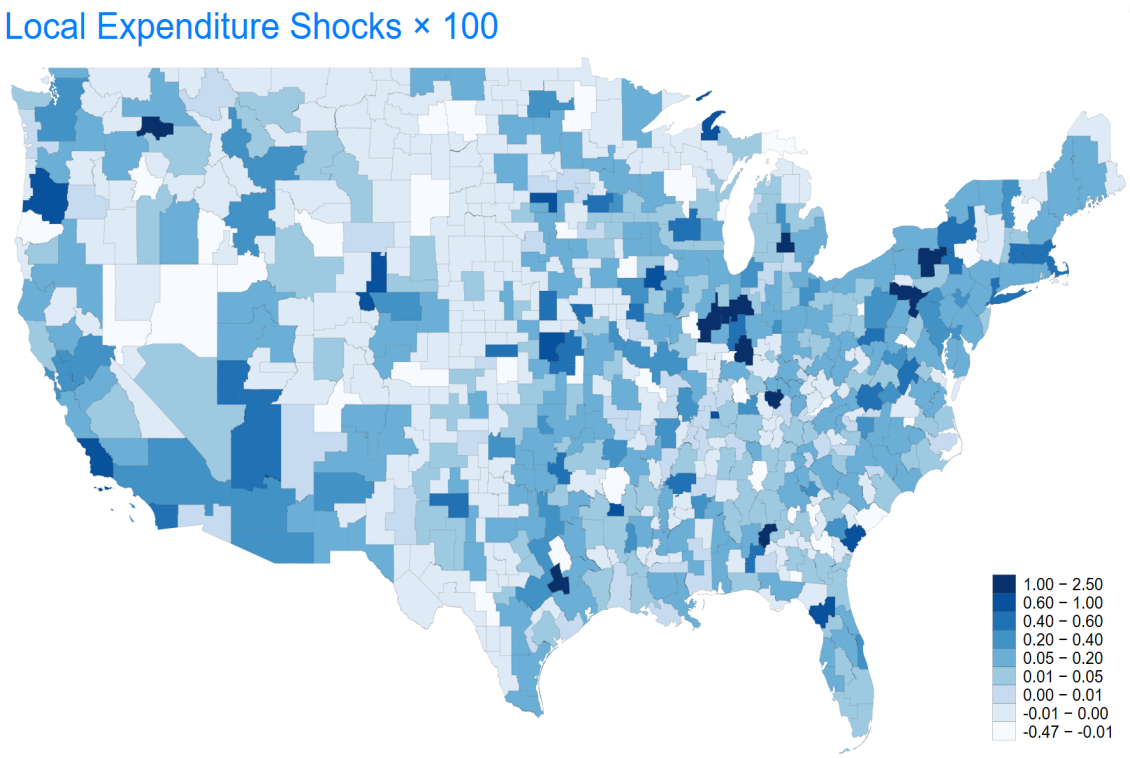
In some estimations, I also use the changes in enrollment relative to the CZ's initial population, which measure temporary population shocks and are defined as:

$$\hat{\mathcal{P}}_r^f = \frac{\sum_{\omega \in \Omega_r} \Delta \text{Enrl}_r^f(\omega)}{\text{Pop}_{rt-1}}, \tag{4}$$

where $\Delta \text{Enrl}_r^f(\omega)$ is the change in full-time international student enrollment at university ω between 2000 and 2018, and Pop_{rt-1} denotes the local population in 2000. $\hat{\mathcal{P}}_r^f$ and $\hat{\mathcal{X}}_r^f$ are in similar magnitude and strongly correlated: $\hat{\mathcal{P}}_r^f$ has an average of 0.20 and a standard deviation of 0.22 , the correlation is 0.91.

[11] In 2000, the US totaled 7.03 trillion dollars in personal consumption and 1.3 trillion in government spending.

Figure 1: The Local Expenditure Shock From Educational Exports and the Most Affected Commuting Zones



The Most Affected CZs:

1. Campbellsville, KY (2.50%) – Campbellsville University
2. State College, PA (2.46%) – Pennsylvania State University
3. Champaign, IL (1.78%) – UIUC
4. Bloomington, IN (1.51%) – Indiana University Bloomington
5. Pullman, WA (1.44%) – Washington State University
6. Auburn, AL (1.39%) – Auburn University
7. Lansing, MI (1.30%) – Michigan State University
8. Bryan, TX (1.26%) – Texas A&M University
9. Lafayette, IN (1.26%) – Purdue University
10. Elmira, NY (1.14%) – Elmira College
11. Brookings, SD (0.90%) – South Dakota State University
12. Iowa City, IA (0.90%) – University of Iowa

Notes: The left panel shows the local demand shock, $\hat{\mathcal{X}}_r^f$ for 722 CZs. The right panel displays CZ that are most affected. The value of $\hat{\mathcal{X}}_r^f$ is given in the parenthesis. The shock values are multiplied by 100, so each value represents the percentage changes relative to the initial population or consumption in 2000.

3 Instrumental Strategy

Estimating equation (1) using Ordinary Least Squares (OLS) may cause endogeneity concerns. One issue is that universities in economically thriving areas are more likely to expand and become attractive for international students. In this case, $\hat{\mathcal{X}}_r^f$ could be correlated with local demand or supply factors, $\hat{\mathcal{G}}_r$ and $\hat{\mathcal{U}}_r$.

A second concern is the measurement error in $\hat{\mathcal{X}}_r^f$: the student expenses are based on universities' estimated costs, which may not perfectly reflect actual expenditures. This section motivates and introduces an instrument that exploits factors exogenous to U.S. labor market conditions.

3.1 Motivating the Exogenous Shifts

Table 1 presents the number of international students enrolled in the United States versus the combined total for three other English-speaking countries (Australia, Canada, and the United Kingdom). Panel A displays the top five source countries that sent international students to the United States in 2000, with the total number shown in the first row.

Over the study period, international student enrollments increased substantially, not only in the U.S. but also in other developed countries. As shown in the first row, the number of international students in the U.S. more than doubled, rising from 452,000 in 2000 to 987,000 in 2018. The growth in Australia, Canada, and the UK was even more pronounced, with combined enrollments increasing from 366,000 to 1,108,000.

This expansion in international student enrollment was also accompanied by notable shifts in the composition of source countries. In 2000, China, Japan, Korea, and India were the four largest contributors to the U.S. international student population, each sending between 35,000 and 47,000 students. However, these countries followed markedly different trajectories over time. By 2018, China and India had emerged as the dominant sources of U.S. international students. The number of Chinese students surged sevenfold, from 46,900 in 2000 to 333,900 in 2018, while the number of Indian students grew nearly fourfold, from 34,500 to 135,900. Korea experienced only modest growth, with student numbers increasing from 36,200 to 52,400. In contrast, Japan, which was the second-largest source country in 2000, saw a sharp decline, with enrollments dropping from 42,700 to just 14,900.

A similar pattern is observed in Australia, Canada, and the UK, as reported in the final three columns. These three countries collectively attracted an additional 309,700 Chinese students and 119,300 Indian students over the period while also experiencing a decline in enrollments from Japan.

Panel B shows enrollment data for other source countries, not ranked top 5 in 2000, but had experienced increasing outflow of students to developed countries. Countries such as Saudi Arabia, Vietnam, Nepal, Iran, and Nigeria had relatively low international student outflows in 2000 but experienced dramatic increases in student migration to both the U.S. and the other three destinations over the two decades.

While student flows vary across source countries, a given source country tends to experience simultaneous increases or decreases in student flows to both the U.S. and other destinations. Several factors contribute to this pattern. The first is differential economic development and growth across source countries. Over the two decades covered in this study, China, India, and Southeast Asian countries experienced rapid economic growth, enabling more families to afford the costs of higher education abroad (Bound, Braga, Khanna and Turner, 2020). In contrast, Japan's declining international student numbers coincide with prolonged economic stagnation, characterized by low growth and deflation since the 1990s. Rising tuition costs in the U.S. and declining disposable incomes in Japan may have further discouraged Japanese students from pursuing higher education abroad. Appendix Figure D.3 reveals a strong positive association between economic growth and the propensity for international student outflows: countries that experienced faster economic growth were increasingly likely to send students abroad for higher education. This positive relationship aligns with the empirical findings of Bird and Turner (2014), who show that home-country economic conditions and exchange rate fluctuations predict changes in international student enrollment.

Second, increasing secondary school attainment in many developing economies has also led to a growing demand for higher education abroad.[12] However, the rapid rise in student populations has outpaced the expansion of university capacity in these countries, creating significant demand for higher education and fueling the growth of international student mobility (Bound et al., 2009). Third, in the early 2000s, competing destinations such as the UK, Canada, and Australia implemented student-friendly visa policies to attract more international students. These policies simplified visa application processes and introduced immigration pathways that provided clearer opportunities for long-term employment after graduation.[13]

[12]In China, for instance, secondary school enrollment grew by 15 million between 1997 and 2017, reaching approximately 83 million. Over the same period, post-secondary enrollment surged by 38 million, increasing from a baseline of about 6 million. India experienced a similarly dramatic expansion, with secondary school enrollment rising by 61 million and post-secondary enrollment increasing by 27 million between 1997 and 2017 (Bound et al., 2021).

[13]For example, the UK launched the Prime Minister's Initiative (PMI) in 1999 to increase international enrollment and expanded it in 2006 with the introduction of the Post-Study Work Visa, which allowed graduates to remain in the country for two years. Canada strengthened its appeal through the Post-Graduation Work Permit (PGWP), which extended post-study work rights to three years, and the Canadian Experience Class (CEC), which provided a direct route to permanent residency for international graduates. Similarly, Australia streamlined visa processing through the Streamlined Visa

Table 1: International Students to Developed Countries (in thousands) by Top Origins

Source	United States			Other Three Countries		
	2000	**2018**	**Changes**	**2000**	**2018**	**Changes**
Panel A: Top Source Countries in 2001						
Total	451.9	987	535.1	366.4	1107.8	741.5
China	46.9	333.9	287.0	12.4	322	309.7
Japan	42.7	14.9	-27.8	9.3	6.9	-2.5
Korea	36.2	52.4	16.2	5.6	19.4	13.8
India	34.5	135.9	101.4	8.4	127.7	119.3
Canada	20.9	26.5	5.6	4.6	8.9	4.4
Panel B: Other Major Source Countries in 2018						
Saudi Arabia	4.5	47.3	42.8	2	17.1	15.1
Vietnam	1.5	25.6	24.1	1.5	22.1	20.6
Nepal	2.2	14.4	12.2	.2	33.7	33.5
Iran	1.5	11.8	10.3	1.5	7.9	6.5
Nigeria	2.6	12.8	10.1	2.4	19.6	17.2

Notes: The data is sourced from the UNESCO Institute for Statistics. The first three columns report the number of international student enrollments in 2000 and 2018, along with the change over this period. The last column aggregates the changes for Australia, the UK, and Canada. All values are reported in thousands. Panel A presents the top five origin countries in 2000, while Panel B lists other origin countries that experienced an increase in enrollment during this period. For Canada, the reported figures exclude Canadian students who studied domestically.

3.2 The Shift-Share Instrument

Motivated by the aforementioned external factors, I construct a shift-share instrument utilizing changes in international student enrollments in three other countries. First, I project international student inflow to each US university, ω, as follows

$$\Delta \text{Enrl}^{\text{ACU}}(\omega) = \sum_{g} \left[S_{cg}^{1990} \times S_{c}^{2000}(\omega) \times \Delta \text{Enrl}_{g}^{\text{ACU}} \right] \tag{5}$$

where $\Delta \text{Enrl}_{g}^{\text{ACU}}$ represents the overall change in international student enrollment to universities in other developed countries, Australia, Canada, and UK combined. g is one of the 30 major source countries.[14]

The term S_{cg}^{1990} denotes the share of immigrants from source country g who resided in state c in 1990. To compute this, I use data from the 1990 IPUMS Census, restricting the sample to immigrants aged 18 to 65. Here, I measure immigrant enclaves at the state level, a more aggregated geographic unit than U.S. commuting zones (CZs)—do so allows me to exploit variation in university's openness to international students, $S_{c}^{2000}(\omega)$, when allocating students across regions. Specifically, $S_{c}^{2000}(\omega)$ is the share of international students attending university ω relative to the total number of interna-

Processing (SVP) system and introduced the 485 Graduate Work Visa in 2007, granting graduates up to 18 months of post-study employment.

[14]The enrollment data for all the top 30 source countries are provided in Appendix Table C.3.

tional students hosted by state c in the initial year. I estimate $S_c^{2000}(\omega)$ using IPEDS data from the year 2000.[15]

The shift-share instrument is constructed as

$$\hat{\mathcal{Z}}_r = \frac{\sum_{\omega \in \Omega_r} \Delta \text{Enrl}^{\text{ACU}}(\omega)}{\text{Pop}_{rt-1}}. \tag{6}$$

The numerator adds up, $\Delta \text{Enrl}^{\text{ACU}}(\omega)$, the projected changes in international student enrollment to each university within CZ r. The denominator is the CZ-level population in 2000. $\hat{\mathcal{Z}}_r$ is interpreted as the predicted local population shock due to international students.

Identification and Inference. The strategy of leveraging outcomes from other countries is inspired by Autor, Dorn and Hanson (2013) and has been adopted in the study of automation (Acemoglu and Restrepo, 2020). To illustrate the exogenous component that provides identification, one can write

$$\Delta \text{Enrl}_g^{\text{ACU}} = N_g^{2000} \times M_{g,ACU}^{2000} \times \hat{\mathcal{T}}_g^{\text{ACU}} \tag{7}$$

where N_g^{2000} denotes the population with secondary education completion (the potential university applicants) in country g, with a share of $M_{g,ACU}^{2000}$ live in Australia, Canada, and UK combined in 2000. $\hat{\mathcal{T}}_g^{\text{ACU}}$ is the growth rate of g-group enrollment to other three countries combined that can be expressed as $\hat{\mathcal{T}}_g^{\text{ACU}} = \hat{N}_g \hat{M}_{g,ACU} - 1$. Now, it is clear that the growth can be attributed either to changes in secondary school population ($\hat{N}_g$) or to increases in the propensity of receiving education abroad ($\hat{M}_{g,ACU}$).[16] In my setting, identification requires that $\hat{\mathcal{T}}_g^{\text{ACU}}$ satisfies the conditional mean independence assumption (Borusyak et al., 2022, Adao et al., 2019).

One key difference between the identification assumptions in Borusyak et al. (2022) and Adao et al. (2019) is that the former relies on aggregate industry-level variables, while the latter uses industry-region-specific variables. Consequently, in Adao et al. (2019), the number of regions also contributes to the degrees of freedom, provided they are appropriately clustered based on similarities in shares. Throughout this paper, I report both state-level clustered standard errors and Adao et al. (2019) confidence intervals in all estimation results.

To assess the effective number of exogenous shifts that contribute to identification, I compute the Herfindahl-Hirschman Index (HHI) of the aggregate exposure shares, as suggested by Borusyak et al. (2022). The HHI is defined as $\frac{1}{\sum_g s_g}$, where s_g represents

[15] The IPEDS data for 1990 is not available to measure full-time international students.

[16] Here, $\hat{N}_g = N_g^{2018}/N_g^{2000}$ and $\hat{M}_{g,ACU} = M_{g,ACU}^{2018}/M_{g,ACU}^{2000}$.

the share of U.S. international student enrollment from country g in the year 2000, based on data from the UNESCO Institute for Statistics. Using 30 source countries to construct the instrument, the HHI suggests an effective number of shifts of 26, indicating that no single country dominated international student enrollment in 2000.[17]

This instrumental strategy is also closely related to recent immigration instruments constructed by Monras (2020) and Burchardi, Chaney and Hassan (2019). Monras (2020) exploit the currency crisis that led to an unanticipated influx of Mexican immigrants into the U.S., while Burchardi, Chaney and Hassan (2019) leverage time-series variations in origin-specific push factors and destination-specific pull factors over a century. Both approaches improve causal identification by combining exogenous supply and demand shifts, building on Card (2001), whose immigration settlement instrument relied solely on historical shares being exogenous (Goldsmith-Pinkham et al., 2020).

It is also worth mentioning that I construct the instrument based on enrollment shocks, ensuring that it is free from errors arising from measuring the expected expenses. In practice, the instrument can mitigate measurement error issues if the underlying supply factors driving the inflow of international students from a particular origin country are unrelated to how the actual student consumption deviates from the expected expenses. For this condition to hold, source countries experiencing faster economic growth—and thus expected to send a larger number of students—must have actual student expenditures that, while potentially differing from expected levels, do not systematically deviate from those of students from other countries that send fewer students. This assumption ensures that any measurement errors in CZ-level consumption shocks are not correlated with the composition of international students.

Appendix Figure D.2 plots the observed and projected changes in international students across US CZs. It reveals a strong predictive power: a (predicted) unit increase in international students to a U.S. CZs corresponds to a 0.36 (s.e.=0.0080) of the actual increase, with an R-square of 0.80.

4 Estimation Results

This section presents the estimation results. All models are estimated using one-time changes between 2000 and 2018 for over 722 U.S. CZs. Observations are weighted by working-age population in 2000. State-level clustered standard errors (in parentheses) and AKM confidence intervals are reported in all models.

[17] These 30 countries account for over 98% of the changes in international student enrollment.

4.1 Employment Responses in University Industry

I first estimate changes in the university employment-to-population ratio on $\hat{\mathcal{X}}_r$, instrumented by $\hat{\mathcal{Z}}_r$. Table 2 presents the estimates under various specifications. Column (1) reports a sizable and statistically significant coefficient when only controlling for nine division fixed effects, and a regression constant. The estimated coefficient of 1.722 (s.e.=0.610) indicates that a one percent increase in the local expenditure due to international students (relative to the level in 2000) leads to a 1.72 p.p. increase in local university employment to population ratio.

If certain regions are expected to experience secular expansion, local universities might also attract more domestic students. In contrast, international students might have crowded out native students (Borjas, 2007). This suggests that international student enrollment may indirectly impact local outcomes by affecting domestic student enrollment. To address this potential confounder, I control for changes in the domestic enrollment-to-initial population ratio, computed as:

$$\hat{\mathcal{P}}_r^{\text{native}} = \frac{\sum_{\omega \in \Omega_r} \Delta \text{Enrl}_r^{\text{native}}(\omega)}{\text{Pop}_{rt-1}}, \tag{8}$$

where $\Delta \text{Enrl}_r^{\text{native}}(\omega)$ denotes the change in full-time enrollment of domestic students. With this control, the results show that an increase in domestic enrollment is positively associated with university employment, with a coefficient of 1.073 (0.245).[18] Importantly, the coefficient of interest decreases modestly in Column (2), falling to 1.319 (0.582).

Appropriations and other revenue sources fluctuate with business cycles, and tuition fees from international students serve as important revenue streams for public universities, particularly during economic downturns (Bound, Braga, Khanna and Turner, 2020). To account for this factor, I construct changes in universities' revenue shocks from other sources as follows:

$$\hat{\mathcal{X}}_r^{\text{other}} = \frac{\sum_{\omega \in \Omega_r} \Delta \mathcal{X}_r^{\text{other}}(\omega)}{\mathcal{X}_{rt-1}}, \tag{9}$$

where the numerator is university revenue changes from various non-tuition sources, including appropriations (local, state, and federal), investment returns, and other revenue streams, aggregate to the CZ level. The denominator remains as CZ consumption in the initial year. Data on university revenue are available at IPEDS. Column (3) indicates that an increase in universities' other sources of revenue is positively associated

[18] Note that, this coefficient for $\hat{\mathcal{P}}_r^{\text{native}}$ is estimated using OLS and might not have a causal interpretation. The magnitude of this coefficient is comparable to the OLS estimates for $\hat{\mathcal{X}}_r^{\text{foreign}}$ in column (7).

with employment outcomes, though imprecisely estimated. Importantly, incorporating this measure results in only modest changes to the main coefficients of interest.

The large influx of international students analyzed in this study coincides with a period of systematic transformation in the U.S. local labor market. Several economic shocks, such as import competition and technology adoption, that negatively affect labor demand in manufacturing industries might lead to a worker relocation to other industries. Next, I test whether my results are potential confounding to these factors. All control variables are standardized to have a standard deviation of one.

China's productivity and economic growth have not only driven the increase in Chinese imports to the U.S. (Autor et al., 2013), but might also in part contributed to the rise in Chinese international student enrollment in the U.S. (Khanna, Shih, Weinberger, Xu and Yu, 2023). The increases in Chinese students could further motivate trade and FDI between China and the US (Burchardi et al., 2019). To address this concern, in Column (4), I augment the model with a shift-share control of *exogenous* regional import penetration from China, constructed using export growth to other advanced economies between 2000 and 2012 (Autor et al., 2021). Because the shift-share control is constructed using manufacturing employment share only (incomplete shares), I also control for initial manufacturing employment share (Borusyak et al., 2022). Incorporating these two controls does not alter the coefficient of interest.[19]

U.S. regions have experienced varying impacts from technological changes and automation shocks. To account for this, I include two sets of controls. The first is the *exogenous* regional shift-share automation shock (using robot adoption to other countries), taken from Acemoglu and Restrepo (2020). The second set includes the percentage of employment in routine occupations and the offshoring index, which measures the extent to which occupations in a CZ require neither proximity to a specific worksite nor face-to-face contact with U.S.-based workers, following Autor and Dorn (2013).

During this period of my study, regions were also differentially exposed to the 2007 Great Recession, which was characterized by substantial job losses and relatively modest wage adjustments. Recent studies have shown that while regions heavily impacted by the recession experienced a rapid recovery in unemployment rates, the effects on employment-to-population ratios have persisted (Yagan, 2019). I control for local exposure to the Great Recession, following Autor et al. (2021), which calculates shocks based on the annualized log change in national employment by industry between 2006 and 2009 across 479 SIC industries.[20] A similar shift-share measure has been used in

[19]While China shock has no impact on university employment, I show it indeed reduces manufacturing employment, see Appendix Table C.4 column (8).

[20]These shocks are mapped to regions using local industry exposure shares in 2000.

Hershbein and Kahn (2018).

Table 2: The Effects on University Employment using Expenditure Shocks

	2SLS						OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: changes in university employment/population ratio 2000-2018							
$\hat{\mathcal{X}}_r^{\text{foreign}}$	1.722	1.319	1.315	1.364	1.492	1.576	0.611
	(0.610)	(0.582)	(0.580)	(0.602)	(0.574)	(0.594)	(0.270)
$\hat{\mathcal{P}}_r^{\text{native}}$		1.073	1.077	1.077	1.080	1.158	1.331
		(0.245)	(0.244)	(0.244)	(0.235)	(0.244)	(0.234)
$\hat{\mathcal{X}}_r^{\text{other}}$			0.118	0.103	0.092	0.106	0.116
			(0.083)	(0.081)	(0.075)	(0.077)	(0.081)
China shock				0.017	0.078	0.092	0.075
				(0.094)	(0.084)	(0.090)	(0.077)
Manufacturing %				0.071	0.074	0.055	0.056
				(0.079)	(0.091)	(0.102)	(0.094)
Automation					0.085	0.082	0.079
					(0.023)	(0.023)	(0.020)
Routine					0.098	0.098	0.084
					(0.107)	(0.107)	(0.092)
Offshoring					-0.094	-0.064	-0.063
					(0.077)	(0.077)	(0.066)
Recession					0.156	0.135	0.151
					(0.077)	(0.071)	(0.078)
Num. of Children						0.056	-0.006
						(0.049)	(0.043)
Average Age						0.135	0.077
						(0.058)	(0.055)
F-stat	35	29	29	30	37	35	
AKM CI	[1.71, 2.89]	[1.85, 2.82]	[1.93, 3.17]	[1.91, 3.10]	[1.96, 3.28]	[1.52, 2.83]	[0.54, 0.94]
Panel B: pre-trend changes in university employment/population ratio 1990-2000							
$\hat{\mathcal{X}}_r^{\text{foreign}}$	0.221	0.285	0.399	0.379	0.383	0.396	0.208
	(0.213)	(0.215)	(0.217)	(0.212)	(0.213)	(0.224)	(0.101)
AKM CI	[-0.17, 0.76]	[0.02, 0.75]	[0.30, 0.79]	[0.27, 0.77]	[0.27, 0.78]	[0.27, 0.84]	[0.15, 0.30]

Notes: The table reports 2SLS estimates using expenditure shocks in Columns (1)–(6) and OLS estimates in Column (7). In Panel A, the dependent variable is the change in the university employment-to-population ratio in the commuting zone between 2000 and 2018. In Panel B, the dependent variable is a placebo outcome, representing changes between 1990 and 2000. Control variables are standardized to have a unit standard deviation. All models include nine-division fixed effects and use one-time changes between 2000 and 2018 for 722 commuting zones (N = 722). Observations are weighted by the working-age population in 2000. Standard errors, reported in parentheses, are clustered at the state level. The F-stat is based on the Kleibergen-Paap Wald F statistic that clusters observations at the state-level. AKM 95% confidence intervals are reported for each model.

These positive coefficients for China, automation, and recession shocks might pick up some potential labor reallocation from manufacturing to the university sector in regions more exposed to negative demand shocks, though not all are precisely estimated. More importantly, the main coefficient of interest remains stable, which is 1.492 (0.574) as shown in Column (5). The evidence shows that local expenditure shocks from educational exports represent a distinct source of variation in affecting outcomes, separate from these negative demand shocks.

Another component of the structural residual could be unobserved labor supply

shocks. To account for this, I include the number of children per household and the average age of local residents as proxies for labor supply. The sensitivity of estimates may indicate potential endogeneity in shift-share instruments.[21] Column (6) reports a relatively stable coefficient of 1.576 (0.594). Moreover, the first-stage regression yields a strong Kleibergen-Paap F-statistic, exceeding 29 in all cases.

To better interpret the magnitude, consider commuting zones at the 75th and 25th percentiles. The estimates in Column (6) suggest that the former would experience a 0.15 p.p. increase in the university employment-to-population ratio.[22] This corresponds to 10.4% increase in university employment-to-population ratio.[23]

To compare the OLS and 2SLS estimates, Column (7) presents the OLS results with the full set of controls, where the coefficient declines to 0.611 (0.270). OLS estimates may be biased due to both measurement error and potential correlation between unobservables and local export shocks. The systematic difference between the 2SLS and OLS estimates (1.576 vs. 0.611) provides evidence that the IV strategy helps correct for endogeneity bias, which would otherwise attenuate the point estimate toward zero.

To further validate the results, I conducted falsification tests using pre-trend outcomes, based on employment-to-population changes between 1990 and 2000. Panel B reports the corresponding estimates, with each column containing the same set of controls across panels. The coefficients appear to be positive, small, mostly imprecisely estimated, and less stable in the range of 0.221-0.399 for the 2SLS estimates. Given that international student enrollment grew steadily during the 1990s, this trend might be partially captured in these small and positive coefficients. However, the highly imprecise estimates provide reassurance that the estimated employment effects between 2000 and 2018 are unlikely to be confounded by secular changes in regional employment.

Adao, Kolesár and Morales (2019) show that, to a first-order approximation, structural residuals are often shift-share aggregators of unobserved local shocks across industries, with the shares corresponding to local industrial employment shares.[24] This underlying spatial dependence in the residuals can lead to incorrect standard error estimates. To address this, I estimate CZ industry employment shares using 3-digit NAICS codes. In all tables presented in this paper, I report 95% confidence intervals

[21] Since data on immigrant enclaves is partially used in constructing the instrumental variable, I do not include the local foreign-born population share as a proxy.

[22] This effect is computed as $100 \times 1.576 \times 0.00096$. The 75th and 25th percentiles of $\hat{\mathcal{X}}_r^{\text{foreign}}$ are 0.00096 and 0, respectively.

[23] The values are obtained using the aggregate university employment-to-population ratio, which is 1.4 percent for the US.

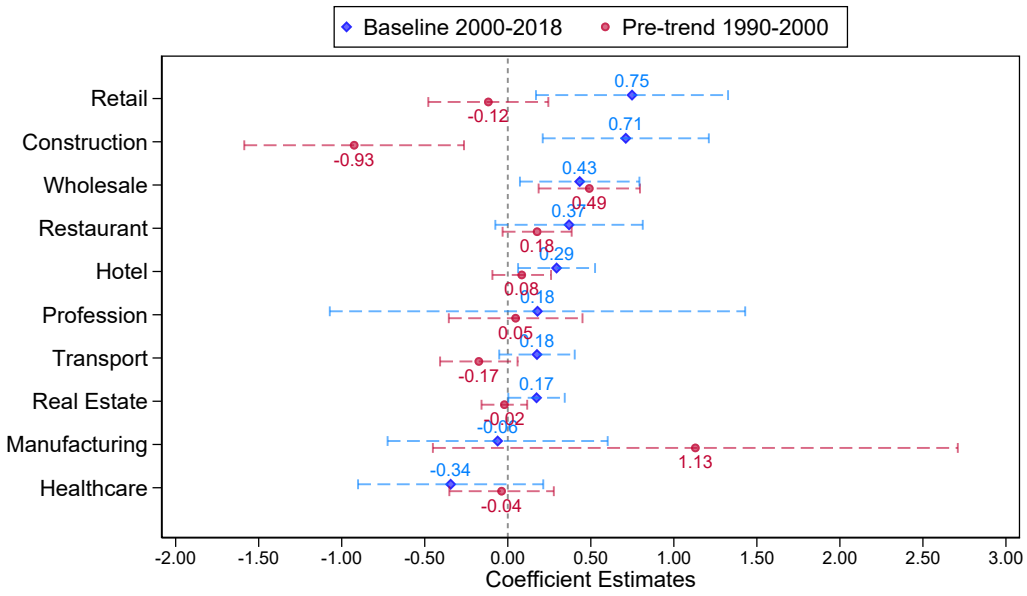
[24] Note that spatial dependence in the residuals and potential inference issues arise from the shares entering the structural residuals, rather than from the share of immigrant enclaves used in constructing the IV.

developed by Adao et al. (2019) (hereafter, AKM 95% CI). In Table 2, consistent with the baseline estimates, the confidence intervals do not contain zero.[25]

4.2 Beyond University Employment

Next, I examine the employment effects on local industries beyond the university sector. All models are built on the specification in column (6) with the full set of controls. The dependent variable of interest is the change in the industry-specific employment-to-population ratio between 2000 and 2018. These industries are either those that students tend to consume from or those whose outputs serve as important intermediate inputs for university production. Appendix A.1 details the IPUM-NAICS codes used to define industries.

Figure 2: 2SLS Estimates by Industries



Notes: The figure displays coefficient estimates and 95% confidence intervals for 2SLS estimates across ten industries. The dependent variable is the change in the industry-specific employment-to-population ratio between 2000 and 2018, plotted in blue. The pre-trend (placebo) outcomes are plotted in red. The model includes the full set of controls used in Column (6) of Table 2. All models are estimated using 722 commuting zones, with observations weighted by the working-age population in 2000.

Figure 2 displays the coefficient estimates and 95% confidence intervals. The baseline estimates using employment changes between 2000 and 2018 are plotted in blue, and the ones using pre-trend changes are plotted in red. Beyond universities, employ-

[25]Note that the AKM 95% confidence interval is relatively narrow compared to state-level clustered standard errors. When estimating CZ-industry-level regressions, the structural residuals theoretically do not involve aggregating employment across industries, which may reduce the severity of spatial dependence.

ment gains from exporting educational services are concentrated in six broad industries. A one p.p. increase in local expenditure shocks leads to a 0.711 p.p. increase in construction employment (s.e. = 0.255), 0.748 p.p. in retail (s.e. = 0.295), 0.433 p.p. in wholesale (s.e. = 0.184), 0.294 p.p. in hotels (s.e. = 0.118), and 0.173 p.p. in real estate (s.e. = 0.087). There are also positive coefficients for restaurants, transportation, and professional services, although imprecisely estimated. Manufacturing employment remains unaffected. In contrast, using pre-trend outcomes as a falsification test, the red plot shows that among the industries listed, only the wholesale industry exhibits a positive and precisely estimated coefficient (0.491, s.e. = 0.156).

The employment gains in local non-tradable industries can be explained by two channels. First, international students consume those goods and services, driving employment growth in industries such as retail, construction, hotels, and real estate. Second, university production linkages stimulate demand in industries that serve as key inputs for universities. Motivated by these findings, Section 6 presents a spatial equilibrium model that incorporates input-output linkages in university production and trade in educational services.

The complete coefficient estimates are reported in Appendix Table C.4, which shows that the coefficients for other shocks—such as those from China, automation, and recessions—have expected signs on industry-specific employment. For example, the China shock has a significant negative impact (-0.645, s.e. = 0.120), consistent with Autor et al. (2021). It also has positive or zero coefficients for other industries, potentially reflecting the small degree of worker relocation across industries.

4.3 Employment Statuses and Wages

Next, I examine the effects on local employment statuses and wages. I first estimate the model using changes in the population share of employed individuals, unemployed persons, and labor force participants as the dependent variables.[26] Panel A shows that a one percent increase in local revenue from export shocks raises the employment-to-population ratio by 3.136 percentage points (s.e. = 1.435). This net employment gain is reflected in a decline in the unemployment rate by -1.137 percentage points (s.e. = 0.460) and an increase in labor force participation by 1.916 percentage points (s.e. = 1.240). The rise in employment comes from both previously unemployed individuals and those outside the labor force, with the latter group contributing more significantly. Column (4) reports a positive but imprecisely estimated coefficient for log annual earnings. While the wage estimate aligns with the expected effects of positive demand

[26]Note that since employees are defined as positive wage earners, while the working-age population includes zero-wage earners, the coefficients in columns (1)–(3) do not necessarily sum exactly.

shocks, its interpretation requires caution, as changes in labor force composition could influence wage dynamics (Autor et al., 2013).[27] Panel B shows no evidence of pre-trends when re-estimating the models using outcome changes from 1990 to 2000 as the dependent variable.

Table 3: Estimates on Employment Statuses and Average Wages

	Panel A: changes in employment and log annual earnings			
	Employed	Unemployed	LFP	Log Average Wages
	(1)	(2)	(3)	(4)
$\hat{\mathcal{X}}_r^{\text{foreign}}$	3.136	-1.137	1.916	6.214
	(1.435)	(0.460)	(1.240)	(4.078)
F-stat	35	35	35	35
	Panel B: Pre-trend changes in employment and log annual earnings			
	Employed	Unemployed	LFP	Log Average Wages
	(1)	(2)	(3)	(4)
$\hat{\mathcal{X}}_r^{\text{foreign}}$	-1.362	-0.033	-1.410	-4.087
	(0.854)	(0.379)	(0.950)	(2.782)
F-stat	35	35	35	35

Notes: Panel A reports 2SLS estimates for changes in the population share of employed individuals, unemployed persons, and labor force participants in the first three columns, while Column (4) examines changes in log annual earnings. Panel B presents 2SLS estimates using pre-trend outcomes from 1990 to 2000. All models are estimated using 2SLS for one-time changes across 722 commuting zones, incorporating nine division fixed effects and the full set of controls. Observations are weighted by the local population in 2000, and standard errors (reported in parentheses) are clustered at the state level.

4.4 Population Adjustments and Other Robustness

Population Adjustments How local shocks affect population adjustments has been extensively studied, and the findings are mixed. Many studies report small and statistically indistinguishable effects (see, among others, Bound and Holzer, 2000, Topalova, 2010, Autor et al., 2013, Dix-Carneiro and Kovak, 2017, 2019), while others find evidence of population movement (see, among others, Greenland et al., 2019, Monras, 2020, Albert and Monras, 2022, Notowidigdo, 2020). One explanation for these mixed results is that local industry shares, commonly used to construct Bartik instruments, often correlate with labor supply factors, potentially invalidating the instrument in population adjustment studies (Goldsmith-Pinkham, Sorkin and Swift, 2020). Alternatively, Borusyak, Dix-Carneiro and Kovak (2023) argues that workers' location choices also depend on shocks in other regions, therefore, when shocks are highly correlated across regions, conventional regression approaches may underestimate true population responses.

While establishing credible causal relationships remains a challenge in this liter-

[27] Specifically, newly employed workers may have lower ability and earnings, and this selection pattern may vary across commuting zones.

ature, I examine whether CZs experiencing larger temporary population shocks (high $\hat{\mathcal{P}}_r$) also exhibit positive population growth. Table C.5 presents OLS regressions of log population changes on $\hat{\mathcal{P}}_r$, the temporary population shock due to foreign enrollment, as defined in Equation (4). For all the estimates here, I report I first only include division fixed effects. The analysis considers total CZ population, as well as age groups 16–30, 31–45, and 56–64. Panel A reports positive and precisely estimated coefficients across all columns. Panel B incorporates the full set of controls from Column (6) of Table 2. In Panel C, I further incorporate two more controls that might predict long term population trend, the initial year's share of college employment, and the share foreign-born population. All coefficients, while remain positive (except for the elder group) but become imprecisely estimated.

For most estimates (excluding the elder group), the coefficient magnitudes exceed one, suggesting that an increase in international students in a CZ is associated with a more than one-to-one increase in the local population. This evidence does not indicate crowd-out in population, and therefore local consumption.

Alternative Shock Measures. I further examine the sensitivity of my baseline estimation using two alternative shock measures. First, I also measure the shock relative to the sum of local personal consumption in goods as services and local government spending as

$$\hat{\mathcal{X}}_r^{alt} = \frac{\Delta \mathcal{X}_r^f}{\mathcal{X}_{rt-1} + \mathcal{X}_{rt-1}^{\text{gov}}}. \tag{10}$$

Here, the only difference from the baseline measure is the denominator incorporates, $\mathcal{X}_{rt-1}^{\text{gov}}$, the local government spending in the initial year.

Second, I estimate a model using CZ-level population shocks, as defined in Equation (4), as the regressor. This shock captures the change in international student enrollment in region r as a share of local population in 2000. While this regression is reduced-form and the coefficients are less straightforward to interpret, consistent results with the baseline would provide reassurance regarding the causal effects estimated.

To make the estimates directly comparable to the baseline, I rescale both shocks to have the same standard deviation as the baseline measure, $\hat{\mathcal{X}}_r^f$. Appendix Tables C.6 and C.7 show that the estimated effects remain similar when using these alternative measures.

5 Employment Responses within CZs

This section addresses two key questions: (1) Who benefits from the employment gains? and (2) Are employment gains stronger in areas near university campuses within com-

muting zones?

5.1 Who Gain the Employment?

International students might contribute to the local labor supply if they stay and work locally after graduation. This section investigates whether the employment gain estimated is a byproduct of increasing foreign labor supply.

To shed light on this mechanism, I estimate the model using the outcome of several groups. I adopt Peri and Basso (2016) to filter American Community Survey (ACS) observations of U.S. foreign-born employees who likely entered the country for college or post-graduate education and obtained a degree between 2000 and 2018. I refer to these individuals as "former F1-visa workers". I employ two measures to identify "former F1-visa workers" based on their age at arrival in the U.S., citizenship status, and other characteristics (see Appendix A.3 for details). The two groups differ only in the scope of origin countries: the first applies to all origin countries, while the second restricts to top 30 source countries of international students.

For each group, I use IPUMS data to measure the changes in each group's employment in CZ's total working age population ratio. Panel A of Table 4 presents the estimates with the full set of controls. Column (1) reports an estimate of 0.401 (s.e. = 0.375) using the population share of "former F1-visa worker" from all countries, while Column (2) reports an estimate of 0.375 (s.e. = 0.165) using the share of "former F1-visa worker" from the top 30 origin countries. These relatively small coefficients, compared to the baseline coefficient, indicate that the results are unlikely to be driven by an increased labor supply.

If the employment gains are not driven by the increased labor supply, then we would expect similar coefficient estimates using the population share of all employees and those excluding former F1 visa workers. To this end, I estimate the models using the population shares for the complement of F1-visa workers as defined. By construction, the sum of the coefficients in (1) and (3), and (2) and (4), exactly matches the estimates using the population share of all employees. Columns (3) and (4) report sizable estimates at 2.736 (s.e. = 1.366) and 2.761 (s.e. = 1.378), respectively. Column (5) examines the population share of U.S. native employees, those either born in the U.S. or born abroad to American parents. Column (6) extends this definition to include immigrant workers who either lack a college degree or arrived in the U.S. before age 15 or after age 27. The coefficients are 4.007 (s.e. = 1.946) and 3.356 (s.e. = 1.585), respectively.

Table 4: CZ-Level Employment By Groups

Dependent variable: changes in group-specific employment/population ratio 2000-2018						
	F1-All	F1-30	Non-F1-All	non-F1-30	US Natives	US Natives +
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Using Expenditure Shocks					
$\hat{\mathcal{X}}_r^{\text{foreign}}$	0.401	0.375	2.736	2.761	4.007	3.356
	(0.181)	(0.165)	(1.366)	(1.378)	(1.946)	(1.585)
F-stat	35	35	35	35	35	35
AKM CI	[0.46, 0.67]	[0.42, 0.64]	[2.49, 5.04]	[2.52, 5.09]	[4.29, 7.27]	[3.36, 6.10]
	Panel B: Using Population Shocks					
$\hat{\mathcal{P}}_r^{\text{foreign}}$	0.491	0.461	3.287	3.317	5.044	4.125
	(0.217)	(0.197)	(1.905)	(1.922)	(2.672)	(2.212)
F-stat	18	18	18	18	18	18
AKM CI	[0.41, 0.57]	[0.38, 0.54]	[2.12, 4.46]	[2.14, 4.50]	[3.66, 6.43]	[2.85, 5.40]

Notes: Panel A reports 2SLS estimates using expenditure shocks. Panel B reports 2SLS estimates using population shocks, as defined in Equation (4). The dependent variable of interest is the changes in CZ-level employment-to-population ratio between 2000 and 2018. All models are estimated with nine division fixed effects, using one-time changes between 2000 and 2018, for over 722 CZs. Observations are weighted by the working-age population in 2000. Standard errors, reported in parentheses, are clustered at the state level. AKM 95% confidence intervals are reported for each model.

In Panel B, I estimate the model using enrollment shocks ($\hat{\mathcal{P}}_r^{\text{foreign}}$) as the regressor. This specification tests whether increases in enrollment translate into a rising foreign labor supply. The estimates in both Panels show consistent conclusions. The evidence suggests that U.S. jobs created by educational exports are primarily filled by U.S. natives and foreign-born workers who did not enter the country on student visas. This finding aligns with anecdotal evidence that international students often obtain an H-1B visa to remain in the U.S. labor market, a process that typically requires employment in specialty occupations or high-skill industries. Additionally, industry-level estimates indicate that job growth is concentrated in low-skill-intensive industries (e.g., retail, construction, hotels, and wholesale), making these sectors unlikely destinations for international student employment.

However, these estimates do not necessarily suggest that the aggregate labor supply increase due to international students is small—an issue I revisit in Section 7.

5.2 The Intra-CZ Geography of Employment Responses

Since university students typically live and consume near campus, job growth is likely to be unevenly distributed across different areas within a CZ. In the remainder of this section, I examine the intra-CZ geography of job growth.

I now use the County Business Patterns (CBP) dataset to track industry employment at the county level.[28] Unlike the census, the CBP records employment data at the

[28]Commuting zones are clusters of counties. On average, a CZ aggregates more than 4 counties.

establishment level, better suited for tracking the location of employment. As discussed in the online Appendix of ADH2013, employment counts for most county-industry cells are suppressed to protect confidentiality. To estimate employment in these suppressed cells, I adopt exactly the algorithm developed by ADH2013; see Appendix B.1 for details.

I estimate equation (1) across US counties. To implement this, I measure the dependent variable as changes in the county-industry employment-to-population ratio between 2000 and 2018.[29] I construct $\hat{\mathcal{X}}_r^f$ and a shift-share instrument at the county level; see Appendix B for details. Instead of division fixed effects, I control for CZ fixed effects and the estimated coefficients reflect industry employment changes in more affected counties (university towns) relative to less affected counties within-CZ.[30] Counties that constitute an entire CZ on their own do not provide variation for estimation, reducing the number of counties to 3,054.

Panel A of Table 5 reports positive and precisely estimated coefficients for three industries—universities, restaurants and drinking places, and real estate—with the largest employment gains occurring in the first two. A one p.p. increase in the local shock leads to a 1.363 p.p. increase (s.e. = 0.206) in university employment and a 2.736 p.p. increase (s.e. = 0.467) in restaurants and drinking places in university towns, relative to other counties within the same CZ. Perhaps surprisingly, the estimates reveal negative and statistically significant coefficients for construction, wholesale, transportation, and manufacturing, suggesting that employment in these industries grew more in less affected counties within the CZ.

The estimates above use county population as the denominator to measure outcomes. However, in some counties, a large share of employees commute across counties for work (Monte et al., 2018). Additionally, residential relocation within a CZ over time may affect local employment patterns. To account for these factors and test the robustness of the findings, I use county-level employment changes relative to CZ population as the outcome variable while keeping CZ fixed effects controlled in the estimation. Panel B presents these estimates. While the smaller coefficient magnitudes reflect the use of CZ population in the denominator, the overall findings remain consistent: employment in university towns grows primarily in universities, restaurants, and drinking places, whereas construction, wholesale, and transportation employment grows more in other counties within the CZ.

[29] County-level population data is obtained from Census tabulations.

[30] Since regression controls (e.g., China shock, automation) are defined at the CZ level, they are absorbed by these fixed effects.

Table 5: County-level Estimates by Industry Employment

	(1) University	(2) Restaurant	(3) Retail	(4) Construction	(5) Wholesale	(6) Hotel	(7) Real Estate	(8) Transport	(9) Manufacturing	(10) Health	(11) Profession
Panel A: Changes in employment / population ratio by industry, with CZ FE											
$\hat{\mathcal{X}}_r^{\text{foreign}}$	1.325	2.659	0.162	-0.158	-0.603	0.037	0.088	-0.290	-0.741	-0.005	-0.383
	(0.197)	(0.452)	(0.094)	(0.081)	(0.125)	(0.092)	(0.027)	(0.056)	(0.146)	(0.073)	(0.365)
N	3,052	3,052	3,052	3,052	3,052	3,052	3,052	3,052	3,052	3,052	3,052
F-stat	57	57	57	57	57	57	57	57	57	57	57
AKM CI	[1.20, 1.52]	[2.31, 3.16]	[0.14, 0.19]	[-0.31, -0.01]	[-0.83, -0.41]	[-0.06, 0.13]	[0.06, 0.13]	[-0.42, -0.17]	[-1.21, -0.31]	[-0.06, 0.05]	[-1.00, 0.21]
Panel B: Changes in other county employment / population ratio by industry, with CZ FE											
$\hat{\mathcal{X}}_r^{\text{foreign}}$	0.240	0.690	0.024	-0.071	-0.126	0.003	0.013	-0.050	-0.343	0.009	-0.158
	(0.041)	(0.208)	(0.014)	(0.029)	(0.028)	(0.014)	(0.004)	(0.010)	(0.209)	(0.014)	(0.106)
N	3,052	3,052	3,052	3,052	3,052	3,052	3,052	3,052	3,052	3,052	3,052
F-stat	57	57	57	57	57	57	57	57	57	57	57
AKM CI	[-0.30, -0.19]	[-1.12, -0.30]	[-0.04, -0.01]	[-0.02, 0.16]	[0.03, 0.23]	[-0.02, 0.01]	[-0.02, -0.01]	[0.02, 0.09]	[0.06, 0.64]	[-0.03, 0.01]	[-0.13, 0.46]

Notes: The dependent variable in Panel A is the changes in county-industry employment to county population ratio, and in Panel B is the changes in county-industry employment to CZ population ratio. All models are estimated with CZ fixed effects using 2SLS, one-time changes between 2000 and 2018 across counties. Observations are weighted by the county-level population in 2000. Standard errors, reported in parentheses, are clustered at the state level. AKM 95% confidence intervals are reported for each model.

These findings on geographic employment responses highlight the geographic extent of an industry's products (Rossi-Hansberg et al., 2021). For restaurants and drinking places, proximity to university campuses is crucial for serving the growing student demand. The larger coefficients estimated from county-level regressions, compared to the smaller coefficients from CZ-level regressions, suggest that local restaurant owners are relocating establishments from further areas within the CZ to university towns. Employment responses in construction, wholesale, and transportation, however, appear to be much less localized. A possible explanation is that university areas generally have high population density and rent, making it less attractive for businesses in these industries to establish physical locations. Instead, businesses in these industries may be established further away, relying on workers to commute to deliver goods and services.

6 General Equilibrium Analysis

I now present a spatial general equilibrium model, building on the trade and economic geography frameworks (Allen and Arkolakis, 2014, Redding and Rossi-Hansberg, 2017), where I incorporate trade in educational services.[31] It considers multiple regions within the United States as well as the rest of the world (ROW), denoted by r or ℓ. There are three industries: manufacturing goods (T), universities (U), and local non-tradable (N). The consumption of educational services (E) is a composite of university sector (U) and non-tradable goods (N). Exports of educational services affect demand for non-tradable industries through two channels. First, through direct consumption on E and thus, N. Second, university production uses non-tradable as intermediate inputs (Caliendo and Parro, 2015). I assume that workers are perfectly mobile across industries within the region. Based on empirical evidence, I assume that population is immobile across regions.

The model serves two key objectives. First, it defines how regions interact with each other, allowing me to recover the missing intercept using the model. Since the counterfactual differs from the initial equilibrium only by removing educational service exports, the estimated effect captures the impact of exporting educational services. Second, I use the model to analyze the economic mechanisms generating the large employment responses.

[31] The model abstracts from international students' post-graduation employment decisions.

6.1 Model Setup

6.1.1 Preference

Individuals in each region r consume three types of goods: manufacturing (T), higher education (E), and non-tradables (N). Conditional on employment statuses $s \in \{e, u\}$, the utility is

$$U_{rs}^{i} = \varepsilon_{s}^{i} \prod_{j \in \{T,E,N\}} \left(\frac{C_{rj}}{\alpha_j}\right)^{\alpha_j} \tag{11}$$

where ε_s^i is the i.i.d. Fréchet idiosyncratic preferences of being employed or unemployed, with a shape parameter θ. α_j are the expenditure shares that add up to one. The manufacturing consumption follows an Armington aggregator

$$C_{rT} = \Big[\sum_{\ell} C_{\ell rT}^{\frac{\sigma_T - 1}{\sigma_T}}\Big]^{\frac{\sigma_T}{\sigma_T - 1}}, \tag{12}$$

where $C_{\ell rT}$ is the tradable goods produced by region ℓ and consumed in region r. σ_T is the elasticity of substitution. For education service, I assume the upper nest is an Armington aggregator of

$$C_{rE} = \Big[\sum_{\ell} C_{\ell rE}^{\frac{\sigma_E - 1}{\sigma_E}}\Big]^{\frac{\sigma_E}{\sigma_E - 1}}. \tag{13}$$

$C_{\ell rE}$ is a composite of consumption on education services which aggregates consumption in U and N as

$$C_{\ell rE} = C_{\ell rU}^{\lambda_{\ell U}} C_{\ell rN}^{\lambda_{\ell N}}, \qquad \lambda_{\ell U} + \lambda_{\ell N} = 1 \tag{14}$$

Students spend $\lambda_{\ell U}$ fraction of their expense on university, and $\lambda_{\ell N}$ on non-tradable goods. In calibration, I assume these expenditure shares are the same among international, in-state, and domestic out-state students.

Living in region r, workers earn a wage of W_r if employed, and receive non-employment benefits b_r otherwise. I assume that non-employment benefits are funded locally through an income tax on employed workers.[32] Given budget constraints, one can derive the indirect utility as

$$V_{re}^{i} = \varepsilon_{e}^{i} \frac{W_r}{P_r}, \qquad V_{ru}^{i} = \varepsilon_{u}^{i} \frac{b_r}{P_r} \tag{15}$$

where P_r is the consumer price index in the region r, discussed later.

[32] Since preferences are identical for both employed and unemployed individuals, the market-clearing condition remains the same as in a model where only employed workers consume, without transfers.

6.1.2 Production

I assume the university sector produces using labor and intermediate inputs as follows

$$Q_{rU} = A_{rU} L_{rU}^{\gamma_L} M_{rT}^{\gamma_T} M_{rN}^{\gamma_N}. \tag{16}$$

Here, M_{rT} is the intermediate input from manufacturing, and M_{rN} is the intermediate input from non-tradable. γ_L, γ_T, and γ_N are the expenditure shares for labor, manufacturing, and non-tradable inputs, with $\gamma_L + \gamma_T + \gamma_N = 1$. The price per university output is

$$p_{\ell U} = \Gamma \frac{1}{A_{\ell U}} W_{\ell}^{\gamma_L} P_{rT}^{\gamma_T} p_{rN}^{\gamma_N} \tag{17}$$

where $\Gamma = \prod_{j \in \{L,T,N\}} \gamma_j^{-\gamma_j}$ is a constant.

For manufacturing and non-tradable industries, I assume linear production functions with labor being the only inputs. $p_{\ell N} = \frac{W_\ell}{A_{\ell N}}$ is the price for non-tradables, and P_{rT} is the manufacturing price index in region r, which I discuss later. I use lowercase p to denote the output price and uppercase letter P to denote the aggregate price index or the absorption price for T and E industries.

Motivated by the literature on theory on production externalities (Ethier, 1982) and recent empirical work (Kline and Moretti, 2014, Dix-Carneiro and Kovak, 2017), I assume local agglomeration force as a function of sectoral employment for manufacturing and university sector, $A_{rT} = L_{rT}^{\kappa_T} \bar{A}_{rT}$, and $A_{rU} = L_{rU}^{\kappa_U} \bar{A}_{rU}$. κ_T and κ_U are the agglomeration elasticity, and $\bar{A}_{rT}$ and $\bar{A}_{rU}$ are productivity fundamentals. Agglomeration elasticity is zero in non-tradable industries.

6.1.3 Equilibrium

Labor Supply. The fraction of employed individuals is

$$\Lambda_{e|r} = \frac{W_r^\theta}{W_r^\theta + b_r^\theta}. \tag{18}$$

Given the empirical evidence, I assume workers are immobile across regions.

Expenditure Shares. For manufacturing industry, I denote iceberg trade cost as $d_{\ell r}$ for goods shipping from ℓ to r. In equilibrium, region r' expenditure shares on manufacturing and educational services, produced by ℓ is

$$\Pi_{\ell r T} = \frac{p_{\ell r T}^{1-\sigma_T}}{\sum_{\ell'} p_{\ell' r T}^{1-\sigma_T}}, \qquad \Pi_{\ell r E} = \frac{p_{\ell r E}^{1-\sigma_E}}{\sum_{\ell'} p_{\ell' r E}^{1-\sigma_E}} \tag{19}$$

where $p_{\ell rT} = \frac{d_{\ell r} W_\ell}{A_{\ell T}}$. $p_{\ell rE} = \tau_{\ell r} p_{\ell U}^{\lambda_{\ell U}} p_{\ell N}^{\lambda_{\ell N}}$. $p_{\ell U} = \frac{W_\ell}{A_{\ell U}}$ and $p_{\ell N} = \frac{W_\ell}{A_{\ell N}}$. $\tau_{\ell r}$ is the iceberg cost for education services, which captures two factors. First, it reflects the price difference between international (or out-of-state) and in-state domestic students. Second, it accounts for policy restrictions that create friction for international students studying abroad. The counterfactual exercise will send $\tau_{\ell r}$ to infinity.

Price index. The prices for manufacturing goods and educational services in region r are

$$P_{rT} = \Big[\sum_\ell p_{\ell rT}^{1-\sigma_T}\Big]^{\frac{1}{1-\sigma_T}}, \qquad P_{rE} = \Big[\sum_\ell p_{\ell rE}^{1-\sigma_E}\Big]^{\frac{1}{1-\sigma_E}}.$$

The consumer price index in the region r is $P_r = P_{rT}^{\alpha_T} P_{rE}^{\alpha_E} p_{rN}^{\alpha_N}$.

Market Clearing Conditions. Each region has a population of N_r and an employment of $L_r = N_r \Lambda_{e|r}$. The labor market clearing condition in each region is

$$W_r L_r = \sum_\ell \Pi_{r\ell T} \alpha_T I_\ell + \sum_\ell \lambda_{r\ell U} \Pi_{r\ell E} \alpha_E I_\ell + \alpha_N I_r + \sum_\ell \lambda_{r\ell N} \Pi_{r\ell E} \alpha_E I_\ell \tag{20}$$

where $I_r = W_r L_r + D_r$ is the total expenditure from residents in the region r, and D_r is the deficit of region r. I assume D_r is exogenous (Caliendo and Parro, 2015). The right-hand side of equation (20) sums up the revenue from three industries.

Specifically, the value added in the university sector is $\gamma_L \sum_\ell \lambda_{rU} \Pi_{r\ell E} \alpha_E I_\ell$, where $\alpha_E I_\ell$ denotes region ℓ's total spending on education services. A share $\Pi_{r\ell E}$ of this spending is allocated to education services provided by region r, within which a fraction λ_{rU} is collected by university. γ_L fraction of university revenue is then earned by employees.

Second, the valued added in manufacturing is $\sum_\ell \Pi_{r\ell T} \alpha_T I_\ell + \gamma_T \sum_\ell \lambda_{rU} \Pi_{r\ell E} \alpha_E I_\ell$. The first term captures consumer demand from all regions; the second is the input demanded by the university sector.

Finally, $\alpha_N I_r + \sum_\ell \lambda_{rN} \Pi_{r\ell E} \alpha_E I_\ell + \gamma_N \sum_\ell \lambda_{rU} \Pi_{r\ell E} \alpha_E I_\ell$ is the value added in the nontradable sector. The first term represents consumption from local residents. The second is the consumption of education composite (by domestic and international students). The last term captures the input demanded by the university sector.[33]

6.2 Calibrated Parameters

I calibrate the model to year 2018. Solving the model requires information on wages, population, and employment rates $\{W_r, N_r, \Lambda_{e|r}\}$, trade matrix in manufacturing and education services, $\{\Pi_{\ell rT}, \Pi_{\ell rE}\}$, and $\{\sigma_E, \sigma_T, \gamma_L, \gamma_T, \gamma_N, \alpha_T, \alpha_E, \alpha_N, \lambda_{\ell rU}, \lambda_{\ell rN}, \kappa_T, \kappa_U, \theta\}$. Ta-

[33] Note that since $\gamma_L + \gamma_T + \gamma_N = 1$, the sources can be summed to obtain the right-hand side of Equation (20).

ble 6 outlines the parameter calibration, which I briefly describe below and leave the details in Appendix E.1.

Table 6: Parameter Values and Calibration Strategy

Parameter	Definition	Source	Value
σ_E, σ_T	EoS. across varieties	Costinot and Rodríguez-Clare (2014)	6
γ_L, γ_T, γ_N	Input shares	BEA Industry Economic Accounts	–
$\alpha_T, \alpha_E, \alpha_N$	Expenditure shares	IPUMS, BEA, IPEDS	–
$\lambda_{\ell U}$, $\lambda_{\ell N}$	Expenditure shares	IPEDS	–
$\Pi_{\ell rE}$	CZ-to-CZ trade in education	IPEDS	–
$\Pi_{\ell rT}$	CZ-to-CZ trade in goods	Model inversion (see 6.3)	–
κ_T	Agglomeration elas. in Manufacturing	Adao et al. (2023)	0.05
κ_U	Agglomeration elas. in University	Indirect Inference (see 6.3)	0.03
θ	Labor supply elasticity	IV estimates (see 6.3)	2

I set $\sigma_T = 6$ following Costinot and Rodríguez-Clare (2014). σ_E has not been estimated before. Since σ_E and κ_U both affect employment in a similar way, I fix $\sigma_E = 6$ and estimate κ_U to match the reduced-form estimates. The input shares, γ_L, γ_T, and γ_N, in university production are estimated using the BEA Industry Economic Accounts, based on gross output, value added, labor compensation, and intermediate inputs in the education sector. The consumption shares, α_T, and α_E, are computed using total expenditure in each industry by subtracting intermediate goods expenditure (if any) and dividing by total absorption. The non-tradable consumption share is given by $\alpha_N = 1 - \alpha_T - \alpha_E$. The parameters $\lambda_{\ell U}$ and $\lambda_{\ell N}$ represent the fractions of student expenditure allocated to universities and non-tradables, respectively, in region ℓ. These are estimated using IPEDS expense data.

CZ-to-CZ trade in manufacturing goods is estimated using the model and under a parametric assumption on trade costs (see next page). IPEDS has enrollment and expense (tuition and living expense) data on non-aliens breaking down by in-state and out-of-state by each institution, which I use to estimate CZ-to-CZ trade in education service. Briefly, I allocate in-state (out-state) enrollment to CZs within-state (outside) proportional to CZ income, using in-state and out-of-state tuition and living expenses, I can compute the matrix of trade in education service among counties.

Since the export shock operates in university and non-tradable sectors, I found the quantitative results are insensitive to κ_T. I set $\kappa_T = 0.05$ in manufacturing following the literature.

For the ROW, data on population, employment, and GDP are obtained from the World Development Indicators database, subtracting the corresponding U.S. values from world aggregates. I measure the expenditure shares of US imports from the ROW

in manufacturing consumption as the ratio between US imports divided by manufacturing output plus imports and subtract exports. The expenditure share of ROW manufacturing imports from the US is measured similarly. For manufacturing, I retrieve U.S. import and export data from Comtrade. Manufacturing outputs for the US and the ROW are obtained from the world development indicators. I allocate aggregate US exports across CZs based on the share in national manufacturing employment, while US imports are allocated proportional to CZ income. For educational services, the export volume of each cz is observed from IPEDS. I assume the U.S. does not import educational services from the rest of the world (ROW).

6.3 Estimation

I estimate other model parameters and fundamentals sequentially in two main steps. The first step inverts the model to solve county manufacturing the total factor productivity, A_{rT}, which rationalizes the observed wage and manufacturing employment in 2018. Second, I estimate the labor supply and the agglomeration elasticities structurally.

Model Inversion to Obtain Trade Flows. I invert the model to obtain A_{rT} in 2018 in manufacturing industries and predict CZ-to-CZ trade flows in manufacturing, following Redding (2016) and Monte, Redding and Rossi-Hansberg (2018).

The procedure requires a parametric assumption of trade costs $d_{\ell r} = \text{Dist}_{\ell r}^{\psi}$, a value of trade elasticity $\sigma_T = 6$ and $\psi = 0.43$.[34] Given local manufacturing employment and wages, and trade costs $d_{\ell r}$, I solve for A_{rT} that rationalize these observables in 2018 (see Appendix E.3 for details). Since this step solves A_{rT}, rather than $\bar{A}_{rT}$, it does not need value of κ_T. After that, I used the estimated A_{rk} and to obtain the CZ-to-CZ trade shares using Equation (19).

Labor Supply Elasticity. I estimate the following equation

$$\Delta \ln L_r = \theta \Delta \ln W_r + \Delta \mathcal{U}_r \tag{21}$$

where $\Delta \ln L_r$ and $\Delta \ln W_r$ represent the log changes in CZ employment and average wages, respectively. Deriving from equation (18), the residual equals $-\Delta \ln(W_r^{\theta} + b_r^{\theta})$ and captures the unobserved local labor supply factor. Since some international students may stay and work in the local labor market after graduation, $\hat{\mathcal{X}}_r^f$ cannot be used to identify the labor supply curve, as it could potentially affect local employment beyond wages. Instead, I instrument $\Delta \ln W_r$ using the exogenous China shock and the

[34] $\psi = 0.43$ is implied from setting $(1 - \sigma_T)\psi = -1.29$ following Monte et al. (2018).

Automation shock.[35] Table C.8 reports the estimates under different specifications.

Notably, the employment response inevitably depends on θ. Here, I adopt a conservative estimate, setting $\theta = 1.57$, which falls within the range of estimates found in the literature (see Table C.9).

Calibrating Trade Deficit. Before simulating counterfactuals, it is important to ensure that the labor market clearing equation (20) holds in the base year 2018. One approach is to calibrate model-consistent industry employment, as proposed by Faber and Gaubert (2019). My approach follows Caliendo and Parro (2015): in the baseline equilibrium, where $\hat{\tau}_{\ell r} = 1$, I solve for D_r such that equation (20) holds.[36] After that, I solve for the counterfactual equilibrium while holding D_r constant.

The Agglomeration Elasticities. I estimate the the agglomeration elasticity, $\Theta = \{\kappa_U\}$ while solving the GE model using indirect inference approach. The structural estimation proceeds in two steps.

a) **Solving for General Equilibrium (Inner Problem).** Guessing parameter values for $\Theta = \{\sigma_E, \sigma_T, \gamma_L, \gamma_T, \gamma_N, \alpha_T, \alpha_E, \alpha_N, \lambda_{\ell rU}, \lambda_{\ell rN}, \kappa_T, \theta\}$, I solve a counterfactual equilibrium where US exports in educational services are reduced to zero, turning $\tau_{\ell r}$ to infinite, for ℓ as CZ and r as the ROW. I use the exact hat algebra (Dekle, Eaton and Kortum, 2008), and express the equilibrium system in changes (see Appendix E.2).

b) **Indirect Inference (Outer Problem).** Denote $\mathcal{F}(\Theta)$ as the collection of data and endogenous model outcomes (wages, employment, prices) solved from the inner problem. The second step searches parameter values Θ to match the same differential effects implied from the reduced-form estimates. I minimize the following objective function

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \left[m\big(\Theta; \mathcal{F}(\Theta)\big) - m^{\text{RF}} \right]' \times V \times \left[m\big(\Theta; \mathcal{F}(\Theta)\big) - m^{\text{RF}} \right]. \tag{22}$$

$m(\Theta; \mathcal{F}(\Theta))$ is a 4×1 vector of targeted moments predicted by the model, while m^{RF} is derived from the reduced-form estimates. I select four moments: (1) the 75-to-25 percentile difference in the university and (2) in the overall employment-to-population ratio; (3) the standard deviation of changes in the university and in (4) the overall employment-to-population ratio. For $m(\Theta; \mathcal{F}(\Theta))$, I set $\tau_{\ell r}$ to infinity.

[35] For both instruments, I construct the shift-share IV using China's export growth (or robot adoption) in other advanced economies.

[36] Here, the hat variable denotes proportional changes, see Appendix E.2.

For the reduced-form effect, I first measure $\hat{\mathcal{X}}_r^{2018}$ using international student total expenses in 2018 relative to the local gross consumption in goods and services in 2018, consistent with the counterfactual exercise. For university employment-to-population ratio, I multiply $\hat{\mathcal{X}}_r^{2018}$ by the estimates in Column (6) of Table 2, and for overall employment-to-population ratio, it is multiplied by the estimates in Column (1) of Table 3. After that, I compute the relevant statistics for m^{RF}.[37] V is a 4×4 diagonal matrix with entries being, $(1/m^{\text{RF}})^2$. This normalization ensures that all moments contribute equally to the minimization, balancing their scales.[38]

The intuition behind this calibration strategy is straightforward: models with higher κ_U predict more dispersed effects across CZs. In Appendix Figures E.1 and Figure E.2, I provide suggestive evidence that the minimizer of the objective function is unique (at least locally) and that each of the four moments contributes to the identification. This procedure estimates $\hat{\kappa}_U = 0.065$.

The strong agglomeration elasticity is in line with an important point made by Adao, Arkolakis and Esposito (2023): spatial general equilibrium models generally require strong agglomeration effects, high labor supply elasticity, or input-output linkages to explain the large employment responses observed in reduced-form regressions. Since my estimates indicate that labor supply elasticity is not particularly strong, the model must instead rely on input-output linkages and strong agglomeration elasticity to match the differential effects observed in the empirical estimates, as demonstrated in my calibrated model.

6.4 The Quantitative Results

Now, I assess the employment effects of exporting educational services by setting $\tau_{\ell r}$ to infinity for all U.S. CZs to the ROW.

The Employment Gain. At the aggregate level, the model estimates that educational service exports generate approximately 948,000 jobs. Since the counterfactual scenario only changes $\tau_{\ell r}$, the estimated employment gains are entirely attributable to educational service exports. These gains are concentrated in university-related and low-skill service industries, with each sector contributing 425,000 and 736,000 jobs, respectively. The positive demand shock leads to a decline of 213,000 manufacturing jobs, through sectoral relocation.

The Multiplier. I decompose the market clearing condition 20 into two components.

[37] Since, in the reduced-form estimates, $\hat{\mathcal{X}}_r^f = 0$ for CZs that do not host universities, I compute both $m(\Theta; \mathcal{F}(\Theta))$ and m^{RF} among 521 CZs that host at least one university.

[38] I constrain the weighting matrix to ensure a consistent estimator, though it may not achieve the smallest asymptotic variance.

The first component measures the total export revenue:

$$\Delta R_r^{\text{Export}} = \sum_{\ell} (\Pi_{r\ell E} - \Pi'_{r\ell E}) \alpha_E I_\ell. \tag{23}$$

Here, $\Pi_{r\ell E}$ and $\Pi'_{r\ell E}$ represent the observed and counterfactual trade shares in educational services, respectively. The second component captures the income effects:

$$\Delta R_r^{\text{Income}} = \sum_{\ell} (\Pi_{r\ell T} \alpha_T I_\ell - \Pi'_{r\ell T} \alpha_T I'_\ell) + \alpha_N (I_r - I'_r) + \sum_{\ell} \Pi'_{r\ell E} \alpha_E (I_r - I'_r) \tag{24}$$

where I_ℓ and I'_ℓ are the observed and counterfactual income.[39]

I compute two model predictions to understand the plausibility of this large employment gain. First, I compute the multiplier of export service as $\frac{\Delta R_r^{\text{Export}} + \Delta R_r^{\text{Income}}}{\Delta R_r^{\text{Export}}} = 1.96$. In a recent review, Chodorow-Reich (2019) suggests a cross-sectional fiscal spending multiplier in the range of 1.5 to 1.8. My estimated value is on the high end of fiscal multipliers previously estimated for the U.S. A key distinction that sets my estimates apart from prior literature is that the revenue endowment originates externally, rather than being generated through domestic taxation or financing. Interestingly, multipliers from external endowments have been studied in developing economies, where they appear to be notably large. For instance, Egger et al. (2022) estimate a local transfer multiplier of 2.5 in Kenya, while Khanna, Murathanoglu, Theoharides and Yang (2022) find that income earned through Philippine out-migration significantly boosted long-run domestic income in migrant-origin areas, in line with a multiplier of approximately 2.9.

Second, I also compute the cost per job, an object that literature often used in studying employment multiplier. In 2018, total U.S. exports in educational services amounted to $32 billion. Based on the estimated employment gains, the implied cost per job is approximately $33,750, aligning with macroeconomic estimates of employment multipliers. For comparison, Chodorow-Reich (2019) and Serrato and Wingender (2016) estimate a cost per job ranging from $30,000 to $50,000. These consistent results align with previously established estimates, bolstering confidence in the interpretation of my findings and enhancing their plausibility.

7 Conclusion

This paper examines the impact of rising U.S. education exports on local labor markets. I measure local exports in higher education services using data on international

[39] Note that the term $\Pi_{r\ell T} \alpha_T I_\ell - \Pi'_{r\ell T} \alpha_T I'_\ell$ also absorb the equilibrium adjustments in manufacturing trades.

student enrollment and the expected student tuition and living expenses. To examine the impacts on local labor market outcomes, I leverage exogenous shifts in international student enrollment in other high-income countries. I find that regions experiencing larger revenue shocks see greater relative employment gains. These gains are concentrated in the university sector and low-skill industries such as retail, construction, and wholesale trade. Importantly, using CBP data, county-level estimates reveal that the intra-CZ geography of these employment effects varies across sectors based on their degree of localization: job creation in restaurants and retail increases more in the county where the university is located, relative to nearby counties. In contrast, employment grew relatively more in construction, wholesale, and transportation industries in nearby counties than in university towns.

To quantify these effects, I develop a spatial general equilibrium model incorporating both goods trade and service exports, estimating key parameters to match my reduced-form results. I find that educational service exports alone generate 948,000 U.S. jobs. To understand the plausibility of the estimates, I find the model implies a multiplier from export service lies in the range of the existing multiplier estimates.

One important question is the extent to which international students have contributed to long-term increases in the foreign labor supply. I conclude my discussion by providing suggestive evidence on this matter. Applying the filtering measures outlined in Section 5.1, I find that the stock of former F1-visa employees from all origins grew from 482,000 in 2000 to 883,000 in 2018—an increase of 401,000. Focusing on the top 30 source countries for international students, this increase is similar at 368,000. Since the total U.S. immigrant labor force expanded from 17.1 million to over 28.3 million between 2000 and 2018, these calculations suggest that international students contributed approximately 3.3% to 3.6% of this growth.[40] These numbers confirm that the long-run labor supply shock from former international students transitioning into the U.S. workforce is relatively small (Beine, Peri and Raux, 2023).

Prior research has shown that skilled immigration is a key driver of innovation and patenting (Kerr and Lincoln, 2010, Hunt and Gauthier-Loiselle, 2010, Terry, Chaney, Burchardi, Tarquinio and Hassan, Forthcoming), as well as wage and productivity growth (Peri et al., 2015). Policies that restrict international student mobility may therefore have unintended negative consequences in these areas. I look forward to exploring them in future research.

[40] Computed as $0.401/(28.3 - 17.1) = 3.3\%$ and $0.368/(28.3 - 17.1) = 3.6\%$.

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Online Appendix

Exporting Education or Importing Labor? The Labor Market Impacts of International Students

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A Data Appendix

A.1 Data Sources

Integrated Postsecondary Education Data System (IPEDS). The IPEDS dataset, collected and published by the National Center for Education Statistics, provides comprehensive data on over 2000 U.S. postsecondary institutions. It includes detailed information on university characteristics, such as institutional type (public, private, or for-profit), student enrollment by degree type, nativity, full-time or part-time status, and the share of in-state versus out-of-state students. I measure international students using "nonresident aliens". According to IPEDS, those are students who are not U.S. citizens, have a temporary visa, and do not have the right to remain in the country indefinitely.

Additionally, the IPEDS provides data on university employees by employment status (full-time or part-time), as well as financial information, including funding from appropriations (local, state, and federal), investment returns, and other revenue streams. I focus on two time periods: 2000 and 2018. Specifically, I examine full-time student enrollment and full-time university employees, aggregating enrollments across all degree types (bachelor's, master's, and associate degrees). I remove international students who are enrolled in Ph.D. programs since most of them are likely to receive scholarships and living stipends.

Notably, IPEDS provides information on in-state and out-of-state tuition fees, as well as costs associated with on-campus and off-campus housing, books, rentals, food, and other living expenses. While these variables may not fully reflect students' actual expenditures outside of tuition and fees, they enable measurement of tuition-related spending and gross expenditure shocks on local communities beyond tuition costs.

American Community Survey. The labor market variables on employment, unemployed status, labor force participation, and income are obtained from the Census Integrated Public Use Micro Samples for the years 1990, 2000, and the American Community Survey (ACS) from 2015 through 2019 (Ruggles et al., 2024). I restrict the sample to US working-age population who are between 16 and 65 years old. All variables are aggregated to 722 CZs.

IPUMS reports industries using the North American Industry Classification System (NAICS) codes

at 4-digit, which is coarser than the 6-digit NAICS code available at the CBP. The 4-digit NAICS codes are modified by the ACS's industry classification scheme and are harmonized across different time periods.[41] The IPUMS NAICS industry code used in CZ-level analysis is defined as follows

- **Construction**: NAICS codes beginning with **23**.
- **Manufacturing**: NAICS codes beginning with **3**.
- **Wholesale Trade**: NAICS codes beginning with **42**.
- **Retail Trade**: NAICS codes beginning with **44**, as well as **45121, 45221, and 454111**.
- **Transportation**: NAICS codes beginning with **481, 4853, 485M, 487, 488, 491, and 492**.
- **Real Estate**: NAICS codes beginning with **531 and 5313**.
- **Healthcare**: NAICS codes beginning with **6214, 6216, 621M, 622, and 6231**.
- **Hotel and Accommodation Services**: NAICS codes beginning with **7211**.
- **Restaurants and Drinking Establishments**: NAICS codes beginning with **7224 and 722Z**.

UNESCO Institute for Statistics. I draw data from the UNESCO Institute for Statistics to measure the number of international students to other advanced economies in 2000 and 2018 by countries of origin. I chose three English-speaking countries, Australia, Canada, and the United Kingdom, as the other competing destinations for international students, and look at 30 countries of origin that are the major sources of international students.[42]

Consumer Expenditure Survey (CE). Maintained by the Bureau of Labor Statistics, CE data is a well-known consumption survey that has been conducted continuously since 1980. The survey is a representative sample of US households, consisting of over 5,000 households in each year's survey. Each household is interviewed about their expenditures for up to four consecutive quarters. Each interview records expenditures on detailed categories over the preceding three months. The final interview records information on earnings, income, and taxes from the preceding 12 months, aligning with the period captured for expenditures. Income and expenditure variables are all recorded at the household level.

To obtain CZ-level consumption and measure $\mathcal{X}_{rt-1}^{\text{Gross}}$ in year 2000, I extract state-level consumption in goods and services from the Bureau of Economic Analysis (BEA). I use CES data to allocate state-level consumption to CZ, which I detail in Appendix A.2 next.

A.2 Projecting CZ-level Consumption

The Consumer Expenditure (CE) Survey has recently been used in the immigration context to examine how consumption behavior influences immigrants' location choices across U.S. cities (Albert and Monras, 2022). Since the CE data only provides geographic information at the state level, I estimate CZ-level consumption in two steps. First, I use household-level CE data to estimate a linear regression model that predicts the logarithm of household gross consumption of goods and services as a function of log household income and a rich set of household characteristics (note that these characteristics are also observed at the ACS). Second, I apply the estimated model to predict household consumption for each

[41] See here for IPUMS USA industry and NAICS codes.

[42] The origin countries include China, India, South Korea, Saudi Arabia, Vietnam, Malaysia, Thailand, Iran, Italy, Brazil, Pakistan, Nepal, Nigeria, Russia, Germany, Mexico, Philippines, Turkey, Hong Kong, Indonesia, and Japan.

household in ACS 2000, and aggregate for 722 commuting zones in the contiguous U.S. Finally, I rescale the variable by a constant to ensure that the aggregated CZ-level consumption matches the total implied by the Bureau of Economic Analysis (BEA).

I use CE data to project household consumption based on income and demographic characteristics. I combine CE samples from the years 2000–2002, which include 54,778 households. Since the data only includes geographical information at the state level, I proceed in three steps to estimate county-level consumption.

Specifically, I estimate an OLS regression of the logarithm of household gross consumption on the logarithm of household income, four age groups of the household head (31–40, 41–50, 51–60, and 60+), marital status, education level dummies (high school dropout, high school graduate, some college, and college), racial dummies for White and Black, family size dummies (1, 2, 3, 4, 5, 6), a homeownership dummy, census division dummies (eight divisions), a metropolitan residency dummy, and interactions between log income and the age group dummies. Household heads who are high school dropouts, under age 30, unmarried, non-urban residents, non-White, and non-Black, with a family size of one, are used as the benchmark in the regression. The estimated model has an R^2 value of 0.505 and shows that household consumption increases with income, education attainments, family size, and is higher for individuals who are White, married, homeowners, and live in urban areas.

The second step uses the estimated model to predict household consumption for each household in the 2000 American Community Survey (ACS), which contains richer geographic information. I code the demographic characteristics of ACS individuals to align exactly with the regressors used in the OLS estimates, then use the estimated coefficients to project household consumption for each ACS individual. This process allows me to estimate aggregate consumption for 722 commuting zones (CZs) in the continental United States.

Finally, I allocate BEA state-level consumption to CZs based on the share of CZ consumption (predicted by CE and ACS) within-state.

A.3 Filters for the Former F1-visa Workers

First, for individuals whose highest educational attainment is a bachelor's degree, I classify them as "former-international-student Workers" if they were not born in the U.S. or its territories, do not have American parents, arrived in the U.S. between the ages of 16 and 22, and are not naturalized citizens. For those with a master's or Ph.D., I apply the same criteria but extend the arrival age range to 16 and 26. Immigrants who arrive in the U.S. before age 15 are more likely to have migrated with their families and are unlikely to have previously held an F1 student visa. Conversely, immigrants who arrive after age 27 are more likely to have completed their education abroad before coming to the U.S.

The second measure builds on the first but further restricts the sample to workers born in one of the top 30 source countries of international students. This restriction aims to exclude individuals who came to the U.S. for education on family-sponsored visas or as permanent residents and are unlikely to have held F1 visas. These 30 countries account for 98% of total international student enrollment in the U.S.

B County-level Analysis

B.1 CBP County-Industy Employment

The County Business Patterns (CBP) data, published by the US Census Bureau, track employment by county and industry from 1946 to the present. One well-known issue with these data is that, to protect confidentiality, employment figures for the majority of county-industry cells are suppressed. In my analysis, I extract CBP data for the years 1990, 2000, and 2016 to estimate my model at the county level. I choose 2016 as the ending year because, in CBP 2017, there were major changes in how the data were reported (the Census Bureau now perturbs cells with small employment counts, making these data fundamentally different from earlier periods). Using 2016 as the endpoint ensures that the algorithm developed in Autor, Dorn and Hanson (2013) can be consistently applied across all these years.

The imputation for employment in each county-industry cell follows precisely the online application code of Autor et al. (2013). In 1990, industries were reported using 4-digit SIC codes, whereas in 2000 and 2016, they were reported using 6-digit NAICS codes. The Appendix of Autor, Dorn and Hanson (2013) for details and replication code. Briefly, the imputation procedure involves the following steps: (1) narrowing the possible employment values in cells with bracketed counts based on the firm size distribution and aggregate industry employment; (2) estimating firm sizes within each size bracket by regressing employment on the number of firms across 13 size classes and iteratively updating the estimates until convergence; (3) using these estimates to impute employment for firms identified only by broader industry codes (e.g., 3-digit, 2-digit) and proportionally adjusting employment figures to ensure consistency across aggregation levels; and (4) allocating employment from higher industry levels to more detailed categories based on observed distributions within each county.

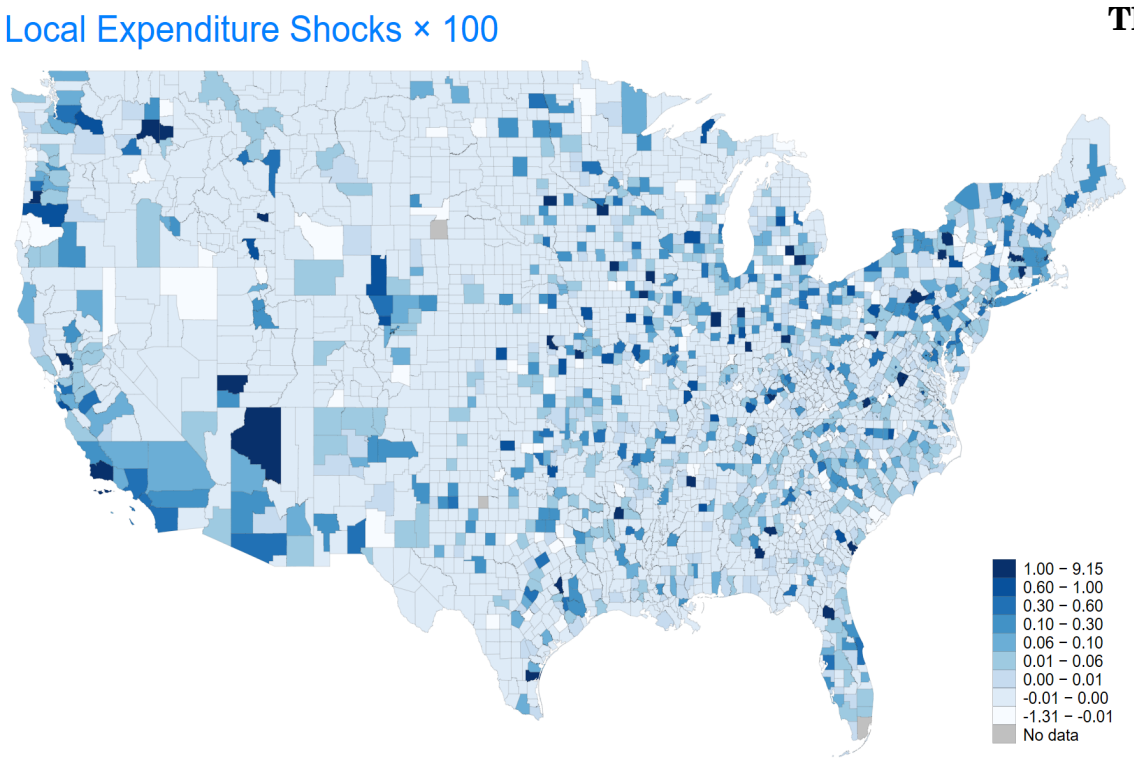
B.2 County-level Expenditure Shock

International students had notable and systematically uneven effects on local demand across counties. The left panel of Figure B.1 illustrates the changes in international student expenditures relative to the initial year's total local expenditure. Darker colors indicate regions experiencing larger positive demand shocks. Among the 3103 counties, 1482 have at least one university. On average, international students contributed to a 0.18% increase in local consumption (inflation-adjusted), with a standard deviation of 0.43%.[43]

The right panel presents a list of the most affected counties. The impact of international students on local consumption is particularly pronounced in small college towns and in counties with multiple universities. Unsurprisingly, compared to commuting zones (CZs), the intensity of the shock is much stronger when analyzed at the county level. The magnitude of the effect reaches as high as 9.15% in Campbellsville, Kentucky, 5.46% in Centre County, Pennsylvania, and 5.14% in Fairfax County, Virginia, among others. In contrast, regions without a university experience no direct demand shocks.

[43]The summary statistics are computed using initial county-level population weights.

Table B.1: The County-Level Demand and Temporary Population Shocks from International Students



The Most Affected Counties:

- Taylor County, KY – Campbellsville University (9.15%)
- Centre County, PA – Pennsylvania State University (5.46%)
- Fairfax County, VA – George Mason University (5.14%)
- Yolo County, CA – University of California, Davis (4.89%)
- Tompkins County, NY – Cornell University and Ithaca College (4.09%)
- Benton County, OR – Oregon State University (3.53%)
- Monroe County, IN – Indiana University Bloomington (3.51%)
- Champaign County, IL – UIUC (3.15%)
- Suffolk County, MA – six universities (3.12%)
- Tippecanoe County, IN – Purdue University (3.00%)

Notes: The left panel shows the local demand shock, $\hat{\mathcal{X}}_r^f$ for US counties. The right panel displays the most affected counties. The value of $\hat{\mathcal{X}}_r^f$ is given in the parenthesis. The shock values are multiplied by 100, so each value represents the percentage changes relative to the initial population or consumption in 2000.

B.3 County-level Shift-Share Instrument

I re-construct the county-level shift-share instrument following the same strategy as previously, but using "shares" at different levels of geographic aggregation. Specifically, when international student inflow to each U.S. university, ω, I compute it as

$$\Delta \text{Enrl}^{\text{ACU}}(\omega) = \sum_{g} S_{cg}^{1990} \times S_{c}^{t-1}(\omega) \times \Delta \text{Enrl}_{g}^{\text{ACU}} \tag{A.1}$$

$\Delta \text{Enrl}_{g}^{\text{ACU}}$ is again, the overall change in international student enrollment to universities in three other developed countries combined. g is one of the 30 major source countries. S_{cg}^{1990} denotes the share of immigrants from source country g who resided in commuting zones c in 1990, conditional on commuting zones that are home to at least one university. This share is measured using the IPUMS Census 1990 (Ruggles et al., 2024). $S_{c}^{t-1}(\omega)$ represents the share of international students attending university ω relative to the total number of international students studying in commuting zone c in the initial year, measured using IPEDS data from the year 2000.

The county-level shift-share instrument is then constructed as follows

$$\hat{\mathcal{Z}}_{r} = \frac{\sum_{\omega \in \Omega_r} \Delta \text{Enrl}^{\text{ACU}}(\omega)}{\text{Pop}_{rt-1}}. \tag{A.2}$$

B.4 The CBP 6-digit NAICS Industry Aggregation

Different from the ACS, CBP reports 6-digit NAICS industries. I classify industry following the ACS groups as much as I could. I apply the NAICS crosswalk over time and use NAICS 1997 system.

- **Construction**: NAICS codes beginning with **23**.
- **Manufacturing**: NAICS codes beginning with **3**.
- **Wholesale Trade**: NAICS codes beginning with **42**.
- **Retail Trade**: NAICS codes beginning with **44**, as well as Book Stores (**451211**), Department Stores (**452110**), Electronic Shopping and Mail-Order Houses (**454110**)
- **Transportation**: NAICS codes beginning with **481–485**, as well as **491 and 492**.
- **Real Estate**: Lessors of Residential Buildings and Dwellings (**531110**), Residential Property Managers (**531311**), Offices of Real Estate Appraisers (**531320**), Other Activities Related to Real Estate (**531390**).
- **Healthcare**: General Medical and Surgical Hospitals (**622110**), Psychiatric and Substance Abuse Hospitals (**622210**), Specialty Hospitals (excluding psychiatric and substance abuse) (**622310**).
- **Hotel and Accommodation Services**: Hotels (excluding casino hotels) and motels (**721110**), Casino hotels (**721120**), Bed-and-breakfast inns (**721191**), All other traveler accommodations (**721199**).
- **Restaurants, Fast Food, and Drinking Establishments**: Full-service restaurants (**722110**), Limited-service restaurants (**722211**), Cafeterias (**722212**), Snack and nonalcoholic beverage bars (**722213**), Food service contractors (**722310**), Caterers (**722320**), Mobile food services (**722330**), Drinking places serving alcoholic beverages (**722410**).

C Additional Results

Table C.1: Average Per Capita Expenses of University Students and U.S. Households

Year	International Students	Domestic Students	US Household per Capita
2000	$23,672	$9,974	$24,614
2018	$42,065	$17,938	$42,559

Notes: The table presents the average expenses for international students, domestic students, and U.S. households per capita. For students, the values are calculated as the total aggregate expenses divided by the total enrollment for international and domestic students, respectively, based on IPEDS data. For U.S. households, the values represent BEA aggregate consumption in goods and services divided by the U.S. population.

Table C.2: Examples of University Expenses in 2018 for Undergraduates

Expense Category	Campbellsville University	Pennsylvania State University	Columbia University	UC Los Angeles
Tuition (In-State)	$25,132	$18,263	$57,231	$13,136
Fees (In-State)	$500	$1,002	$2,647	$1,748
Tuition (Out-State)	$25,132	$33,635	$57,231	$41,032
Fees (Out-State)	$500	$1,002	$2,647	$1,748
Rent (On-Campus)	$7,965	$11,360	$13,635	$15,442
Rent (Off-Campus)	$5,167	$11,360	$17,355	$12,561
Other Living Costs (On-Campus)	$5,071	$4,788	$2,057	$4,196
Other Living Costs (Off-Campus)	$6,461	$4,788	$4,980	$4,856
Books & Supplies	$1,167	$1,840	$1,357	$1,419

Notes: The table presents the IPEDS expenses by categories for different universities in 2018.

Table C.3: International Students to Developed Countries (in thousands) by Top 30 Source Countries in 2000

	United States			Other Three Countries		
Source	**2000**	**2018**	**Changes**	**2000**	**2018**	**Changes**
Total	451.9	987	535.1	366.4	1107.8	741.5
China	46.9	333.9	287.0	12.4	322	309.7
Japan	42.7	14.9	-27.8	9.3	6.9	-2.5
Korea	36.2	52.4	16.2	5.6	19.4	13.8
India	34.5	135.9	101.4	8.4	127.7	119.3
Canada	20.9	26.5	5.6	4.6	8.9	4.4
Thailand	11.5	6.4	-5.1	5.6	14.5	9
Indonesia	11.2	8.5	-2.7	10.6	16.2	5.6
Malaysia	10.6	8.6	-2.0	30.2	31.7	1.5
Mexico	8.9	15.4	6.6	1.6	4.8	3.2
Germany	8.8	7	-1.8	15.5	15.8	.3
Turkey	8.6	9.7	1.1	2.1	5.3	3.2
Hong Kong	8	7	-1.1	24.5	28.1	3.6
Brazil	7.4	14	6.6	1.6	12.4	10.9
United Kingdom	7.1	10.1	3.0	5.5	4.1	-1.3
Russia	6.1	5.1	-1.0	1.5	6.2	4.7
France	5.7	6.3	0.6	16.4	31.8	15.4
Pakistan	5.4	7.4	2.0	3.4	19.7	16.3
Venezuela	4.7	8.1	3.3	.4	1.6	1.1
Colombia	4.6	7.3	2.7	.9	6.7	6
Saudi Arabia	4.5	47.3	42.8	2	17.1	15.1
Spain	3.9	6.1	2.2	7.9	11	3.1
Bangladesh	3.4	7.4	4.0	1.3	10.4	9.1
Italy	2.8	5	2.2	6.4	16.7	10.3
Kuwait	2.8	11	8.2	.8	5.2	4.3
Nigeria	2.6	12.8	10.1	2.4	19.6	17.2
Australia	2.2	4.4	2.1	1.6	2.6	1
Nepal	2.2	14.4	12.2	.2	33.7	33.5
Vietnam	1.5	25.6	24.1	1.5	22.1	20.6
Iran	1.5	11.8	10.3	1.5	7.9	6.5
Oman	.6	3.5	2.9	1	3.4	2.4

Notes: The data is sourced from the UNESCO Institute for Statistics. The first three columns report the number of international student enrollments in 2000 and 2018, along with the change over this period. The last column aggregates the changes for Australia, the UK, and Canada. All values are reported in thousands. For Australia, Canada, and UK, the reported number excludes students who studied domestically.

Table C.4: The Effects on Industry Employment using Expenditure Shocks

	(1) Restaurant	(2) Construction	(3) Retail	(4) Wholesale	(5) Hotel	(6) Real Estate	(7) Transport	(8) Manufacturing	(9) Health	(10) Profession
	Panel A: changes in industry employment/population ratio 2000-2018									
$\hat{\mathcal{X}}_r^{\text{foreign}}$	0.369	0.711	0.748	0.433	0.294	0.173	0.176	-0.061	-0.344	0.179
	(0.226)	(0.255)	(0.295)	(0.184)	(0.118)	(0.087)	(0.116)	(0.338)	(0.285)	(0.638)
$\hat{\mathcal{P}}_r^{\text{native}}$	-0.134	-0.379	-0.159	-0.223	-0.197	-0.060	-0.077	0.027	0.082	-0.058
	(0.087)	(0.112)	(0.101)	(0.073)	(0.047)	(0.043)	(0.053)	(0.221)	(0.159)	(0.183)
$\hat{\mathcal{X}}_r^{\text{other}}$	-0.038	0.070	0.026	0.005	-0.014	-0.017	-0.035	0.092	-0.078	-0.131
	(0.049)	(0.077)	(0.066)	(0.026)	(0.026)	(0.017)	(0.027)	(0.092)	(0.103)	(0.127)
China shock	0.141	-0.038	0.171	0.018	0.010	0.008	0.048	-0.645	0.043	-0.051
	(0.050)	(0.054)	(0.051)	(0.035)	(0.012)	(0.016)	(0.027)	(0.120)	(0.067)	(0.066)
Manufacturing %	-0.274	0.062	-0.341	0.050	0.005	0.182	-0.018	-1.165	0.002	0.193
	(0.061)	(0.081)	(0.087)	(0.045)	(0.028)	(0.036)	(0.043)	(0.140)	(0.088)	(0.092)
Automation	0.003	-0.081	-0.062	-0.026	0.003	0.004	-0.021	-0.110	-0.054	-0.039
	(0.018)	(0.026)	(0.018)	(0.011)	(0.005)	(0.008)	(0.011)	(0.064)	(0.021)	(0.024)
Routine	0.238	0.105	0.205	-0.030	0.050	-0.034	0.091	-0.170	-0.143	-0.434
	(0.049)	(0.074)	(0.063)	(0.047)	(0.015)	(0.019)	(0.033)	(0.108)	(0.077)	(0.080)
Offshoring	-0.049	0.065	0.063	-0.045	-0.007	-0.056	-0.054	-0.100	0.225	0.506
	(0.026)	(0.060)	(0.034)	(0.034)	(0.011)	(0.016)	(0.020)	(0.071)	(0.051)	(0.072)
Recession	-0.085	0.131	-0.008	0.055	0.018	0.072	0.014	0.255	-0.275	0.178
	(0.054)	(0.057)	(0.065)	(0.031)	(0.020)	(0.023)	(0.035)	(0.138)	(0.071)	(0.078)
Num. of Children	0.051	0.203	0.190	0.052	0.054	0.054	0.102	0.129	0.180	-0.241
	(0.052)	(0.050)	(0.049)	(0.027)	(0.019)	(0.011)	(0.020)	(0.058)	(0.078)	(0.101)
Average Age	-0.070	0.186	0.030	0.018	0.048	0.013	-0.012	-0.074	0.013	-0.049
	(0.042)	(0.057)	(0.041)	(0.021)	(0.018)	(0.021)	(0.020)	(0.080)	(0.052)	(0.079)
F-stat	35	35	35	35	35	35	35	35	35	35
AKM CI	[-0.15, 1.40]	[0.02, 1.81]	[-0.10, 2.08]	[0.26, 0.95]	[0.11, 0.67]	[-0.15, 0.63]	[-0.06, 0.57]	[-1.09, 1.01]	[-1.53, 0.52]	
	Panel B: pretend changes in industry employment/population ratio 1990-2000									
$\hat{\mathcal{X}}_r^{\text{foreign}}$	0.177	-0.925	-0.117	0.491	0.084	-0.021	-0.174	1.130	-0.037	0.047
	(0.106)	(0.338)	(0.184)	(0.156)	(0.090)	(0.070)	(0.119)	(0.806)	(0.161)	(0.205)
AKM CI	[-0.05, 0.54]	[-2.14, -0.20]	[-0.53, 0.24]	[-0.15, 1.47]	[-0.45, 0.72]	[-0.24, 0.23]	[-0.57, 0.08]	[-0.85, 3.97]	[-0.40, 0.19]	[-0.39, 0.62]

Notes: The table reports 2SLS estimates using the change in the industry employment-to-population ratio between 2000 and 2018 as the outcome variables in Panel A. In Panel B, the dependent variables are changes between 1990 and 2000 for each corresponding industry. Control variables are standardized to have a unit standard deviation. All models include nine-division fixed effects and the full set of controls. N = 722. Observations are weighted by the working-age population in 2000. Standard errors, reported in parentheses, are clustered at the state level. AKM 95% confidence intervals are reported for each model.

Table C.5: Log Population Changes by Different Groups and Model Specifications

	Dependent variable: changes in log population 2000-2018			
	All	Age 16-30	Age 31-45	Age 45-64
	(1)	(2)	(3)	(4)
	Panel A: Division FE, Lag population growth			
$\hat{\mathcal{P}}_r^{\text{foreign}}$	6.392	5.199	10.053	4.367
	(1.631)	(1.761)	(2.226)	(2.217)
	Panel B: Division FE, Lag population growth, Controls			
$\hat{\mathcal{P}}_r^{\text{foreign}}$	1.953	1.293	2.115	-1.596
	(1.048)	(1.591)	(1.554)	(1.306)
	Panel C: Division FE, Lag population growth, More Controls			
$\hat{\mathcal{P}}_r^{\text{foreign}}$	1.970	1.322	2.200	-1.448
	(1.012)	(1.583)	(1.403)	(1.447)

Notes: The Table reports changes in log working age population on $\hat{\mathcal{P}}_r^{\text{foreign}}$ instrumented by $\hat{\mathcal{Z}}_r$. All models include the changes in log working age population (for corresponding group) between 1990 and 2000 as controls. Additionally, panel A includes division fixed effects, panel B includes division fixed effects and the full set of controls. Panel C further add additional controls. All models are estimated using one-time changes between 2000 and 2018, for over 722 CZs. Observations are weighted by the working-age population in 2000. Standard errors, reported in parentheses, are clustered at the state level. AKM 95% confidence intervals are reported for each model.

Table C.6: Robustness Check Using Shock Measures, $\hat{\mathcal{X}}_r^{\text{gov}}$ that Incorporates Local Government Spending

	(1) University	(2) Restaurant	(3) Construction	(4) Retail	(5) Wholesale	(6) Hotel	(7) Real Estate	(8) Transport	(9) Manufacturing	(10) Health	(11) Profession
	Changes in industry employment/population ratio 2000-2018										
$\hat{\mathcal{X}}_r^{\text{gov}}$	1.667	0.390	0.752	0.791	0.458	0.311	0.183	0.186	-0.065	-0.364	0.189
	(0.645)	(0.240)	(0.253)	(0.312)	(0.186)	(0.124)	(0.094)	(0.120)	(0.360)	(0.306)	(0.674)
$\hat{\mathcal{P}}_r^{\text{native}}$	1.155	-0.134	-0.381	-0.161	-0.224	-0.198	-0.061	-0.077	0.028	0.083	-0.058
	(0.244)	(0.087)	(0.112)	(0.102)	(0.072)	(0.048)	(0.044)	(0.053)	(0.222)	(0.161)	(0.184)
$\hat{\mathcal{X}}_r^{\text{other}}$	0.104	-0.039	0.069	0.025	0.004	-0.014	-0.018	-0.035	0.092	-0.078	-0.131
	(0.076)	(0.048)	(0.076)	(0.066)	(0.026)	(0.026)	(0.017)	(0.028)	(0.092)	(0.103)	(0.128)
China shock	0.097	0.142	-0.036	0.173	0.019	0.011	0.009	0.048	-0.645	0.042	-0.050
	(0.093)	(0.051)	(0.053)	(0.052)	(0.035)	(0.013)	(0.016)	(0.028)	(0.120)	(0.068)	(0.067)
Manufacturing %	0.077	-0.269	0.072	-0.331	0.056	0.009	0.184	-0.015	-1.166	-0.002	0.196
	(0.111)	(0.060)	(0.079)	(0.083)	(0.045)	(0.028)	(0.037)	(0.042)	(0.141)	(0.090)	(0.090)
Automation	0.078	0.002	-0.083	-0.064	-0.028	0.003	0.004	-0.021	-0.110	-0.054	-0.040
	(0.025)	(0.018)	(0.025)	(0.016)	(0.010)	(0.004)	(0.008)	(0.011)	(0.063)	(0.021)	(0.023)
Routine	0.062	0.230	0.089	0.188	-0.040	0.043	-0.037	0.087	-0.168	-0.135	-0.438
	(0.118)	(0.048)	(0.071)	(0.060)	(0.045)	(0.016)	(0.020)	(0.033)	(0.109)	(0.081)	(0.083)
Offshoring	-0.068	-0.050	0.063	0.061	-0.046	-0.008	-0.056	-0.055	-0.100	0.226	0.506
	(0.083)	(0.027)	(0.060)	(0.035)	(0.033)	(0.012)	(0.017)	(0.019)	(0.071)	(0.052)	(0.072)
Recession	0.134	-0.085	0.130	-0.009	0.055	0.018	0.072	0.014	0.256	-0.275	0.178
	(0.072)	(0.054)	(0.057)	(0.066)	(0.032)	(0.020)	(0.023)	(0.035)	(0.138)	(0.071)	(0.078)
Num. of Children	0.069	0.054	0.209	0.196	0.056	0.057	0.056	0.104	0.129	0.177	-0.240
	(0.055)	(0.053)	(0.051)	(0.050)	(0.027)	(0.019)	(0.012)	(0.021)	(0.060)	(0.079)	(0.103)
Average Age	0.161	-0.064	0.197	0.042	0.025	0.053	0.016	-0.009	-0.075	0.008	-0.046
	(0.066)	(0.045)	(0.057)	(0.044)	(0.022)	(0.019)	(0.022)	(0.020)	(0.081)	(0.054)	(0.088)
F-stat	28.7	28.7	28.7	28.7	28.7	28.7	28.7	28.7	28.7	28.7	28.7
AKM CI	[1.38, 2.42]	[-0.21, 1.29]	[-0.07, 1.66]	[-0.20, 1.93]	[0.17, 0.89]	[0.09, 0.59]	[-0.10, 0.51]	[-0.06, 0.50]	[-0.94, 0.88]	[-1.28, 0.40]	[-0.45, 0.92]
	Panel B: pretend changes in industry employment/population ratio 1990-2000										
$\hat{\mathcal{X}}_r^{\text{gov}}$	0.418	0.187	-0.979	-0.124	0.519	0.089	-0.022	-0.184	1.195	-0.039	0.050
	(0.238)	(0.112)	(0.346)	(0.195)	(0.172)	(0.095)	(0.074)	(0.127)	(0.880)	(0.170)	(0.217)
AKM CI	[-0.05, 0.54]	[-2.14, -0.20]	[-0.53, 0.24]	[-0.15, 1.47]	[-0.45, 0.72]	[-0.24, 0.23]	[-0.57, 0.08]	[-0.85, 3.97]	[-0.40, 0.19]	[-0.39, 0.62]	

Notes: The table reports 2SLS estimates using the change in the industry employment-to-population ratio between 2000 and 2018 as the outcome variables in Panel A. In Panel B, the dependent variables are changes between 1990 and 2000 for each corresponding industry. The regressor incorporates local government spending when measuring the demand shocks. Control variables are standardized to have a unit standard deviation. All models include nine-division fixed effects and the full set of controls. N = 722. Observations are weighted by the working-age population in 2000. Standard errors, reported in parentheses, are clustered at the state level. AKM 95% confidence intervals are reported for each model.

Table C.7: Robustness Check using Population Shocks

	(1) University	(2) Restaurant	(3) Construction	(4) Retail	(5) Wholesale	(6) Hotel	(7) Real Estate	(8) Transport	(9) Manufacturing	(10) Health	(11) Profession
Panel A: Changes in industry employment/population ratio 2000-2018											
$\hat{\mathcal{P}}_r^{\text{foreign}}$	2.314	0.542	1.043	1.099	0.636	0.431	0.254	0.258	-0.090	-0.505	0.263
	(0.967)	(0.365)	(0.427)	(0.508)	(0.309)	(0.191)	(0.136)	(0.174)	(0.494)	(0.408)	(0.937)
$\hat{\mathcal{P}}_r^{\text{native}}$	1.082	-0.151	-0.414	-0.196	-0.244	-0.212	-0.069	-0.085	0.030	0.099	-0.067
	(0.271)	(0.097)	(0.129)	(0.117)	(0.085)	(0.053)	(0.046)	(0.057)	(0.229)	(0.166)	(0.205)
$\hat{\mathcal{X}}_r^{\text{other}}$	0.127	-0.033	0.080	0.036	0.011	-0.010	-0.015	-0.032	0.091	-0.083	-0.128
	(0.092)	(0.048)	(0.081)	(0.072)	(0.032)	(0.028)	(0.016)	(0.027)	(0.092)	(0.103)	(0.126)
China shock	0.086	0.140	-0.041	0.168	0.016	0.009	0.008	0.047	-0.644	0.044	-0.051
	(0.091)	(0.051)	(0.053)	(0.054)	(0.037)	(0.013)	(0.016)	(0.028)	(0.120)	(0.068)	(0.064)
Manufacturing %	0.005	-0.285	0.039	-0.365	0.036	-0.004	0.176	-0.023	-1.163	0.013	0.188
	(0.107)	(0.067)	(0.089)	(0.099)	(0.048)	(0.029)	(0.035)	(0.043)	(0.138)	(0.087)	(0.099)
Automation	0.088	0.005	-0.079	-0.060	-0.025	0.004	0.005	-0.020	-0.111	-0.056	-0.039
	(0.023)	(0.019)	(0.028)	(0.021)	(0.014)	(0.006)	(0.007)	(0.011)	(0.064)	(0.020)	(0.025)
Routine	0.165	0.254	0.136	0.237	-0.012	0.063	-0.026	0.099	-0.172	-0.157	-0.427
	(0.113)	(0.053)	(0.078)	(0.069)	(0.048)	(0.016)	(0.019)	(0.034)	(0.107)	(0.071)	(0.082)
Offshoring	-0.122	-0.062	0.039	0.035	-0.061	-0.018	-0.062	-0.061	-0.098	0.237	0.499
	(0.083)	(0.028)	(0.063)	(0.040)	(0.035)	(0.011)	(0.016)	(0.020)	(0.071)	(0.047)	(0.067)
Recession	0.100	-0.093	0.115	-0.025	0.046	0.012	0.068	0.010	0.257	-0.268	0.174
	(0.083)	(0.055)	(0.063)	(0.072)	(0.033)	(0.020)	(0.023)	(0.036)	(0.139)	(0.070)	(0.084)
Num. of Children	0.081	0.056	0.214	0.202	0.059	0.059	0.057	0.105	0.128	0.174	-0.238
	(0.058)	(0.056)	(0.056)	(0.056)	(0.031)	(0.019)	(0.012)	(0.022)	(0.061)	(0.079)	(0.103)
Average Age	0.140	-0.068	0.188	0.032	0.019	0.049	0.013	-0.012	-0.074	0.012	-0.049
	(0.059)	(0.043)	(0.058)	(0.043)	(0.023)	(0.018)	(0.021)	(0.020)	(0.080)	(0.051)	(0.080)
F-stat	18	18	18	18	18	18	18	18	18	18	18
AKM CI	[1.38, 2.42]	[-0.21, 1.29]	[-0.07, 1.66]	[-0.20, 1.93]	[0.17, 0.89]	[0.09, 0.59]	[-0.10, 0.51]	[-0.06, 0.50]	[-0.94, 0.88]	[-1.28, 0.40]	[-0.45, 0.92]
Panel B: pretend changes in industry employment/population ratio 1990-2000											
$\hat{\mathcal{P}}_r^{\text{foreign}}$	0.581	0.259	-1.359	-0.172	0.721	0.123	-0.030	-0.256	1.659	-0.055	0.069
	(0.335)	(0.164)	(0.558)	(0.274)	(0.244)	(0.136)	(0.103)	(0.178)	(1.248)	(0.238)	(0.302)
AKM CI	[-0.05, 0.54]	[-2.14, -0.20]	[-0.53, 0.24]	[-0.15, 1.47]	[-0.45, 0.72]	[-0.24, 0.23]	[-0.57, 0.08]	[-0.85, 3.97]	[-0.40, 0.19]	[-0.39, 0.62]	

Notes: The table reports 2SLS estimates using the change in the industry employment-to-population ratio between 2000 and 2018 as the outcome variables in Panel A. In Panel B, the dependent variables are changes between 1990 and 2000 for each corresponding industry. The regressor of interests is population shock defined in Equation (4). Control variables are standardized to have a unit standard deviation. All models include nine-division fixed effects and the full set of controls. N = 722. Observations are weighted by the working-age population in 2000. Standard errors, reported in parentheses, are clustered at the state level. AKM 95% confidence intervals are reported for each model.

Table C.8: 2SLS Estimates on Labor Supply Elasticity with Various Specification

Dependent variable: changes in log employment between 2000 and 2018				
	(1)	(2)	(3)	(4)
$\Delta \ln W_r$	2.559	2.328	1.575	1.834
	(0.929)	(0.547)	(0.616)	(0.561)
$\hat{\mathcal{P}}_r^{\text{native}}$		11.055		8.680
		(6.181)		(5.155)
$\hat{\mathcal{X}}_r^{\text{other}}$		-0.795		-0.374
		(1.448)		(1.324)
Manufacturing %		-17.897		-12.194
		(5.523)		(3.693)
Routine		3.844		4.647
		(3.063)		(2.750)
Offshoring		-0.073		1.047
		(2.220)		(2.168)
Recession		-18.894		-11.427
		(5.635)		(3.847)
Num. of Children		3.757		4.377
		(2.179)		(2.443)
Average Age		-4.204		-2.686
		(2.412)		(2.298)
N	722	722	722	722
F-stat	27	27	30	23

Notes: This table reports 2SLS estimates of labor supply elasticity under different specifications. The dependent variables is the changes in log CZ employment, and the regressor of interest is the changes in log CZ average wages which is instrumented by the exogenous China shock and automation shock. All models are estimated using 2SLS for one-time changes for 722 CZs. Observations are weighted by the working-age population in 2000. Standard errors, shown in parentheses, are clustered at the state level. Since the China shock and Automation shock are used as instruments, they are not included as control variables.

Table C.9: Labor Supply Elasticity Estimates: Previous Studies[†]

Paper	Estimates	Instruments	Level of Variation
Fajgelbaum et al. (2019)	1.36–2.25	Bartik & Tax	States (1980–2010)
Serrato and Wingender (2016)	1.18–1.61	Bartik & Tax	County (1980–2009)
Diamond (2016)	2.12–4.03	Bartik	MSA (1980–2000)
Adao et al. (2019)	1.2–1.5	Bartik or China shock	Cz (1990–2007)
Galle et al. (2023)	1.56	China shock	Cz(1990–2007)

Notes: [†] Fajgelbaum et al. (2019) estimate migration elasticity across US states; values are drawn from the top three rows of their Table 1. Serrato and Wingender (2016) estimate migration elasticity across US counties, based on their Table 6. Both Diamond (2016) estimate migration elasticities across US cities, separately for non-college and college workers. For Diamond (2016), values are from Column (3) of Table 5. Adao et al. (2019) and Galle et al. (2023) estimate migration elasticity across US commuting zones; values are from Column (2) of Table 3 for the former and Column (2) of Table 1 for the latter.

D Additional Figures

Figure D.1: International Students Enrollment and Export Educational Services in the United States

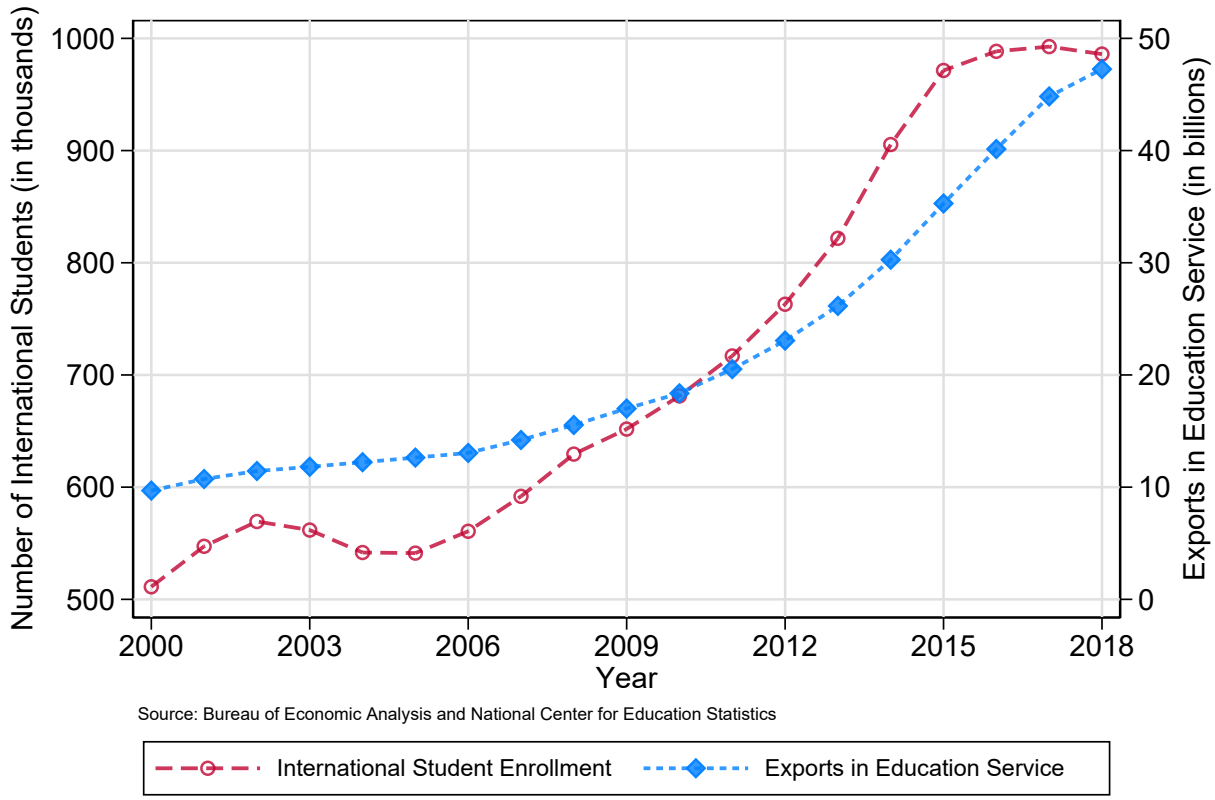
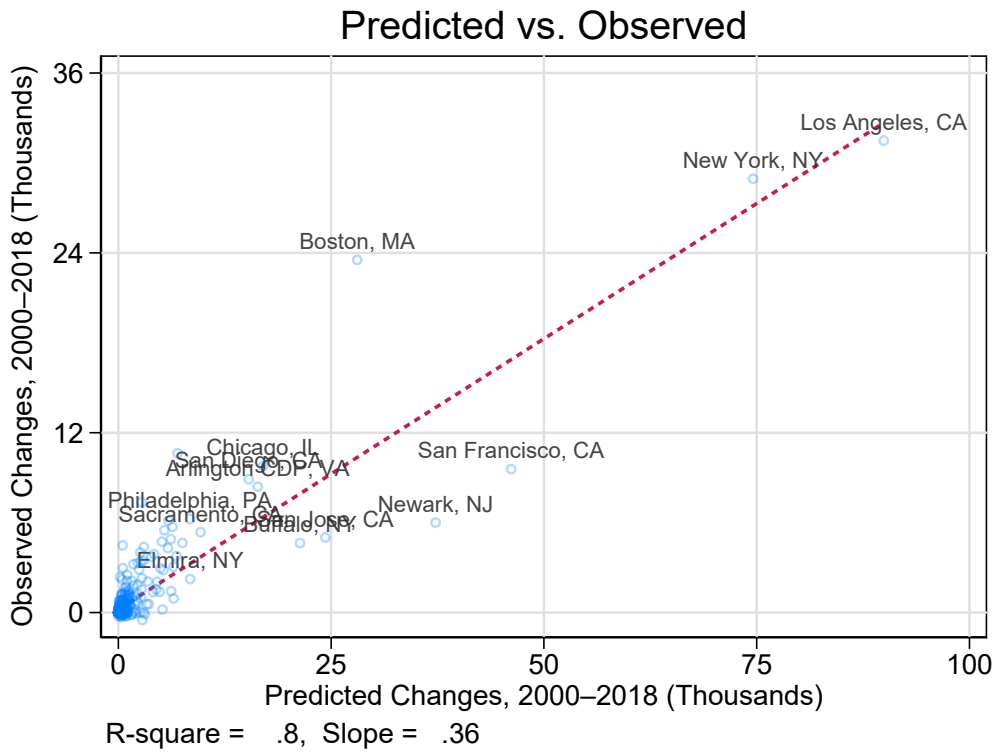
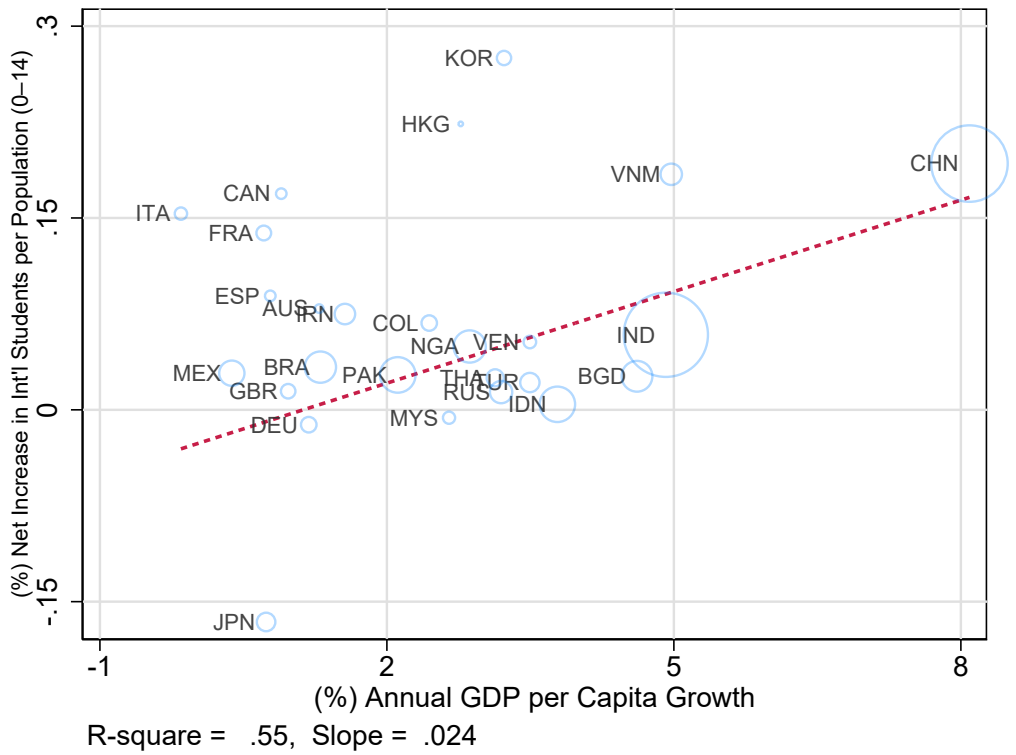


Figure D.2: Observed and Projected Changes in International Students to U.S. Commuting Zones, 2000-2018



*Notes:*The changes in enrollment to the other three countries are based on data from the UNESCO Institute for Statistics, while changes in enrollment in U.S. universities are derived from IPEDS, focusing on full-time international students.

Figure D.3: Changes in International Students Relative to Population (Aged 0–14) and Country Growth Rates



Notes: This figure plots changes in the number of international students across four major destination countries relative to the size of the population aged 0–14 in 2000 against the annual GDP per capita growth rate across major source countries. I use the population aged 0–14 in 2000 as a proxy for the college-age population in 2018.

E Technical Details

E.1 Parameter Calibration

Input Shares. I use the BEA Industry Economic Accounts to compute the input shares for the university industry. Since the BEA reports industries by broad categories, my calculations are based on the 'Educational Services, Health Care, and Social Assistance' sector, which reports a gross output of $2,839,262$ million, labor compensation of $1,449,668$ million, and intermediate inputs in manufacturing of $287,878$ million. I calculate the labor share as $\gamma_L = 0.51$, defined as the ratio of labor compensation to gross output, while the shares of other inputs are $\gamma_T = 0.1$ and $\gamma_N = 0.39$."

Expenditure Shares. The consumption shares α_T, α_E, and α_N are calibrated using the total expenditure of in each sector, subtract the intermediate goods expenditure and divided by total absorption. Specifically, I calibrate α_T, the expenditure shares on tradable goods as

$$\frac{\sum_r w_r L_{rT} + D_T}{\sum_r w_r L_r + D_T + D_E}. \tag{A.1}$$

The first term in the numerator is the wage bill in manufacturing industries, this measures model-based manufacturing output (as labor is the only input). The second term, $D_T = \text{import}_T - \text{export}_T$ is the deficit in manufacturing. According to BEA, the US deficit in manufacturing is 0.4 of manufacturing output: $D_T = 0.4 \sum_r w_r L_{rT}$. The denominator is the US absorption, which is the sum of total income, $\sum_r w_r L_r$, and trade deficit in manufacturing and education. I obtain $\alpha_T = 0.0963$.

Similarly, to obtain the expenditure shares on educational services, I compute as

$$\frac{1}{\lambda}\frac{1}{\gamma_L}\frac{\sum_r w_r L_{rU} + D_E}{\left(\sum_r w_r L_r + D_T\right)} \tag{A.2}$$

where L_{rU} is university employment, and D_E is US deficit in education. Since I assume the ROW does not export education to the US, D_E equals the negative of international student spending in 2018. Here, $1/\gamma_L$ captures the fact that intermediate inputs are used. λ is the tuition payment as a share of students' overall spending (tuition, rent, other living expenses) aggregating over all US universities using IPEDS data, $\lambda = 0.67$. The multiplication of $1/\lambda$ reflects the fact the education is consumption composite of university and local non-tradable sectors. This gives $\alpha_E = 0.0588$. The expenditure share on non-tradable is computed as $\alpha_N = 1 - \alpha_T - \alpha_E$.

CZ-to-CZ trade in education service. The IPEDS has enrollment data on non-aliens breaking down by in-state and out-of-state by each institution. I allocate in-state enrollment to counties within-state proportional to income; similarly, I allocate out-state enrollment to outside counties proportional to income. Using in-state and out-of-state tuition and living expenses, I can compute the matrix of trade in education service among counties.

The ROW. Data on population, employment, and GDP are obtained from the World Development Indicators database. I subtract the corresponding U.S. values from world aggregates. I measure the expenditure shares of US imports from the ROW in manufacturing consumption as the ratio between US imports divided by manufacturing output plus imports and subtract exports. The expenditure share of ROW manufacturing imports from the US are measured similarly. For manufacturing, I retrieve U.S.

import and export data from Comtrade. Manufacturing outputs for the US and the ROW are obtained from the world development indicators. I allocate aggregate US exports across counties based on county's share of national manufacturing employment, while US imports are allocated using county-level income.

For educational services, I estimate the export volume of each U.S. region by summing the total tuition and living expenses of international students in 2018, using data from IPEDS. I assume the U.S. does not import educational services from the rest of the world (ROW).

E.2 Equilibrium in Changes.

I use x' to denote variables in counterfactual and $\hat{x} = x'/x$. The labor market clear condition in counterfactual is

$$w_r' L_r' = \sum_\ell \Pi_{r\ell T} \hat{\Pi}_{r\ell T} \alpha_T I_\ell' + \sum_\ell \Pi_{r\ell E} \hat{\Pi}_{r\ell E} \alpha_E \lambda_{r\ell} I_\ell' + \alpha_N I_r' + \sum_\ell \Pi_{r\ell E} \hat{\Pi}_{r\ell E} \alpha_E (1-\lambda_{r\ell}) I_\ell' \tag{A.3}$$

where I_ℓ' is the counterfactual expenditure that equals $W_r L_r \hat{w}_r \hat{\Lambda}_{e|r} + D_r$. In the counterfactual, I set $\hat{\hat{A}}_{\ell T} = \hat{\hat{A}}_{\ell U} = \hat{A}_{\ell N} = \hat{b}_r = 1$. I also set $\hat{\tau}_{\ell r} = 1$ for pairs between US CZs.

The changes in the employment ratio are

$$\hat{\Lambda}_{e|r} = \frac{\hat{w}_r^\theta}{\Lambda_{k|r} \hat{w}_r^\theta + \Lambda_{u|r} \hat{b}_r^\theta} \tag{A.4}$$

The changes in region r' expenditure shares in manufacturing goods is

$$\hat{\Pi}_{\ell r T} = \frac{\hat{L}_{\ell T}^{(\sigma_T - 1)\gamma_T} \left(\hat{d}_{\ell r} \hat{w}_\ell\right)^{1-\sigma_T}}{\sum_{\ell'} \hat{L}_{\ell' T}^{(\sigma_T - 1)\gamma_T} \left(\hat{d}_{\ell' r} \hat{w}_{\ell'}\right)^{1-\sigma_T} \Pi_{\ell r T}} \tag{A.5}$$

The changes in region r's expenditure shares in education services is

$$\hat{\Pi}_{\ell r E} = \frac{\hat{p}_{\ell r E}^{1-\sigma_E}}{\sum_{\ell'} \hat{p}_{\ell' r E}^{1-\sigma_E} \Pi_{\ell r E}} \tag{A.6}$$

where

$$\hat{p}_{\ell r E} = \hat{\tau}_{\ell r} \hat{p}_{\ell U}^{\lambda_{\ell U}} \hat{p}_{\ell N}^{\lambda_{\ell N}}, \qquad \hat{p}_{\ell U} = \hat{L}_{\ell U}^{-\gamma_U} \frac{\hat{W}_r}{\hat{\hat{A}}_{\ell U}}, \qquad \hat{p}_{\ell N} = \frac{\hat{W}_r}{\hat{A}_{\ell N}} \tag{A.7}$$

The absorption prices for table goods and educational services in r are

$$\hat{P}_{rT} = \hat{L}_{rT}^{-\gamma_T} \Big[\sum_\ell \left(\hat{d}_{\ell r} \hat{W}_\ell\right)^{1-\sigma_T} \Pi_{\ell r T} \Big]^{\frac{1}{1-\sigma_T}}, \qquad \hat{P}_{rE} = \Big[\sum_\ell \hat{L}_{rU}^{(\sigma_E - 1)\lambda_{\ell U}\kappa_U} \left(\hat{\tau}_{\ell r} \hat{W}_\ell\right)^{1-\sigma_E} \Pi_{\ell r E} \Big]^{\frac{1}{1-\sigma_E}} \tag{A.8}$$

The changes in the consumer price index in region r equals $\hat{P}_r = \hat{P}_{rT}^{\alpha_T} \hat{P}_{rE}^{\alpha_E} \hat{P}_{rN}^{\alpha_N}$.

E.3 Model Inversion.

I invert the model to obtain county TFP in 2018 in manufacturing industries and county-to-county trade flows in manufacturing. The procedure requires a parametric assumption of trade costs $d_{\ell r} = \text{Dist}_{\ell r}^{\psi}$, a value of trade elasticity $\sigma_T = 6$ and $\psi = 0.43$. Given local manufacturing employment and wages, and trade costs $d_{\ell r}$, I solve for A_{rT} from the following

$$W_r L_{rT} = \sum_\ell \frac{\left(d_{r\ell} w_r / A_{rT}\right)^{1-\sigma_T}}{\sum_{r'} \left(d_{r'\ell} w_{r'} / A_{r'k}\right)^{1-\sigma_T}} \Big[\alpha_T L_\ell w_\ell + D F_{\ell T} \Big]. \tag{A.9}$$

$DF_{\ell T}$ is the trade deficit, which I allocate the aggregate deficit in manufacturing to each US region proportionally based on income. Note that, the above equation (A.9) is consistent with the market clear condition in Equation (20), since non-manufacturing sectors cancel out on both sides. I use this equation to solve A_{rk} for productivity in tradable sectors that rationalizes the observed wage and employment in tradable industry. After that, I used the estimated A_{rk} to predict the county-to-county trade shares using Equation (19).

E.4 Structural Estimation

I estimate the two agglomeration elasticities, $\Theta = \{\kappa_U\}$ while solving the GE model using GMM. The structural estimation proceeds in two steps.

Solving for General Equilibrium (Inner Problem). Guessing parameter values for $\hat{\Theta} = \{\hat{\kappa}_U\}$, and given data on $\{W_r, N_r, \Lambda_{e|r}, \Pi_{\ell rT}, \Pi_{\ell rE}\}$, parameter values $\{\gamma_L, \gamma_T, \gamma_N, \alpha_T, \alpha_E, \alpha_N, \lambda_{\ell U}, \lambda_{\ell N}, \sigma_E, \sigma_T\}$, I first calibrate the model-implied deficit D_r, similar to Caliendo and Parro (2015). D_r is solved using such that Equation (A.3) holds in the observed economy, where $\hat{\tau}_{\ell r} = \hat{d}_{\ell r} = \hat{A}_{\ell k} = \hat{w}_r = \hat{\Lambda}_{e|r} = 1$.

Given the calibrated deficit D_r, I simulate a counterfactual world that shuts down US export services to ROW. I turn $\tau_{\ell r}$ to infinite, for ℓ as US county and r as the ROW. I solve the counterfactual using the exact hat algebra (Dekle, Eaton and Kortum, 2008). $\hat{d}_{\ell r} = \hat{A}^0_{\ell k} = 1$. The equilibrium solution is solved through contraction mapping algorithm (Alvarez and Lucas, 2007).

1. Initial guess: $\{w_r^t\} = [1, ..., 1]$, and t index for the number of iteration. I use Equation (A.4) to compute changes in employment rate, Equation (A.5) to compute changes in expenditure shares in goods and services, Equation (A.8) to compute changes in price.
2. Compute the counterfactual total wage payment in county r using the left hand side of Equation (A.3), denoted as LHS_r^t.
3. Compute the counterfactual revenue in county r using the right hand side of Equation (A.3), denoted as RHS_r^t.
4. Compute the difference as :

$$Z_r\big(\{w_r^t\}\big) = \text{LHS}_r^t - \text{RHS}_r^t. \tag{A.10}$$

Stop the procedure if $\max_r Z_r\big(\{w_r^t\}\big) < 10^{-5}$. Otherwise, update:

$$w_r^{t+1} = w_r^t + \kappa \cdot \frac{\sqrt{Z_r(\{w_r^t\})^2}}{\max\big\{\text{LHS}_r, \text{RHS}_r\big\}}, \quad \kappa \in (0,1). \tag{A.11}$$

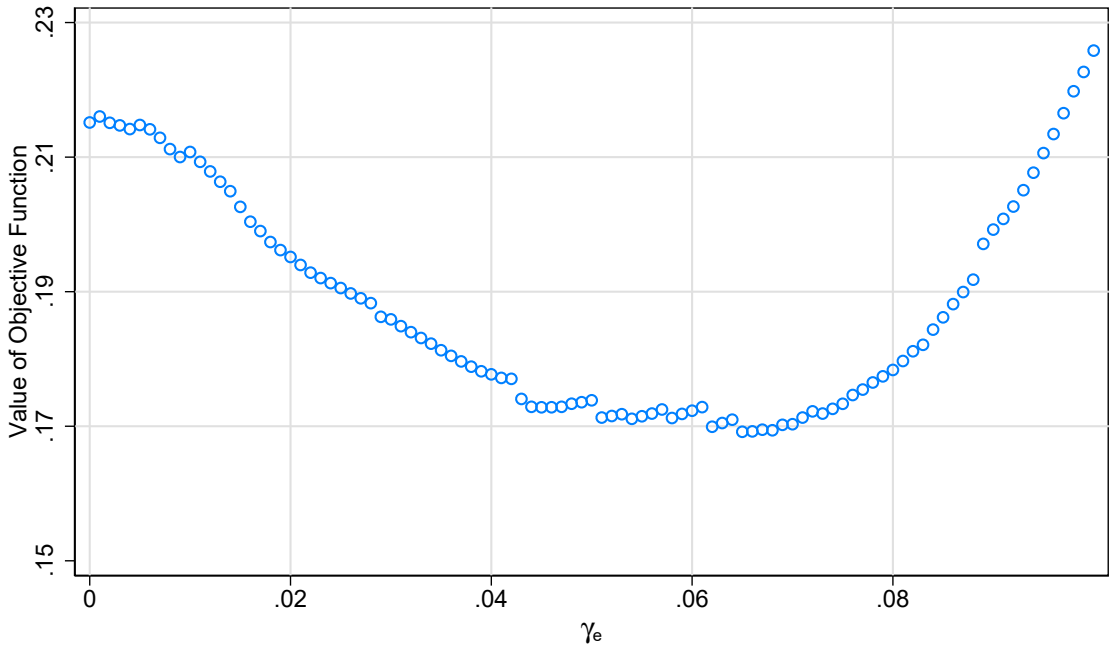
Indirect Inference (Outer Problem). Denote $\mathcal{F}(\Theta)$ as the collection of data and endogenous variables (wages, employment, prices) solved from the inner problem. The second step searches parameter values Θ to match the differential effects implied from the reduced-form estimates. I minimize the following objective function

$$\hat{\Theta} = \underset{\Theta}{\text{argmin}} \ \Big[m\big(\Theta; \mathcal{F}(\Theta)\big) - m^{\text{RF}}\Big]' \times V \times \Big[m\big(\Theta; \mathcal{F}(\Theta)\big) - m^{\text{RF}}\Big], \tag{A.12}$$

where $m(\Theta; \mathcal{F}(\Theta))$ is a 2×1 vector of targeted moments predicted by the model, and m^{RF} is from the reduced-form estimates. I choose two moments (1) the 75-to-25 percentile differences in university employment-to-population ratio, and (2) the standard deviation of changes in university employment-to-population across 722 CZs.

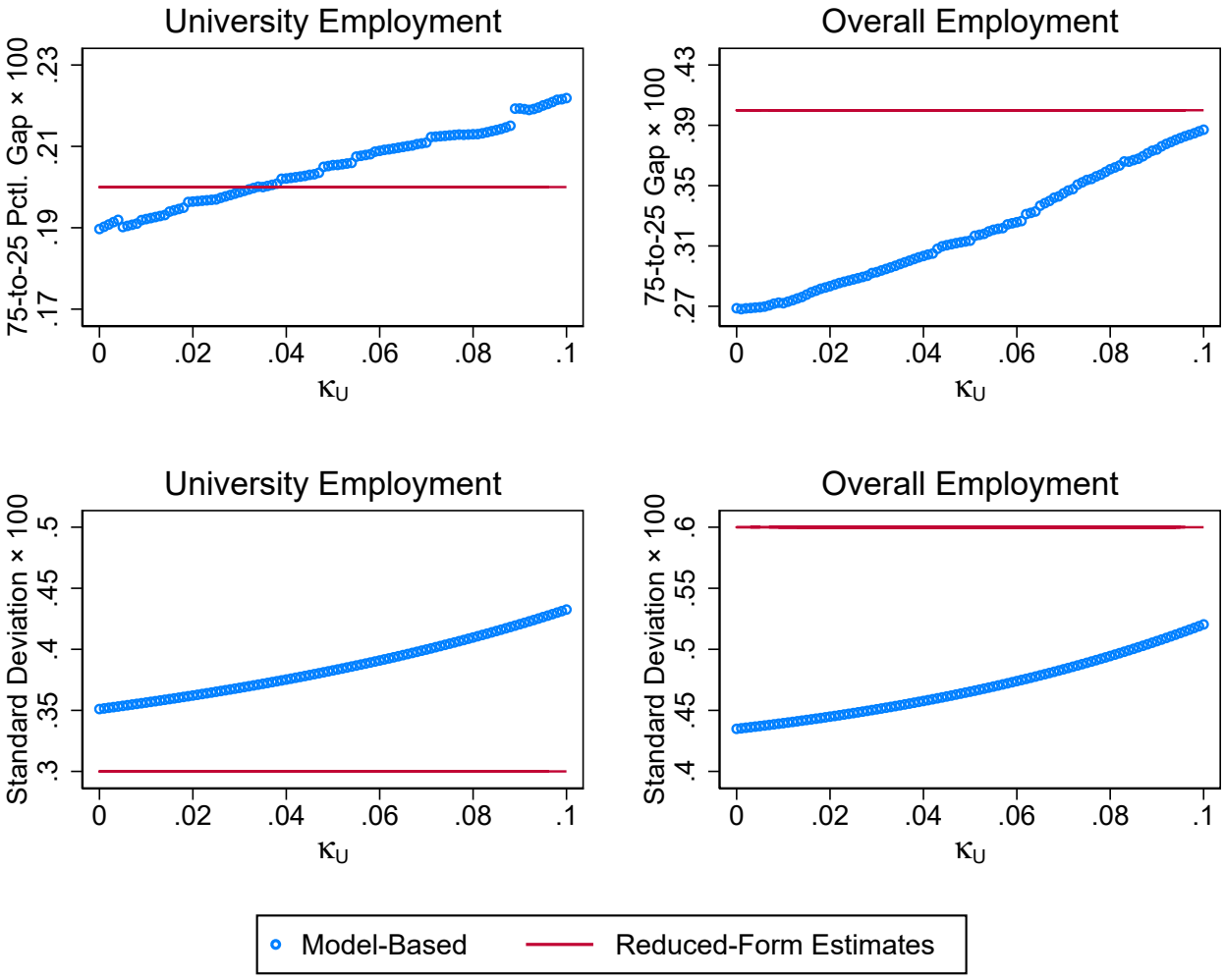
For $m(\Theta; \mathcal{F}(\Theta))$ and m^{RF}, I compute the effects of export education service in 2018. For $m(\Theta; \mathcal{F}(\Theta))$, I turn $\tau_{\ell r}$ to infinite. Additionally, I measure international student expenses as a share of local gross consumption in goods and services in 2018, $\hat{\mathcal{X}}^{f}_{r,2018}$, and combine it with the estimates in Column (6) of Table 2 to compute m^{RF}. V is the 2×2 weighting matrix, which I choose as a diagonal matrix with entries $(1/m^{\text{RF}})^2$. The weighting matrix normalizes the scale of the two moments, ensuring that they contribute equally to the minimization.

Figure E.1: Values of Objective Function under Different Values of γ_e



Notes: Each dot represents the value of the objective function that the indirect inference procedure minimizes.

Figure E.2: Evidence of the Indirect Inference with Different Values of γ_e



Notes: The upper panels compare the 75th-to-25th percentile differences in university-industry employment (left) and overall employment (right). The lower panels compare the standard deviation in university-industry employment (left) and overall employment (right). The blue dot represents the model-based dispersion of the effects on the university employment-to-population ratio, while the red line represents the dispersion implied by the reduced-form estimates. All values are multiplied by 100.

Figure E.1 plots the value of the objective function that the indirect inference procedure minimizes against κ_U. The pattern shows some U-shaped that bottom around 0.06 and trending up after.

In Figure E.2, the upper panels show the model-based 75-to-25 percentile difference across CZs (blue) and the corresponding effect implied by the reduced-form estimates (red) in the university sector, on the left, and for the overall employment on the right. The lower panels compare the model-based standard deviation across CZs (blue) and the corresponding effect implied by the reduced-form estimates (red) for the university (left) and for the overall (right). All values are multiplied by 100.

All four panels in Figure E.2 confirm clear evidence that models with higher κ_U in the university sector predict more dispersed effects in all measures. It also shows that in the upper left, κ_U takes a

value of 0.03 when the data and model agree. In the upper and bottom right, κ_U takes a value of 0.08. In the bottom left, κ_U takes a value of zero to better rationalizes the reduced-form estimates. Therefore, all these four moments contribute to determining the minimizer of the objective function.

F Motivating the Estimation Equation

Below, I outlay the equilibrium conditions to motivate the estimating equation.

Labor demand. I assume perfect competition and workers are the only production factors, such that firm revenue is all earned by workers. This implies the labor demand can be expressed as:

$$L_{rk}^{\text{demand}} = w_r^{-1}\mathcal{R}_{rk}, \tag{A.1}$$

where $\mathcal{R}_{rk}$ is the revenue. w_r is the wage in region r. I assume workers are perfectly mobile within regions across industries so that wages equalize across industries.

Labor Supply. The labor supply to region r and industry k is

$$L_{rk}^{\text{supply}} = w_r^{\theta}\mathcal{U}_{rk}. \tag{A.2}$$

The labor supply can be modeled following Adao et al. (2019, 2023), assuming the idiosyncratic preference of working follows a Pareto distribution with a scale parameter equaling one. In this case, $\mathcal{U}_r = N_r b_r^{-\theta}$. b_r denotes the unemployment benefits for US natives. In my baseline model, I assume immobile workers across regions.

Since the empirical measure uses expenditure data, it requires an assumption that each region is a closed market, such that the revenue equals expenditure, denoted as $\mathcal{X}_{rk} = \mathcal{R}_{rk}$. Assume that university sector uses labor and intermediate inputs to produce, with labor share as γ_L and input shares of γ_k from sector k. For simplicity, assuming other industries use a linear production with labor. Therefore, one can write

$$\mathcal{X}_{rk} = \mathcal{X}_{rk}^n + \gamma_k\mathcal{X}_{rU}^n + \mathcal{X}_{rk}^f + \gamma_k\mathcal{X}_{rU}^f \tag{A.3}$$

where $\mathcal{X}_{rk}^n$ is the native household expenditure on goods k in region r. $\mathcal{X}_{rk}^n$ is the expenditure of international students on goods k in region r. $\mathcal{X}_{rU}^n$ and $\mathcal{X}_{rU}^f$ are the expenditure of US household and international students on university in region r, respectively, where a γ_k share of university's revenue spend on intermediate inputs k.

Let the hat variables represent the log changes between two periods $\hat{X} = \log(X_t/X_{t-1})$. The changes in region and industry employment equal

$$\hat{L}_{rk} = \frac{\theta}{\theta+1}\hat{\mathcal{X}}_{rk} + \frac{1}{\theta+1}\hat{\mathcal{U}}_{rk} \tag{A.4}$$

To proceed, note that $\hat{\mathcal{X}}_{rk}$ measures the changes in revenue, not the shock of interest. I write $\hat{\mathcal{X}}_{rk} = \hat{\mathcal{X}}_{rk}^f \times \hat{\mathcal{G}}_r$, where $\hat{\mathcal{G}}_r$ measures other factors that cause changes in demand.

$\hat{\mathcal{X}}_r^f$ captures the expenditure shock induced by international students, which is measured as the percentage of expenditure change if the only change in the arrival and expenditure of international students.

$$\hat{\mathcal{X}}_{rk}^f = \frac{\Delta\mathcal{X}_{rk}^f}{\mathcal{X}_{rkt-1}} \tag{A.5}$$

where, $\Delta\mathcal{X}_{rk}^f = \mathcal{X}_{rkt}^f - \mathcal{X}_{rkt-1}^f$ represents the expenditure change by international students between 2000 and 2018 in region r, and $\mathcal{X}_{rt-1}$ is the total expenditure in the initial year. Next, assuming λ_k is

expenditure shares on industry k. I can write

$$\Delta \mathcal{X}^f_{rk} = \Delta \mathcal{X}^f_{rk} + \gamma_k \Delta \mathcal{X}^f_{rU} = (\lambda_k + \gamma_k \lambda_U) \Delta \mathcal{X}^f_r \tag{A.6}$$

Assuming expenditure from international students accounts for a very small fraction of local expenditure in the initial year,

$$\mathcal{X}^f_{rkt-1} \approx \mathcal{X}^n_{rkt-1} + \gamma_k \mathcal{X}^n_{rUt-1} = (\alpha_k + \gamma_k \alpha_U) \mathcal{X}^n_{rt-1} \tag{A.7}$$

α_k is expenditure shares on industry k for US household. Then, one can write

$$\hat{\mathcal{X}}^f_{rk} = \frac{\lambda_k + \gamma_k \lambda_U}{\alpha_k + \gamma_k \alpha_U} \frac{\Delta \mathcal{X}^f_r}{\mathcal{X}^n_{rt-1}} = \frac{\lambda_k + \gamma_k \lambda_U}{\alpha_k + \gamma_k \alpha_U} \hat{\mathcal{X}}^f_r \tag{A.8}$$

Thus Equation (A.4) can be rewritten as

$$\hat{L}_{rk} = \frac{\theta}{\theta + 1} \frac{\lambda_k + \gamma_k \lambda_U}{\alpha_k + \gamma_k \alpha_U} \hat{\mathcal{X}}_r + \frac{1}{\theta + 1} \hat{\mathcal{U}}_{rk} \tag{A.9}$$

which links region-industry-specific employment changes to region's consumer expenditure shock caused by international students, $\hat{\mathcal{X}}^f_r$. The effects depend on two sets of model parameters. The first is $\frac{\lambda_k}{\alpha_k}$, which reflects the differences in expenditure in industry k between international students and U.S. households. Intuitively, an expenditure shock $\hat{\mathcal{X}}^f_r$ would induce a larger employment response in industries where international students spend relatively more compared to U.S. households. The second term $-\frac{1}{\theta+1}$ captures the employment adjustments resulting from wage increases.

Put simply, I will estimate equation (A.4) for each industry, and the differences in employment responses would partly reveal the relative consumption patterns of international students compared to a typical U.S. household, assuming demand and supply elasticity do not vary much across industries. Because students tend to spend on non-durable necessities, such as fast food, groceries, and retail stores, we expect to see strong employment responses in those industries.