Trade Liberalization and Chinese Students in US Higher Education

Gaurav Khanna, Kevin Shih, Ariel Weinberger, Mingzhi Xu, and Miaojie Yu

Abstract

We highlight a lesser known consequence of China's growth and integration into the world economy in relation to the United States: the rise of services trade. We demonstrate that the US's trade deficit in goods cycle back as a surplus in exports of education services. Focusing on China's accession to the World Trade Organization, we show that Chinese cities more exposed to this trade liberalization episode sent more students to US universities. Results indicate that growth in housing income/ wealth was an important channel that allowed Chinese families in the top of the income distribution to afford US tuition, consistent with large growth in the share of Chinese students who financed their studies using personal funds. Other mechanisms, such as changing returns to education or information flows, appear to play less of a role. We also inform distributional consequences for the US. Trade liberalization relatively induced increases in the shares of Chinese students studying non-STEM fields and attending less-selective US universities. Student inflows were similar in destinations with low and high levels of human capital, indicating that educational exports dampened regional inequalities. Our estimates suggest that recent trade wars could cost US universities around $1.15 bn in tuition revenue.

Keywords: Trade Liberalization, Migration, International Students, Services

JEL: F16, I25, J24, J61

Center for Global Development
www.cgdev.org

Working Paper 536
July 2020

Trade Liberalization and Chinese Students in US Higher Education

Gaurav Khanna
University of California – San Diego
gakhanna@ucsd.edu, econgaurav.com

Kevin Shih
Queens College CUNY
Kevin.Shih@qc.cuny.edu, kevinyshih.weebly.com

Ariel Weinberger
George Washington University
AWeinberger@gwu.edu, aweinberger.weebly.com

Mingzhi Xu
Peking University
mingzhixu@nsd.pku.edu.cn, mingzhixu.com

Miaojie Yu
Peking University
mjyu@ccer.pku.edu.cn, mjyu.ccer.pku.edu.cn

We thank Robert Feenstra for providing access to Chinese trade data from the Center for International Data at UC Davis. We thank Sen Zhou and the China Institute for Educational Finance Research at Peking University for providing access to the National College Entrance Examination data. We thank Francesca Antmann, Patricia Cortes, Gordon Hanson, Giovanni Peri and seminar participants at the Southern Economic Association, University of Glasgow Migration and Mobility Workshop, Barcelona GSE, Migration and Development Conference (Madrid), Queens College, UC Davis, and Peking University for comments.

Gaurav Khanna, Kevin Shih, Ariel Weinberger, Mingzhi Xu, Miaojie Yu, 2020. "Trade Liberalization and Chinese Students in US Higher Education." CGD Working Paper 536. Washington, DC: Center for Global Development. https://www.cgdev.org/publication/trade-liberalization-and-chinese-students-us-higher-education

Center for Global Development
2055 L Street NW
Washington, DC 20036

202.416.4000
(f) 202.416.4050

www.cgdev.org

1 Introduction

China's remarkable growth over the last two decades began with its entrance into the global economy as "the world's factory." That same growth has culminated in rising tensions with the United States, manifesting in an ongoing trade war with geopolitical tensions rising. In this paper we highlight a lesser known consequence of China's growth and integration into the world economy in relation to the US: the rise of services trade. We propose a new channel through which openness to trade leads to human capital accumulation and flows of individuals from developing countries (Clemens, 2014; Bazzi, 2017; Venables, 1999). We show that trade-driven growth raised wealth among upper-income families, shifting the composition of demand to US services, and higher education in particular. As such, a trade deficit in goods can cycle back as services exports in the developed country.

US higher education has been transformed by a marked increase in international enrollment since 2005, largely driven by students from China. Enrollment from China grew by 400% over this period (Figure 1), generating much needed revenue for universities often to the advantage of domestic students (Bound et al., 2020; Shih, 2017).[1] Concurrently, in the decade after 2005, China's gross domestic product (GDP) per capita quintupled, from $1,500 to more than $7,500.[2] Rapid economic growth in China not only increased the affordability of US higher education, but also expanded the size of college-ready high-school graduate cohorts. A major driver of this structural change was increased demand for Chinese commodity exports following China's accession to the World Trade Organization (WTO) in 2001 (Zhu, 2012). In this paper we demonstrate how this episode of trade liberalization was a crucial determinant of Chinese imports of higher education from the United States.

We exploit variation in trade liberalization stemming from the reduction in tariff uncertainty with the US during China's 2001 accession to the WTO. Previously, regular Congressional approval was required to maintain low Normal Trade Relations (NTR) tariff rates on Chinese imports, and failure to renew would result in a sudden jump to higher non-NTR rates. In 2001, the United States made NTR tariff rates permanent. Differences between NTR tariffs and non-NTR tariffs across products help measure the reduction in uncertainty when NTR rates were made permanent in 2001. Elimination of the uncertainty of sudden tariff spikes induced greater commerce between the United States and China, and export-driven growth in Chinese cities (Figure 2) (Pierce and Schott, 2016). We develop a city-level exposure measure that is the average gap between NTR and non-NTR rates across products, weighted by the composition of exports by product within cities prior to 2001. This allows

[1]However, tensions have now spilled over to education as well, as the US moved to expel Chinese students with ties to the Chinese military (US to Expel Chinese Graduate Students, NYT, 28 May, 2020).

[2]Source: World Bank OECD National Accounts.

us to compare student flows from cities that were more and less intensely affected by the conferral of permanent NTR rates (PNTR).

We find a significant and positive association between trade liberalization and student flows – an increase of 10 percentage points (p.p.) in PNTR exposure led to an increase in Chinese student enrollment in the US on the order of around 32 students per one million city residents. The implied total number of students flows due to trade liberalization alone accounted for a quarter of the total number of Chinese students who went to study in the US during this period. As such, the WTO accession induced substantial student flows, and not just internal migration as shown previously (Facchini et al., 2019).

Our analysis of service trade is possible due to a unique combination of data; we combine a new database of international student flows obtained from a Freedom of Information Act (FOIA) request to USCIS with detailed city-level Chinese exports derived from customs data, China's statistical yearbook, and Urban Household Surveys. Our results inform the consequences of the 2018 US-China trade war — a counterfactual exercise using our estimates indicates that the tariff increase of 20 p.p. in 2018 could cost US universities around 30,000 Chinese students in the next 10 years, a loss of \$1.15 billion in tuition revenue, or 8% of educational services exports to China.[3] This loss is likely an underestimate, as it does not account for broader effects on local economies surrounding universities.

Alongside increases in scale, we find changes in the composition of Chinese students. Large shares of Chinese students traditionally enrolled in Doctoral programs, which often have funding for students. Trade liberalization induced a shift towards undergraduate studies, which generally have little funding for foreign students who make full-sticker price tuition payments. Related analysis emphasizes this, showing that PNTR exposure dramatically increased the share of students who finance their education primarily through personal funds, rather than through scholarships or fellowships. These results indicate that there was rising wealth/income in highly affected cities. Given the large average cost of US tuition, about \$40,000 per year, we examine income channels relevant to the *top* of the income distribution, such as real estate appreciation and rental/own-business income growth.[4]

We demonstrate that trade liberalization increased global demand for Chinese manufactured goods and subsequently the wealth of city residents. PNTR exposure led to an increase in exports of 29% to 40% at the city level. Expanding wealth allowed families with means to finance the large cost of paying for housing and tuition in the United States. Given limited investment opportunities in China, a meaningful fraction of this wealth expansion occurred

[3] Institute for International Education (2019) estimates that there were more than one million international students in 2019 (a third of which were from China), and they contributed \$45 billion to the US economy.

[4] Consistent with the findings of inequality growth in China (Piketty, Yang and Zucman, 2019).

through housing ownership (Chen and Wen, 2017). We show that trade liberalization increased city-level housing prices and real estate income, contributing to related findings on city-level employment and investment growth (Potlogea, Cheng et al., 2017) and wage growth (Erten and Leight, 2020). Although wealth and income growth is a predominant mechanism behind our reduced-form effects, we explore and find a lesser role for other channels, such as changing returns to education, and increased information flows.

Our findings also speak to distributional impacts in US higher education, which informs a broader literature on the growing regional inequality in the United States. While Chinese students initially tended towards STEM (science, technology, engineering and mathematics) majors, trade liberalization induced large responses for those in social sciences and business-related majors. Additionally, trade liberalization increased the share of students in less selective universities. We also find that trade liberalization induced student flows in equal proportion to universities in areas of the United States with low and high levels of human capital. This carries implications for local labor markets, where public discourse has stressed the negative impacts of rising deficits in commodity imports from China. Unlike Bloom et al. (2019), where reallocation leads to regional inequality, increasing education exports has the potential to lift all regions, as universities expand nationwide. Given the recent increase in regional labor-market inequality, as high-paying skilled services expand in dense high-paying labor markets (Eckert, Ganapati and Walsh, 2019), an important conclusion from our findings is that the increase of educational services exports *dampens* this trend.

These empirical findings are robust to a variety of robustness and falsification tests suggested by the recent shift-share literature (Goldsmith-Pinkham, Sorkin and Swift, 2020; Borusyak, Hull and Jaravel, 2018; Jaeger, Ruist and Stuhler, 2018; Adao, Kolesar and Morales, 2019). We show an absence of differential pre-trends in economic and education outcomes across Chinese cities in the years preceding 2001. Our benchmark estimates are robust to the exclusion of large, coastal cities as well as industries with the highest Rotemberg weights, and correcting inference for correlation across cities in baseline industry shares. We also exploit alternative sources of exogenous variation in export growth: the expiration of the Multifiber Arrangement (MFA) quotas in 2005 and growth in world import demand (WID). The sizes and patterns of the estimates are remarkably similar, bolstering our confidence in the notion that trade liberalization helped expand the number of Chinese students studying in the United States.

This paper contributes to two strands of the trade literature: the importance of labor reallocation, and the role of demand in driving trade patterns. Prior research documents the detrimental impacts of Chinese trade on US manufacturing (Autor, Dorn and Hanson, 2013; Pierce and Schott, 2016).[5] Although the United States experienced substantial import competition in physical goods, less is known about trade in services, which has grown to account for over a third of US trade activity (Eaton and Kortum, 2018). We elucidate the welfare consequences of trade by exploiting detailed data on trade in *educational services*, containing the universe of international students in the United States by city of origin, degree, university, field of study, level of program, and detailed information on financial support. We show that trade-driven income growth in China generated strong demand for a particular US service: higher education. We complement recent studies by Wang et al. (2018), Bloom et al. (2019), and Caliendo, Dvorkin and Parro (2019), which emphasize that trade with China raised employment in non-manufacturing industries. We add to these existing channels on changes in relative production costs, by showing that trade dynamics increased the *demand* for services as a result of greater wealth abroad. There is scant evidence on how income affects demand and ultimately trade patterns (Dingel, 2016; Fajgelbaum, Grossman and Helpman, 2011). In our case, the US exports in high-quality education and income growth in China shifts its import demand towards this service. As such, our findings indicate that a trade deficit in goods cycled back into the US as a trade surplus in educational services.

We speak to the migration literature by relating to two strands of studies that explain an inverted-U shaped relationship between migration and development (Clemens, 2014). The first strand highlights how better prospects at home may result in *out*-migration, as income gains are used to overcome migration-cost barriers.[6] Canonical models suggest that although greater income allows individuals the ability to afford migration costs, it also raises the opportunity cost of emigrating (Angelucci, 2015; Bazzi, 2017). These migration costs are quantifiable for international students as standard tuition and living expenses at US higher education institutions. Furthermore, many international students view study in the US as a pathway to join the US labor market, and so better income opportunities at home may lower the option value of a US degree (Bound et al., 2015; Shih, 2016). As such, it is unclear whether economic growth at home, induced by trade liberalization, would lead to more out-migration. We resolve this ambiguity, by showing that income/wealth generation, attributable to trade liberalization, encouraged student flows to the United States.[7]

[5] Studies have also found (relative) declines in income in localities exposed to import competition in India (Topalova, 2010), Brazil (Dix-Carneiro, 2014), and Denmark (Hummels et al., 2014).

[6] While student flows are distinct from work-related migration, they are closely intertwined. Students also consider costs (travel, tuition and board, being away from family, etc.) in manners similar to the migration costs borne by economic migrants. They also are considerate of relative returns to studying abroad, especially as a large fraction of students go abroad with the aim of joining the US labor market (Bound et al., 2015; Amuedo-Dorantes, Furtado and Xu, 2019; Rosenzweig, 2006). As such, we sometimes use the term student "migrants" to capture the flows of international students from abroad.

[7] We study Chinese prefecture-level cities. In the exposition we use cities and prefectures interchangeably.

The second strand of studies offer theoretical justifications for whether migration and trade are substitutes or complements. Although the standard Heckscher-Ohlin model predicts that trade is a substitute for migration, extensions to this model can result in a complementary relationship (Venables, 1999).[8] There is scant evidence in this regard, although studies mostly reject substitutability (Collins, O'Rourke and Williamson, 1997). Our paper provides an unexplored channel for trade and migration as complements.

Our findings inform related studies on trade and education. Li (2018) finds that export expansion reduces educational attainment within China given its comparative advantage in low-skill sectors, while Liu (2017) finds that high-school completion increases in cities facing larger tariff reductions. Atkin (2016) finds that an expansion in low-skilled manufacturing jobs in Mexico raises high school dropouts. We corroborate that the rise in international student flows does not appear to be driven by higher returns to education.

The remainder of the paper is structured as follows. Section 2 describes China's accession to the WTO, and section 3 discusses the motivation for how income growth from trade liberalization might lead to student emigration. Section 4 describes the empirical strategy and tests our identification assumptions. Section 5 presents the main results and their implications, and section 6 tests possible mechanisms. Section 7 concludes the paper.

2 China's Accession to the WTO

On December 11, 2001 China joined the WTO. An important facet of this policy change was that it converted the uncertain Most Favored Nation (MFN) tariff regime to a PNTR tariff regime. Since 1980, the United States has granted low MFN tariffs to Chinese products; however, this required annual Congressional renewal, as China did not have MFN status.[9] This situation generated uncertainty over the longevity of the low-tariff regime, which inhibited further expansion of trade and commerce between the United States and China (Pierce and Schott, 2016; Handley and Limão, 2017). Termination of MFN status would have increased tariffs faced by US importers by more than eight-fold, from an average tariff of 4% (under MFN status) to 35% (Facchini et al., 2019), and would have affected over 95% of US imports from China (Pregelj, 2001), with the possibility of further retaliation.

Conversion to the NTR regime made the low MFN tariffs permanent and no longer required Congressional renewal. The conferral of the PNTR tariff regime did not change actual tariffs, but altered the uncertainty that Chinese exporters and US importers faced. This reduction in uncertainty had substantial impacts on trade. Within one year of receiving

[8] With factor price equalization (FPE), the incentives to migrate are reduced. However, if FPE does not hold, for example with fixed factors, the result is reversed.

[9] One exception was in 1998, when Congress extended MFN status for a three-year duration, expiring in 2001. For an in-depth discussion of the history of China's MFN status, see Pregelj (2001).

PNTR, China's exports to the US grew by 57%, and within the first five years, they grew by 177%.[10] Although NTR tariffs applied only to trade with the United States, this accounts for a meaningful one-fifth of all Chinese exports (Potlogea, Cheng et al., 2017).

We derive plausibly-exogenous variation in exposure to the conferral of PNTR across Chinese cities. We utilize the potential spike in tariffs under loss of MFN status – the gap between NTR and non-NTR tariff rates (henceforth, NTR gap) – as a proxy for the size of the policy treatment. We measure the intensity of PNTR across cities by examining the composition of export activity across industries within each city in 1997, prior to the policy change. For each city, we measure its exposure to PNTR by calculating the sum of the NTR gaps across industries, weighted by the city's industry export shares.

The conferral of PNTR had major impacts on structural transformation and internal migration in China (Facchini et al., 2019). Hence, comparisons across Chinese cities must address issues of changing composition due to internal migration. However, an advantage of examining student emigration is that the reported city of origin is unlikely to be impacted by rural-urban worker migration. The *hukou* system ties access to schooling to the individual's city of birth, making it difficult for families to migrate for work with their children.

Importantly, conferral of PNTR was unlikely to have been predicted or known in advance. Previous work describes the debates around China's accession to the WTO as being far from one-sided, as Congressional threats to allow MFN status to expire were credible (Pierce and Schott, 2016). We provide formal checks of this identifying assumption, and show that city-level PNTR exposure was uncorrelated with economic factors in the years preceding 2001. Chinese cities experiencing strong export growth, high economic activity, or growth in their education sector prior to 2001 did not experience differential intensity of treatment.

3 Why Exports Affect Student Migration

Our empirical framework estimates reduced-form effects of PNTR exposure on Chinese student migration to the US for higher education. In this section, we delineate and elucidate possible mechanisms underlying this relationship, and we use this framework to inform our empirical investigation of the mechanisms in section 6. While other work highlights complementarities between trade and migration (Venables, 1999), we introduce a new channel via which trade-induced income dynamics generate demand for certain types of services (like higher education), driving the flow of individuals across country-borders.

Consistent with the recent trade literature, we view PNTR as a trade liberalization shock, which led to the proliferation of exports of Chinese manufactured goods. In turn, this

[10] Statistics calculated based on US imports from China reported in December from the Census Bureau. See https://www.census.gov/foreign-trade/balance/c5700.html.

contributed to the structural transformation of China's economy, giving rise to manufacturing and generating substantial economic growth (e.g., Erten and Leight, 2020; Brandt et al., 2017; Manova and Zhang, 2012; Khandelwal, Schott and Wei, 2013; Potlogea, Cheng et al., 2017). Similar to the development and migration literature, economic growth may have opposing impacts on student out-migration, such that the net effect is ambiguous (e.g., Clemens, 2014; Angelucci, 2015; Bazzi, 2017). We explore three channels through which export-driven economic development operates: (1) income/wealth generation, (2) changing returns to education and (3) increased information.

First, trade liberalization that creates increased demand for Chinese manufactured products may generate income and wealth. Wealth relaxes financial constraints, increasing the number of households that can afford the cost of US higher education – roughly $40,000 per year for tuition and board during this period. We formalize a simple theoretical framework in Appendix B, which demonstrates this to be the case when education is considered an investment good. If education is an investment, then financially constrained households will respond to income shocks by funding their education (in this case, their education abroad).[11] This conforms with Sun and Yannelis (2016), who causally link credit constraints and the demand for college education. Our model shows that the difference in prices (home versus foreign tuition) determine the magnitude of the educational response to income shocks.

When education is considered a consumption good, increases in income/wealth will reallocate expenditures toward less essential services, like education, when preferences are non-homothetic (Linder, 1961; Matsuyama, 1992). If the income elasticity of demand for educational services exceeds one (as is estimated for services in Comin, Lashkari and Mestieri (2019)), then growth in income increases the expenditure share on education. Although the growth literature focuses on structural change due to sectoral differences in income elasticities, in an open economy the demand for educational services can be met by imports (e.g., sending students overseas) instead of labor reallocation. As a further check for the prominence of income and wealth as a mechanism for the rise in education spending, we explore the evolution of the services expenditure share in liberalization-exposed cities.

What are the sources of income/wealth growth attributable to trade liberalization? As Bound et al. (2020) discuss, almost all the educational expenditures for international students from China are from families, rather than via scholarships or loans. Prior literature has

[11] In our framework, households choose where to get their education, at home in China or abroad. They also choose how much to borrow from the future $\bar{b}$. In maximizing their two-period utility, they take into account their wealth, the price of education at home, the price abroad, and how much they can borrow b from period 2. With household first-order conditions, one can show that the decision to go abroad depends on the relative prices of schooling abroad and domestically, and for households reaching the binding constraint $b = \bar{b}$, schooling responds to income shocks. For non-constrained households, the education decision does not depend on wealth.

linked PNTR exposure to increased wage income at the county level in China (Erten and Leight, 2020) and greater employment and investment growth (Potlogea, Cheng et al., 2017). Different from prior literature, we explore possible growth in real estate income and wealth in cities highly exposed to PNTR, as a result of tremendous in-migration of rural workers to fill manufacturing demand (Facchini et al., 2019; Tombe and Zhu, 2019). Recent literature has documented the importance of the real estate sector to China's economy, where, without a developed financial sector, investment growth and capital gains mainly derive from the housing market (Liu and Xiong, 2018; Chen et al., 2017).[12]

Different from income/wealth generation, trade liberalization may have impacted the returns to education by altering the relative demand for particular skills. Changes in the returns to education may either increase or decrease educational investments for migrants (McKenzie and Rapoport, 2011; de Brauw and Giles, 2015; Kuka, Shenhav and Shih, 2020). Growth in the relative demand for unskilled labor might encourage college-ready cohorts to work immediately and forego higher education. Greater outmigration of students would occur if trade shocks raised the return to a US degree in the Chinese labor market.[13] Alternatively, this could occur if the returns to college rise alongside an inelastic supply of higher education within China.[14] We empirically assess returns to education in section 6, by examining whether PNTR created differential benefits to skill-intensive relative to non-skill-intensive industries. We also examine capacity limits at top universities in China.

Finally, China's integration with the US economy and its supply chains may have fostered information flows. Existing literature has highlighted the interlinkages between migration and trade networks (Bahar and Rapoport, 2018; Parsons and Vézina, 2018). US universities could become more visible and information on opportunities and admissions procedures clearer to potential Chinese students. We empirically explore this channel in section 6, by exploring the role of city-level export growth with *non*-US destinations, where commerce brings relatively less information about US higher education opportunities.

Several "countrywide" factors likely impacted the enrollment of Chinese students in US universities (e.g. appreciation of the yuan and US immigration policy). In the next section, we describe our empirical approach, and emphasize that it captures *relative* changes in out-migration across Chinese cities based on their exposure to trade shocks. As such, comparing within-city changes abstracts from national shocks that equivalently affect all cities.

[12] As of 2016, property-related loans made up 25% of banking assets.

[13] There is an additional channel when studying student migration, which is that many students attempt to stay in the host country after their studies. This should be attenuated by economic growth as economic opportunities increase in the origin country.

[14] In the model in Appendix B, this represents an increase in the relative price of domestic universities.

4 Empirical Strategy and Data

Although PNTR tariffs were conferred to China as a whole, the impact varied substantially across industries and regions. Our primary empirical framework leverages the differential policy impact across Chinese cities based on their pre-2001 industrial activity. PNTR provided larger benefits to some industries, so that cities with existing economic activity in those industries stood to gain much more than cities whose economic activity was concentrated in other industries. We develop a city-level measure of exposure to PNTR, and then link this to student migration to the United States.

4.1 Establishing the Baseline Empirical Specification

We examine the relationship between city PNTR exposure and student emigration to US universities, using the following general specification:

$$\Delta S_c = \gamma PNTR_c + \delta Z_c + \epsilon_c \tag{1}$$

Our primary outcome variable measures growth in the number of students S from city c that matriculate at US institutions. The granularity of our data allows us to examine heterogeneity by level of study, institution attended, amount of funding, and major field of study. The explanatory variable of interest is a city-level measure of exposure to trade uncertainty, $PNTR_c$. We include city-level controls (Z_c) that may affect trade flows and general access to foreign markets. We first describe the construction of each variable along with the data sources, and then clarify our identifying assumptions.

4.1.1 Growth in the Number of Chinese Students, ΔS_c

We obtain data on Chinese students through a Freedom of Information Act (FOIA) request from the Student Exchange and Visitors Information System (SEVIS), maintained by the United States Citizenship and Immigration Services (USCIS). The data contain records for every foreign student visa by year of matriculation from 2004 to 2013. The information includes the student's city of origin, gender, university, level of study/program type, major field of study, start and end dates, and amount of financial support by source.

We aggregate the individual-level data to obtain total students by year of entry and city of origin, and also group subtotals by program/funding characteristics. For each city we then calculate the change in the number of students in 2013 relative to 2004. As cities differ greatly in size, we standardize these changes by the 2004 city population of residents with non-agricultural hukou status, from the China City Statistics Yearbook.[15] As city population

[15] We use the non-agricultural population (i.e., the urban population) for two reasons. First, this ensures consistency with the evaluation of mechanisms, where we use household-level data from the Urban Household

is measured in thousands of persons, our dependent variable measures the change in the number of Chinese students per 1,000 city residents.

4.1.2 City-Level PNTR Exposure, $PNTR_c$

City-level differences in PNTR exposure are captured by the industrial structure of the city in 1997. We begin by defining a measure of the size of the PNTR policy treatment for each 4-digit International Standard Industrial Classification (ISIC) industry i, as the gap between NTR and non-NTR tariff rates in 1999, using data from Pierce and Schott (2016).[16] Specifically, we define the NTR gap as:

$$NTRGap_i = NonNTRRate_i - NTRRate_i \tag{2}$$

NTR gaps have no time variation as they only depend on the non-NTR rates (i.e., set under the Smoot-Hawley 1930 Tariff Act) and NTR rates that apply to all WTO trade partners.

Figure 3a illustrates industry-level variation in NTR tariffs (blue) and non-NTR tariffs (red), for each 4-digit ISIC product. Some products had a substantial difference between NTR and non-NTR rates. For instance, recorded media faced non-NTR tariffs of nearly 60% compared with an NTR tariff of a 2%. Hence, PNTR eliminated the risk that recorded media exporters might suddenly see tariffs spike by 58 p.p. In contrast, PNTR had less of an effect on tobacco, which had equivalently high non-NTR tariffs but also relatively high NTR rates. Tobacco-producing cities were less impacted by PNTR. NTR gaps are shown in Figure A.2, which reveals substantial variation, with some industries facing almost no gap and others having a gap upward of 60%. The mean NTR gap across all industries is 30%.

We measure each city's exposure by summing these industry-level NTR gaps, weighted by each city's existing activity in each industry as follows:

$$PNTR_c = \sum_i \left(\beta_{ci} \times NTRGap_i\right), \quad \beta_{ci} = \frac{X_{ci}^{1997}}{\sum_j X_{cj}^{1997}}\ , \tag{3}$$

To capture existing industrial activity we measure each industry's share of total city exports,

Surveys of the National Bureau of Statistics of China. Second, using the total city population, which includes the population in agricultural residency status and migrant workers population, may increase the measurement error in the standardized student enrollment. Households in agricultural residency status and migrant workers have more difficulty in finding regular jobs in cities, compared with households in non-agricultural residency status. Instead, the two population groups are found to participate mostly in informal labor markets where the working conditions comprise long hours, low pay, and little or no social protection. Therefore, they are less relevant to the discussion of studying abroad. Nonetheless, we present results where we use the total city population in the denominator as a robustness check of our main results.

[16]Following Pierce and Schott (2016), we also aggregate and concord 8-digit Harmonized System tariff rates to our preferred level of aggregation at the 4 digit ISIC industry level.

prior to the conferral of PNTR, using data on exports by industry and city from the China Customs Database, which were harmonized and generously provided by the University of California, Davis, Center for International Data (Feenstra et al., 2018).[17] We use 1997 as the base year, as it is the earliest year available in the data. Industry export shares are calculated by dividing exports of industry i from city c (X_{ci}^{1997}) by total exports from city c ($\sum_j X_{cj}^{1997}$).[18] Cities with large export shares in high NTR gap industries have both substantial economic activity and exports of knowledge/infrastructure, which allowed them to capitalize immediately following China's WTO accession. In a robustness check, we construct an alternative exposure measure that uses city-level employment shares by industry in 1990, calculated using data from the Annual Survey of Industrial Production (ASIP) of the National Bureau of Statistics (NBS) of China.[19]

As our measure of PNTR exposure is a weighted average of NTR gaps, it is informative about the average reduction in uncertainty or expected tariffs facing each city. We illustrate the variation in our PNTR exposure measure across cities in Figure 3b, with capital cities labeled for reference. The weighted average NTR gap ranges between 0 and 53 p.p., with the average city facing a 31 p.p. difference between NTR and non-NTR tariffs.[20]

4.1.3 City-Level Control Variables, Z_c

We control for city-specific characteristics that might be correlated with the city's exposure to PNTR and number of students migrating to US universities. First, the quality of contract enforcement has been shown to increase comparative advantage and exports from industries requiring relationship-specific investment (Nunn, 2007). Such industries, in turn, often utilize high-tech and skill-intensive labor. We construct city-level controls for contract intensity that account for initial city comparative advantage affecting exports and produc-

[17]We utilize information on the quantity and value of exports classified by the Harmonized System for all international transactions from China. Exports are categorized by the destination country and city of origin. The 4-digit city codes provided in the customs data identify a level of geography more disaggregated than the standard prefecture cities in China. Hence, we aggregate city codes in the customs data up to the prefecture level, based on the reported city name. In some regions of China, the exporting location is unspecified in a category called "other". In the end, the original 479 city codes in the customs data are aggregated to 275 prefecture cities including four municipalities.

[18]Exports do not include those categorized as process and assembly nor process with imported materials.

[19]ASIP surveys all types of firms (state-owned / non-state owned) whose revenue is more than five million RMB each year in the manufacturing sector. ASIP provides employment at the firm level, which we aggregate to obtain total employment at the city-industry level. Notably, the ASIP industry classification uses the China Standard Industrial Classification (GB/T4754-1994 and GB/T4754-2002) at the 4-digit level. To be consistent with the tariff and trade data, we concord the China Standard Industrial Classification to ISIC Revision 3 at the 4-digit level, using the crosswalk provided by the NBS of China.

[20]However, there is substantial variation across cities. Cities whose industries would benefit from PNTR include near-coastal cities in the southeast, such as Shanghai, Nanjing, and Jinan, but also several prefectures in the northeast, central, and even western regions. Cities in the west (Tibet), northeast, south (Yunnan province), and even some coastal cities saw very little exposure to PNTR.

tivity in skill-intensive industries, and possibly growth in demand for higher education. Data on contract intensity by industry are from Nunn (2007).[21] We take a weighted average of industry contract intensity measures, using initial city export shares in 1997 as weights.

Second, prior to China's accession to the WTO, Chinese firms required licenses to export directly, with less than half of all firms reported having export licenses in 2000. Bai, Krishna and Ma (2017) show that the ability to export directly had large impacts on productivity growth. We use data on the fraction of export revenues in total exports within an industry that is licensed to export directly. The time-varying industry data are provided by Bai, Krishna and Ma (2017), and we use only 2000 data to control for the exposure of prefectures to liberalization, as China phased out these licenses through 2004. We then use our 1997 export shares to create a weighted sum of the share of industry revenues with direct export licenses. This control helps account for cities' differential initial access to foreign markets, and the potential persistent impacts of initial access on later city-level outcomes.

Finally, we control for other aspects of the initial industrial structure of the city with initial tariff rates imposed by China. Tariffs on imported inputs and final goods have been shown to affect the productivity of Chinese firms (Yu, 2015). Import tariffs are applied tariff rates by China in 2000, averaged across origins, which we source from the World Integrated Trade Solution–Trade Analysis and Information System. We also construct input tariffs using the 2002 input output table for China, combined with output tariffs during that year.[22] In all these cases, we map the industry data to the prefecture-level using the same 1997 export shares to create a weighted sum of import and input tariffs.

4.1.4 Sample Summary

The resulting sample allows reliably tracking of 275 Chinese prefecture cities over time (see Figure 3b), for which we can measure their exposure to PNTR and growth in the number of students going to the United States over 2004-13. Although there are 343 cities in China, our sample comprises over 90% of employment and population, and over 80% of all export activity. As such, our sample cities are broadly representative of the Chinese economy.[23]

Table 1 shows summary statistics for our sample in 2004 and 2013. Between 2004 and 2013, the cities experienced sharp growth in economic activity. The cities experienced more modest growth in population. In contrast, the average number of Chinese students studying

[21] Contract intensity is measured by the proportion of intermediate inputs employed by a firm that require relationship-specific investments by the supplier. This measure is time-invariant and varies by 3-digit ISIC Revision 2 industries, which we concord to 4-digit ISIC Revision 3 industries.

[22] The input-output table is available for 120 industry groups ("scode" classification), of which 70 are manufacturing industries.

[23] We capture all tier 1 cities (e.g. Beijing, Shanghai, Chongqing, Nanjing, and others.) and tier 2 cities (e.g. Xiamen, Kunming, Harbin, and others.). Most of the cities missing in our analysis are those in western China, Tibet and Xinjiang, which have more rural populations and lower economic activity.

abroad in the United States increased by over ten-fold. Although all levels of higher education saw growth over this decade, students pursuing associate and bachelor's degrees stand out with substantial growth. Furthermore, 63% of matriculating students in 2004 pursued STEM degrees, but that share fell to 35% in 2013. The declining share of STEM students was offset by increases in social sciences and arts and humanities. Interestingly, the composition of students by university selectivity, grouped into quartiles by admissions rates, remained roughly similar, with some increase in the share of students in the least selective (tier 4) universities. Notably, the fraction of students that received scholarship funding decreased from 62% to 22%.

4.2 Validating Identifying Assumptions

The validity of our design depends on whether the cities' exposure to PNTR was exogenous to other determinants of student emigration. We examine whether cities whose industries saw large reductions in expected tariffs, on average, had different educational capacity or trends in student enrollment. As the SEVIS data only begin in 2004, we cannot assess pre-trends in student emigration. Hence, we utilize data from the City Statistical Yearbook that provide alternative measures of educational activity within each city prior to 2001. Specifically, we focus on the number of students attending college domestically, the number of domestic colleges, the number of domestic students attending secondary/middle schools, and the number of secondary/middle schools.[24]

Figure 4 shows the relationship between PNTR exposure and educational growth within cities prior to PNTR. Cities that had very low levels of PNTR exposure do not appear different from those with high levels of PNTR exposure in their educational trajectories in the years preceding PNTR.

We formally quantify and test these relationships by estimating specification (1) and replacing the dependent variable with our pre-trend measures of education: (1) growth in the number of postsecondary institutions, (2) growth in domestic college enrollment, (3) growth in the number of secondary schools, and (4) growth in secondary enrollment. Growth is measured in log changes using available data on cities from 1997 to 2000, the period just prior to PNTR conferral.

In Table 2, columns (1) to (4) show the results of this exercise. Panel A shows results without controls. We report results with the full set of controls in panel B. This is our preferred specification. The results show no substantial or statistically significant correlation between the educational trajectory within cities prior to PNTR, and cities' PNTR exposure.

[24] Secondary education and schools are often referred to as "middle" schools in China, and they cover the equivalent of high schools and junior high schools in the United States.

Hence, any effects on student emigration are unlikely to be explained by differences between cities with high and low exposure in terms of educational pre-trends.

We also examine two other features of our PNTR measure. First, we assess whether PNTR exposure differed on the basis of pre-trends in exports. This helps test whether the policy was exogenous across cities, and also whether the enactment of the policy itself might have been driven by cities with the most to gain. Second, we examine whether PNTR exposure had an effect on exports after the policy was enacted. This provides a first-stage sanity check that the policy reduced uncertainty and increased exports.

Figure 4 along with Table 2, column (5), show the relationship between PNTR exposure and the log change in exports from 1997 to 2000. PNTR exposure is not correlated with city-level export growth in the pre-period, and hence the policy did not benefit particular cities on the basis of their existing trade volume. However, as Figure 5 and Table 2 column (6), show, the policy had a substantial impact on exports following its enactment. Moving from a city at the 25th percentile in PNTR exposure relative to one at the 75th percentile (roughly 10 p.p.) increased exports by 29-40 p.p. As such, the intensity of PNTR appeared to be exogenously distributed across cities with respect to their initial characteristics, and PNTR had a substantial impact on export growth following its enactment.

5 Results

5.1 Student Flows to US Universities

We now examine whether student migration is associated with greater exposure to PNTR. Figure 5 plots each city's PNTR exposure against growth in exports (the first stage), and growth in the number of students studying in the US from 2004 to 2013 as a share of their 2004 population. Cities whose existing composition of industries would face reductions in tariffs experienced greater increases in student emigration.

We estimate our benchmark equation (1) in Table 3. Column (1) excludes controls and shows that greater PNTR exposure is positively and significantly associated with student emigration. Since we focus on long differences in student migration, the effects of time-invariant city characteristics and time-varying national-level trends are accounted for in the estimation. The only remaining threats to identification are initial city-level factors that correlate with PNTR exposure and have persistent, long-term impacts on student migration.

To that end, we assess the sensitivity of our results by gradually including various control variables that measure initial city-level factors that determine future access to foreign markets. In Table 3, column (2) adds the control for initial contract intensity. Column (3) further adds the control for initial import tariffs. Column (4) includes the control for input tariffs. Finally, column (5) fully saturates the model, including the control for the initial share of revenue in export licenses.

Across all specifications, the effect of PNTR exposure remains stable, and positive and statistically significant at the 99% level. Coefficient stability to controls lowers the likelihood that confounding omitted variables are biasing our estimates (Altonji, Elder and Taber, 2005). Our preferred estimates come from the model with the full set of controls in column (5), which indicates that moving from a city at the 25th percentile to a city at the 75th percentile – roughly a 11.4 p.p. increase in PNTR exposure – increased student emigration to the United States by 37 per one million city residents. Since the average growth across cities was 138 per one million city residents, the magnitude is about 23% of the mean.

The magnitude of the effect of PNTR exposure can be put into perspective by comparing it with secular trends in Chinese students going to the United States. The period 2004-13 saw 170,000 more Chinese students at US institutions relative to 2003. In our specification, the average treatment across all cities is 0.316, which implies that for the average city, 102 students per one million residents went abroad ($0.324 \times 0.316 \times 1000$) as a response to the liberalization. Given the 411 million persons in the non-agricultural population, the elimination of the NTR gap was responsible for a total emigration of 42,080 students to the United States. As such, the trade shock alone explains 25% of the total increase in Chinese international students during this period.

While our primary results focus on growth over the decade between 2004 and 2013, we also split this period into three sub-periods. In Appendix Table A.2 we analyze short-term growth between 2004 and 2007, medium-term growth between 2008 and 2010 (also the Great Recession period), and longer-term growth between 2011 and 2013. The results show positive and significant effects on student out-migration in all periods. However, the effect size grows each period – that is, the influence of PNTR exposure grows over time. This result is consistent with our exploration of wealth/income growth as a mechanism in section 6, which did not happen overnight, and took time for households to accumulate.

5.2 Robustness of PNTR Exposure

To ensure that our strategy of using China's accession to the WTO in 2001, and conferral of permanent NTR tariffs, identifies exogenous growth in exports, we provide a variety of sensitivity checks. We begin with sample refinements to ensure that particularly large or influential cities are not driving the results.

In Table 4, columns (2) and (3), we impose further sample restrictions to assess whether the estimates are not driven by highly influential cities or outliers. In column (2) we remove the four cities under the direct administration of the central government – Beijing, Shanghai, Chongqing, and Tianjin.[25] Column (3) removes capitals and coastal cities, to assess whether the effects are driven by places with political lobbying power or especially strong access to foreign markets. In column (4), we include region fixed effects. The effect decreases in this case due to the loss in variation – there are now only about 45 cities per region – but remains significant. The last column varies the outcome slightly: we compute the change in the number of students normalized by total population of the city including its rural areas. Although the coefficient drops by half, "*per one million population*" in this case refers to a much larger population, about three times larger.

5.3 Sensitivity of the Shift-Share Approach

Our measure of PNTR exposure falls under a broader class of variables that measure local exposure to national policy treatments, often referred to as Bartik or Shift-share instruments. We further examine the strength of our measure of PNTR exposure in light of recent work clarifying identification challenges with Bartik instruments (Goldsmith-Pinkham, Sorkin and Swift, 2020; Borusyak, Hull and Jaravel, 2018; Jaeger, Ruist and Stuhler, 2018; Adao, Kolesar and Morales, 2019). While industry-specific NTR gaps measure the intensity of treatment, the city-level export shares help in appropriately weighting treatment intensity as a better reflection of city-level exposure. We use export shares in 1997, predating PNTR by four years. Goldsmith-Pinkham, Sorkin and Swift (2020) clarify that the lagged shares provide a crucial source of identifying variation, and causality hinges on the exogeneity of the lagged shares. Borusyak, Hull and Jaravel (2018) suggest that what we need are "exogenous" shifters, in this case the NTR gaps. Jaeger, Ruist and Stuhler (2018) propose that we would ideally have a structural break rather than relying on secular trends – in this context, joining the WTO is the break we exploit. Adao, Kolesar and Morales (2019) document a procedure to correct the standard errors for the correlation across cities with similar industrial shares.

We provide several tests that support our research design. A first concern pertains to whether past shocks persist over time such that they continued to impact outcomes during the period under study. If lagged shares are correlated with unobserved determinants of future student emigration, the shift-share approach will be invalid (Goldsmith-Pinkham, Sorkin and

[25] The administrative units are currently based on a three-level system in China. The country is first divided into provincial units, including provinces (e.g., Jiangsu Province), autonomous regions (e.g., Tibet), and municipalities directly under the central government (e.g., Beijing, Shanghai, Chongqing, and Tianjin). Prefecture-level divisions are the second level of the administrative structure, and most provincial units except municipalities are divided into only prefecture-level cities without any other units. Notably, large prefectures are subdivided into (autonomous) counties and county-level cities. Finally, townships or towns are the third level of the administrative structure. In this paper, the unit of analysis is the municipal city (i.e., municipality) and prefecture city. For details, see http://xzqh.mca.gov.cn/statistics/2018.html. As government policies can favor municipalities more than other prefecture cities (Wang (2013)), we exclude the four municipalities for robustness.

Swift, 2020). For example, Jaeger, Ruist and Stuhler (2018) demonstrate that the short-run wage impacts of concurrent immigration inflows using shift-share instruments may be confounded by variation in wages arising from continued adjustment to past immigration shocks. We note that the lack of correlation between our measure of PNTR exposure and city-level pre-trends in education or exports helps assuage these concerns, as endogenous past shocks would likely have an apparent impact on past outcomes.

As another robustness check, we lag the initial shares even further, to reduce the scope for persistent shocks to affect later outcomes. We construct a similar measure of PNTR exposure using city-level *employment* by industry in 1990.[26] Specifically, for each city, we interact the share of employment in each industry with the industry-specific NTR gaps, and sum over all industries, as in equation (3). The second row in Table 5 shows the results when using this alternative PNTR exposure measure. The estimated effect is similarly positive and significant at the 1% level. While the coefficient appears over twice as large as our main effect (reported again in the first row), the magnitudes are nearly identical, as the variation in PNTR exposure using 1990 employment shares is on a smaller scale. Moving from a city at the 25th percentile to the 75th percentile – roughly 5.7 p.p. for the 1990-weighted PNTR exposure – increases student emigration by 42 per one million city residents.

We implement a second check, introduced by Goldsmith-Pinkham, Sorkin and Swift (2020), that examines the weights that different initial shares play in the estimation. We use our initial PNTR exposure measure, which relies on export shares, and calculate Rotemberg weights for each industry's export share.[27] Appendix Table D.4 shows the top 30 industry weights. As a robustness check, we remove the top five industries from our PNTR exposure measure and rerun the analysis. The results of this check, shown in the third row in Table 5, are similar to our main findings. Finally, in column (6), we report standard errors using an adjustment outlined by Adao, Kolesar and Morales (2019), which accounts for the correlation across cities in industrial shares, and find that our results are still precisely estimated.

5.4 Alternative Instruments

We complement our main analysis with two additional sources of variation that do not rely on the PNTR policy.[28] First, following Autor, Dorn and Hanson (2013), we use world-import demand shocks by industry, excluding the United States, and weight these by initial export shares to create a city exposure measure. Second, we use the expiration of textile quotas

[26] The earliest we can get data on city-level exports by industry is 1997, at least using current city codes (severely limited data are available for earlier periods).

[27] Shift-share instruments may be decomposed into weighted combinations of just-identified estimates, each using a single baseline share as an instrument. The weights on these individual instruments are called Rotemberg weights, and capture how important each baseline share is in the overall identifying variation.

[28] Details of the construction are described in Appendix C.

under the MFA, as in Khandelwal, Schott and Wei (2013). Our measure of city exposure to MFA quotas uses the Brambilla, Khandelwal and Schott (2010) data to assign each ISIC industry an exposure measure, based on the quota "fill rate" in 2001, and we aggregate to the city level by weighting industries using 1997 exports by city and industry. Our MFA instrument is thus a city-level weighted average of quota reductions (gradually implemented through 2005), which captures the importance of textiles and garment industries in the city.[29]

The results using city exposure to world import demand and MFA quota reductions are shown in Table 5, columns (4) and (5). These estimates also show a positive and significant association with student emigration. In magnitudes, they also imply very similar changes in student emigration per million residents as our preferred PNTR exposure measure. These results help corroborate the idea that positive export demand shocks for manufactured goods within cities led to growth in student emigration.

5.5 Migration Elasticities by Type and Compositional Changes

In Table 6, we estimate migration elasticities by student characteristics, and examine how the composition of students changed in response to trade shocks. In particular, we study how the migration response differed by the level and field of study, sources and amounts of funding, and quality of US institution attended. These differences in elasticities determine changes in student composition attributable to the trade shock and are indicative of the mechanisms that we examine in section 6. For instance, full fee-paying undergraduate students are more responsive to PNTR shocks than subsidized doctoral students, suggesting that income changes are a likely mechanism underlying our main results.

We estimate specification (1), altering the dependent variable to reflect enrollment growth by academic level. The results for undergraduate, master's, doctoral, and other students are shown in Table 6, panel A, columns (2) to (5). We report our main estimates again in column (1). The subsequent columns reflect how total growth is distributed across academic levels.

The coefficient estimates show that all levels, except doctoral programs, saw significant positive growth in the number of Chinese students. In Table 6, in the second row in panel A, we report the effect for each academic level as a proportion of the total effect, by dividing the coefficients for each academic level by the coefficient for total students (column 1). It appears that the overall growth in students was driven by bachelor's and master's students – nearly 50% and 30% of the total inflow associated with PNTR exposure, respectively. These programs are more likely to be self-funded compared with doctoral programs.

To understand the changes in student composition attributable to trade shocks, we com-

[29] The MFA instrument and PNTR exposure measure are correlated (0.68), which suggests that textiles and garments faced large uncertainty from tariffs. However, there is much independent variation from the MFA instrument that can be leveraged.

pare the proportions of students in 2004, reported in Table 6, row 3, with the proportion of the effect for each academic level, in row 2. For ease, we also provide the difference in these proportions in row 4.[30] Although only 7% of Chinese students entering in 2004 matriculated in bachelor's degree-granting programs, 47% of the inflow generated by PNTR exposure occurred at the bachelor's level, an increase of 40 p.p. In contrast, doctoral students initially accounted for nearly half of all students matriculating in 2004. Given that there was no statistically significant increase in doctoral students associated with PNTR exposure, the change in proportion attributable to trade is dramatic. While master's students also saw sizable inflows, these were in line with previous proportions, as was the inflow for associate degree students. Finally, there is also a slight trade-induced compositional shift toward students in other academic levels, which mainly include non-degree-granting programs.

In Table 6, panel B, we focus on major field of study, separately assessing changes in the number of students in STEM, arts and humanities, and social sciences in columns 2, 3, and 4, respectively. As business comprises a large fraction of international students, we separately report business majors in column 5. While all fields saw growth in the number of Chinese students in response to the trade shock, the results indicate that there were meaningful shifts in the composition attributable to trade. This trade-induced shift was away from STEM and toward arts and social sciences. Comparing to the baseline proportions, the estimates indicate that PNTR exposure increased the share of students in arts and social sciences by 10 p.p. Business majors, the most popular social sciences major among international students, sustained an even larger increase in the share of Chinese students. This may reflect again the income mechanism, as STEM degrees are more likely to receive other funding, whereas business students rely on their own income. In Table A.1, in the appendix, we add detail by showing the composition of the field of study by level of study.

In panel C, we examine changes in the composition of students by the quality of the US universities they attend. We measure quality using admissions rates from the Integrated Postsecondary Educational Data System (IPEDS). We group US universities into quartiles based on their admissions rates, with the first quartile representing the most selective schools and the fourth quartile comprising the least selective institutions. The results indicate that although all universities saw significant increases in the number of Chinese students, the changes in composition mainly occurred in the least selective institutions. The share of Chinese students grew slightly in the fourth quartile and shrank slightly in the third quartile; indicating potential movement from less selective to the least selective institutions.

In Table 6, panel D, we focus on whether the rise in the number of Chinese students

[30] For visual clarity, Figure A.3 is bar graph that compares the proportional effect for each student type with the proportion of students in 2004.

was driven by those with or without funding. We examine the number of students who were funded by scholarships, grants, or other institutional resources ("Has funding") and the number of students who primarily used personal and family income to finance their studies ("No funding"). In 2004, 57% of Chinese students received some form of scholarship, grant, or other financial assistance. The migration elasticities with respect to the trade shock are a lot larger for unfunded students than for funded students. This is consistent with the elasticities by level of study and our hypothesis that rising wealth is an important mechanism in sending students abroad. The change in student composition that depends on trade shocks substantially shifted the composition away from funded to unfunded students.

In Table 6, panel E, we examine growth in the number of students quartile of the personal funds distribution in 2004. The export shock explains student migration of those in the upper quartiles of the distribution, those with substantial personal funds.

5.6 US Regional Inequality

We also investigate whether PNTR exposure induced Chinese students to move to high or low human capital localities in the US.[31] This speaks to whether the rise in educational exports exacerbated or dampened the rise in regional inequality in response to trade-induced labor reallocation. Bloom et al. (2019) find that, in general, reallocation due to the China shock has increased spatial inequality, as large multinationals eliminate jobs in industry and created new service jobs in places with the highest human capital. Our findings also imply that employment in the US has reallocated to services. However, increasing education exports has the potential to lift all regions as universities expand nationwide.

In the last panel in Table 6, we split the outcome, changes in number of students studying abroad, by the human capital of the *destination* city. We match the cities of the US universities to commuting zones.[32] For each commuting zone, we calculate the fraction of adults that have completed college education, using the 1990 decennial census. Panel F displays the results, with the outcome split into four quartiles based on the fraction of persons with a college degree in the destination commuting zone. We find that PNTR exposure induced a rise in services exports *for all types* of commuting zones. This might not be surprising, since US universities are geographically dispersed. Yet, along with the results on no selection on university quality, this suggests that the reallocation to educational services has dampened the disparities across regions induced by labor reallocation to other types of services. Hurting the market for higher education, as we explore next in the context of a trade war, would imply a further negative shock to localities most exposed to the fall of manufacturing.

[31] There is a recent literature on rising regional disparities in labor markets (Eckert, Ganapati and Walsh, 2019). We provide evidence of whether education exports exacerbate or dampen regional inequality.

[32] There are more than 3,000 cities, aggregated into about 700 commuting zones.

5.7 Policy Counterfactuals: Consequences of a Trade War

Our results speak to the consequences of trade wars and uncertainty over tariffs. Since 2017, this uncertainty resurfaced as US-China trade relations soured, and the US government instituted across-the-board tariffs on goods from China. The United States has departed from PNTR rates, and by mid-2019, average tariffs on Chinese goods increased to nearly 20% (PIIE, 2020).[33] An agreement in January 2020 (i.e., the phase-I deal) reduced tariffs imposed on Chinese goods in exchange for concessions, yet tariff uncertainty remains significant – tariff increases can be levied if China is deemed not to be holding up its end of the deal.

We use our estimates on the effect of tariff uncertainty to make simple inferences on possible future changes in international student flows and services exports if Chinese industries faced 20% higher tariffs. Our reduced-form results on the effect of PNTR exposure on student out-migration (Table 3) indicate that a 10 p.p. increase in tariffs leads to 32 fewer students per million city residents over a 10-year period.[34] As the increase in tariffs on Chinese products in 2020 was about 20 p.p. across the board, enrollment should decline by 640 students in cities that have a population of 10 million. Given China's urban population (the denominator in our outcome) this implies about 30,000 fewer students over 10 years.

Assuming average tuition of $40,000 per year implies that, over 10 years, US institutions would lose $1.15 billion in tuition revenue. That is a 3% reduction in educational services exports and an 8% reduction in education exports to China, not including general equilibrium multiplier effects that may reverberate across local economies (Acemoglu et al., 2016).[35]

6 Mechanisms

We explore several candidate explanations for why and how trade liberalization induced large numbers of Chinese students to migrate to the United States. In section 3, we outlined possible channels by which trade liberalization induced by PNTR exposure could generate student out-migration. We empirically examine whether increased student flows to US higher education due to PNTR exposure is consistent with (1) income/wealth generation,

[33] Initially, tariffs of 10% were imposed on most Chinese goods ($200 billion of imports), with a higher 25% tariff on a smaller subset of goods (which applied to $34 billion of imports). In the summer of 2019, the United States raised tariffs from 10% to 25% on the former set of goods.

[34] The first-stage and 2SLS results in Table 9, columns (2) and (3), can be used toward a counterfactual 20 p.p. rise in PNTR exposure. The first stage (when all controls are included) implies that a 1 p.p. increase in tariffs lowers exports by 2.88% over a 10 year period, while 2SLS implies an elasticity of student flows to exports of 0.113 over this period. A trade elasticity of 2.88 (with an upper bound of 3.98 in all specifications) is close to that found in the trade literature (Simonovska and Waugh, 2014).

[35] The 3% number does not depend on the exact tuition cost, but on the fact that the United States loses 3% of its total international students in this counterfactual (relative to the number if tariffs were to stay at their pre-trade war level). Similarly, the loss of Chinese students represents 8% of the current stock. Appendix Figure A.1 displays the total numbers of international and Chinese students enrolled over time.

(2) changing returns to education, and/or (3) information flows.

6.1 Income/Wealth Accumulation

Greater income/wealth alleviates credit constraints that families face in financing education abroad. We first investigate whether and how trade liberalization translates into increased income and wealth. Erten and Leight (2020) find increases in income in Chinese counties that experienced high PNTR exposure. Potlogea, Cheng et al. (2017) do not find evidence of changes in wages, but instead find increases in output, employment and investment growth. They explain that the lack of a rise in local wages resulted from increased population growth in export expansion areas. This is consistent with evidence from Facchini et al. (2019) and Tombe and Zhu (2019), which show that cities that benefited the most from PNTR also saw large in-migration of rural workers.[36]

A separate literature documents how the ensuing economic growth contributed to tremendous asset price appreciation. Large increases in wealth are likely manifested in capital gains, given the growth of the real estate sector (Chen et al., 2017) and the growing importance of wealth in the inequality observed in China – Piketty, Yang and Zucman (2019) find that the ratio of national wealth to national income increased from 350% to 700% between 1978 and 2015, and wealth became more concentrated. We view the rise in wealth, including capital gains, such as housing, to be the most likely mechanism for student out-migration, due to the large costs of financing living and studying in the United States. Therefore, we examine real estate price data and survey data which identify real estate income.[37]

To start, we confirm some of the results on economic growth found in the previous literature. The first two columns in Table 7 show that cities with the most exposure to exports experienced relatively larger GDP growth, and this effect was large.[38] However, as in Potlogea, Cheng et al. (2017), we find that GDP per capita did not increase significantly, likely due to simultaneous population growth in cities that were highly exposed to PNTR. Although the effect on population growth is not significant, the coefficient implies that cities with 10 p.p. larger PNTR exposure experienced 2.5% larger population growth, and, from the last two columns in Table 7, we see that this was enough to make the growth in GDP per capita statistically indistinguishable from zero. The growth in total GDP combined with population growth would drive up housing wealth, although not necessarily average wages.

The results on self-financing of education suggest that financial constraints are indeed

[36] We find limited gains in average wages but substantial increases in other income, including capital gains.

[37] In 2017, housing sales were 16.4% of China's GDP (Liu and Xiong, 2018). The housing market is also a big part of the local economy. For example, local governments rely on revenue from land sales, which means that appreciations will have important feedback effects for wealth generated in the local economy.

[38] Cities with 10 p.p. larger PNTR exposure experienced 5.4% larger GDP growth. The outcomes in Table 7 are long differences of log values.

an important impediment to Chinese students going to the US. In Table 6, panels D and E imply that students without university funding and those with personal funds were more likely to respond to trade shocks. From the summary statistics (Table 1), the fraction of students with no funding increased from 38% in 2004 to 78% in 2013.

Given the importance of personal funds for students going abroad, trade liberalization induces migration if it leads to greater availability of these funds. We can establish two facts: cities that were highly exposed to PNTR experienced larger housing price appreciations, and saw a greater income from real estate and business transactions. Figure 6 reports binned scatter plots of the relationship between the PNTR exposure and various post-treatment growth in outcomes. As average wages (for example from manufacturing) are not nearly sufficient to cover US tuition costs, we instead investigate income sources relevant to the top of the income distribution. First, real estate price data is available from the Wind Economic Database. The first two plots report the relationship between PNTR exposure with residential housing prices and commercial real estate prices.[39] There is a clear positive relationship between the two types of housing prices and PNTR exposure, although only the relationship with commercial prices is statistically distinguishable from zero.

Second, we investigate various outcomes that might inform the proposed mechanism, with data on income from the Urban Household Surveys of China.[40] Plots (c)-(e) of Figure 6 report the effect of PNTR exposure on average reported house price appreciation (complementing the price evidence above), the change in the share of rents in household income, and reported income growth from self-owned businesses. There is a clear, positive effect on real estate and self-business income in cities that more exposed to trade liberalization.

There are two ways in which the real estate boom can manifest in household income. First, properties not only can be sold, but can also generate rental income. Plot (d) of Figure 6 shows that in more liberalized cities, rent becomes a larger part of household income. In Figure A.5, we also document that over time the number of families in China that lease out properties increases, as does the average number of properties per household. Second,

[39] We use data on average residential housing prices (in Chinese yuan per square meter) from Wind Bank. Part of the reason for the difference in results might be due to data coverage. Commercial prices are available from 2002, while residential housing prices are only available beginning in 2005. We can only track between 196 and 204 of the 275 cities in our sample.

[40] The Urban Household Survey (UHS) is similar to the Current Population Surveys in the United States and adopts a stratified and multi-stage probabilistic sampling scheme. The UHS reports household information and economic characteristics, such as household income of different types. The data have been widely used, and detailed information on the UHS is provided by Ding and He (2018). The UHS has been used to study wage inequality (Yang, 1999; Ge and Yang, 2014), and we follow their work in taking changes in the average outcome by city between 2002 and 2007. This constitutes more than 30,000 households and more than 120,000 individuals each year. This covers between 151-204 cities for the analysis, and we are missing data in the last few years of our student sample.

related to the rise in reported self-business income, there is a robust literature on the role of real estate collateral on business cycle amplification and investment (Kiyotaki and Moore, 1997). In the US, Chaney, Sraer and Thesmar (2012) find that collateral has a large effect on investment, and Adelino, Schoar and Severino (2015) find that small business creation is larger due to the collateral lending channel. A similar channel might operate in China to raise profits from entrepreneurship; in fact, Brandt and Lim (2019) find that the entry of privately-owned Chinese firms is the most important cause of China's export growth.

The discussion in section 3 also postulates that growth in wealth can lead to a general reallocation of consumption toward services, because the income elasticity of services is greater than that of other goods. The UHS data allow us to construct total services consumption by households, which we aggregate to the city level. In the last plot in Figure 6, the outcome is the change in the share of services expenditure in total household expenditure. We find that higher PNTR exposure is associated with a reallocation of expenditure toward services.[41] Although suggestive, these results confirm that households in cities with greater liberalization behave in ways consistent with rising wealth.[42]

Overall these results help corroborate the idea that the growth of exports led to income expansion in cities that were strongly affected by China's accession to the WTO. This is especially important for the wealthiest, who likely had substantial wealth in housing assets prior to 2001. As a result, over the long run, more families in the top of the wealth distribution would be able to afford to self-fund the high cost of a US education.

6.2 Returns to Education and Access to Local Colleges

Another possible explanation for the increased student migration would be if trade liberalization increased the returns to higher education. If capacity-constrained Chinese universities were unable to meet the increased demand, students would migrate overseas. Alternatively, in the absence of capacity constraints at Chinese universities, trade liberalization may have increased the return on a US degree. We explore the likelihood of these scenarios.

We examine whether rising incomes in cities affected capacity-constrained local universities and spilled over into more migration abroad. This is less likely in a context where individuals choose a US university over one at home and when there are national markets for university admissions. In Figure A.6, we see no meaningful positive relationship between city-level income growth and admissions of city residents to top universities, nor between

[41] The average expenditure share of services is about 0.26. The data also decompose services into specific types. The share spent on educational services increased significantly. We also find that the share of expenditures on recreation and "self-care" increased.

[42] Although it is known that a large share of income gains in China go toward savings, this does not preclude that a larger share of expenditure will shift to services.

PNTR exposure and admissions (the exact numbers are in Table A.3 and details of the data are in Appendix E).[43] The lack of this relationship suggests that it is unlikely that (1) local returns to education are rising, and (2) local top universities are being crowded.[44]

We further explore the plausibility of changing returns to education as a potential channel, by examining whether trade liberalization in skill-intensive industries or non-skill-intensive industries explain student flows. We construct two new "NTR gap" exposure measures, where the city-level aggregation is split into *only* skill-intensive and *only* non-skill intensive industries.[45] Table 8 reports results comparable to our benchmark specification, where the NTR gap is constructed using a subset of industries. In the first column, we split industries using skill intensity measures from Chinese industries. In the second column, for robustness, we use a measure from Indonesian industries (Amiti and Freund, 2010). PNTR exposure in *non-skill* intensive industries explains nearly all the student flows. Cities with greater exposure in skill-intensive industries do not experience relatively higher student migration.

This result is consistent with our results on industry composition and the previous literature on education in China. The Rotemberg weights summarized in section 5 indicate that textile production – which is not skill intensive – accounts for the most exposed industries. For instance, industries with the three highest Rotemberg weights (Table D.4) are all more than one standard deviation below the mean in skill intensity. Therefore, the industries expanding due to trade liberalization are of lower skill, so that trade liberalization in itself does not necessarily lead to increased returns to education for local residents.

Overall, it appears unlikely that changes in returns to education play a large role. Our results confirm those in Li (2018), who finds that educational attainment in China declined due to export expansion.[46] Additionally, although increases in the returns to US degrees could occur, recent evidence from Chen (2020) shows that, all else equal, job applicants with a US degree receive lower call-back rates than Chinese degree holders.

[43] Details of the data, including the province level quota used in admissions, are included in Appendix E. The detailed results in Table A.3 also include region fixed effects. We measure the eliteness of a university according to its membership in the first-tier class, 211-Project, and 985-Project. Regular colleges and universities can be classified into three tiers according to the admissions process. The first-tier universities are generally considered as the elite or key universities. In 2011, there were 39 universities in the 985-Project list, and 112 universities in the 211-Project list. In terms of eliteness, universities of 985-Project are typically considered better than the 211-Project universities, followed by the first-tier universities.

[44] This does not mean that there is no relationship between city income and the share of students at top universities, just that there is no relationship between changes in income and changes in student shares.

[45] We label industries as skill intensive if they are above the median in the ISIC industry data. The skill share is the share of skilled workers in the industry, based on the ASIP (only available in 2004). We aggregate the firm data into 4-digit ISIC industries. For instance, in ISIC 1810, 5% of the labor force is "skilled". We construct alternative measures using the Indonesian manufacturing census (Amiti and Freund, 2010).

[46] Liu (2017) finds that a reduction in input tariffs raises high school completion.

6.3 Information

Finally, we examine whether trade liberalization increased information flows, such that rising student out-migration occurred as a result of greater knowledge of US educational opportunities. Although it is difficult to capture the flow of information empirically, we assess the strength of this mechanism by examining how student migration responded to the different types of trade flows that cities experienced after the conferral of PNTR. Cities that conducted large amounts of commerce with the United States likely received more US-specific information. In contrast, export activity to non-US destinations likely carried less information specific to US educational opportunities.

We perform empirical checks of the relationship between student migration and city-level exports, using PNTR exposure as an instrument for export growth. We refine our PNTR exposure measure to focus only on potential expansion in non-US destinations by removing exports to the United States from the export shares used to calculate the PNTR exposure measure. Therefore, this PNTR instrument captures exposure to export expansion in industries that likely have fewer ties to the United States.

The results of this exercise are reported in Table 9. Column (1) repeats our main results on the reduced-form effect of PNTR exposure on student flows, and column (2) displays the first stage results using PNTR exposure to predict actual export growth, comparable to the results in Table 2, column (6). In Table 9, column (3) reports the 2SLS estimate with PNTR exposure as an instrument for city-level export growth between 2000 and 2013. We then compare this 2SLS result with the case where exports to the United States *are excluded* from the city-level export growth and the export shares used to create PNTR exposure. Column (4) shows that the effect on student migration holds even when we exclude exports to the United States from total city export growth.[47] Column (5) also removes US exports from city-level export growth and the export shares used to construct PNTR exposure.

Intuitively, if information flows were a dominant mechanism, we would expect to see less of a relationship between student emigration and trade with non-US destinations. The evidence indicates that information flows are unlikely to drive our findings.[48]

The finding that expansions in non-US exports also encouraged student emigration is

[47] We also separately examined three large regions of trade activity – Europe, Asia, and all other trade partners – and found that exports to all these destinations still led to student migration to the United States.

[48] On the other hand, one might ask why our instrument is a strong predictor of exports to non-US destinations. For example, the European Union had already granted China permanent NTR status. We do not think this is surprising, as reducing uncertainty to a market as large as the United States will raise investment and capacity, allowing China to increase exports to other destinations as well. The World Import Demand instrument, which captures demand from the rest of the world, predicted similar changes in student emigration. It is beyond the scope of this paper to link uncertainty with the United States to the overall growth in Chinese exports, but we point out that the rise in wealth reflects that China expanded globally.

consistent with our earlier finding that trade-driven wealth/income creation helped to relax financial constraints and allow families to afford US higher education. Furthermore, in Figure A.4, we show that the increase in Chinese student out-migration was not confined to the United States only, but rather seen in top destinations across the world (e.g., Canada, Australia, and the UK). This suggests that whatever factors drove the growth in international student migration, they cannot be explained by US-specific features alone.

7 Conclusion

International student flows are a function of home and destination country education and labor markets. At least a few important factors drive such flows. The first is the growing need for international students from US universities suffering large adverse shocks to non-tuition sources of revenues (Bound et al., 2020; Shih, 2017). The second is the extent to which home country universities are constrained in the availability of high-quality higher education. The third is the option value of joining the US labor market after obtaining a US degree. The last is the capacity to pay for, and the number of high school graduates prepared for a US university. Our research finds that this final strand explains a substantial portion of the flows of students from China to the United States.

In recent years, however, there has been a dramatic deceleration in international student flows. The year-on-year growth rates for the number of Chinese students in the United States averaged about 22% between 2007 and 2013, but since then it has fallen to less than 5% per year. Given the various determinants of foreign flows, this may reflect a few important global changes, including the growth in universities and labor markets across China, political tensions, and the uncertainty in job prospects for immigrants in the United States.

Local income growth in sending countries generates an important tradeoff for migrants: to forego rising local opportunities or leverage income growth to move abroad. We show that between 2004 and 2013, at least, the latter was the predominant driving force. Recent downturns in student flows suggest that the former may have become an important factor as well. As such, declines in international student flows may hurt public research universities that have become increasingly reliant on tuition revenues from abroad.

Foreign tuition revenues are a crucial aspect of US services exports. The US Commerce Department estimates that in 2017, educational exports added about $34 billion to the US current account; about as large as the combined total exports of soybeans, coal, and natural gas (Rampell, 2018). Although much of the conversation on trade with China has focused on the goods trade deficit, there has been undeservedly little attention on the trade surplus with respect to educational services. We show that these are inextricably linked, as trade-induced income growth in China drove the export of educational services from the US.

References

Acemoglu, Daron, David Autor, David Dorn, Gordon H. Hanson and Brendan Price. 2016. "Import Competition and the Great US Employment Sag of the 2000s." *Journal of Labor Economics* 34(S1):141–198.

Adao, Rodrigo, Michal Kolesar and Eduardo Morales. 2019. "Shift-Share Designs: Theory and Inference." *The Quarterly Journal of Economics* 134(4):1949–2010.

Adelino, Manuel, Antoinette Schoar and Felipe Severino. 2015. "House prices, collateral, and self-employment." *Journal of Financial Economics* 117(2):288 – 306.

Altonji, Joseph G, Todd E Elder and Christopher R Taber. 2005. "Selection on Observed and Unobserved Variables : Assessing the Effectiveness of Catholic Schools." *Journal of Political Economy* 113(1):151–184.

Amiti, Mary and Caroline Freund. 2010. *The Anatomy of China's Export Growth*. University of Chicago Press pp. 35–56.

Amuedo-Dorantes, Catalina, Delia Furtado and Huanan Xu. 2019. "OPT Policy Changes and Foreign Born STEM Talent in the US." *Labour Economics* 61.

Angelucci, Manuela. 2015. "Migration and Financial Constraints: Evidence from Mexico." *Review of Economics and Statistics* 97(1):224–28.

Atkin, David. 2016. "Endogenous Skill Acquisition and Export Manufacturing in Mexico." *American Economic Review* 106(8):2046–85.
URL: *https://www.aeaweb.org/articles?id=10.1257/aer.20120901*

Autor, David, David Dorn and Gordon H Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103(6):2121–68.

Bahar, Dany and Hillel Rapoport. 2018. "Migration, Knowledge Diffusion and the Comparative Advantage of Nations." *The Economic Journal* 128(612):F273–F305.

Bai, Xue, Kala Krishna and Hong Ma. 2017. "How You Export Matters: Export Mode, Learning and Productivity in China." *Journal of International Economics* 104:122–137.

Bazzi, Samuel. 2017. "Wealth Heterogeneity and the Income Elasticity of Migration." *American Economic Journal: Applied Economics* 9(2):219–55.

Bloom, Nicholas, Kyle Handley, Andre Kurman and Phillip Luck. 2019. The Impact of Chinese Trade on US Employment: The Good, the Bad, and the Debatable. In *American Economic Association Annual Meetings*. Vol. 2019.

Borusyak, Kirill, Peter Hull and Xavier Jaravel. 2018. Quasi-Experimental Shift-Share Research Designs. Technical report National Bureau of Economic Research.

Bound, John, Breno Braga, Gaurav Khanna and Sarah E Turner. 2020. "A Passage to America: University Funding and International Students." *American Economic Journal: Economic Policy* 12(1):97–126.

Bound, John, Murat Demirci, Gaurav Khanna and Sarah Turner. 2015. "Finishing Degrees and Finding Jobs: U.S. Higher Education and the Flow of Foreign IT Workers." *Innovation Policy and the Economy* 15. Kerr, Lerner, and Stern (eds.).

Brambilla, Irene, Amit K Khandelwal and Peter K Schott. 2010. China's Experience under the Multi-Fiber Arrangement (MFA) and the Agreement on Textiles and Clothing (ATC). In *China's Growing Role in World Trade*. University of Chicago Press pp. 345–387.

Brandt, Loren, Johannes Van Biesebroeck, Luhang Wang and Yifan Zhang. 2017. "WTO Accession and Performance of Chinese Manufacturing Firms." *American Economic Review* 107(9):2784–2820.

Brandt, Loren and Kevin Lim. 2019. "Accounting for Chinese Exports.".

Caliendo, Lorenzo, Maximiliano Dvorkin and Fernando Parro. 2019. "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock." *Econometrica* 87(3):741–835.

Chaney, Thomas, David Sraer and David Thesmar. 2012. "The collateral channel: How real estate shocks affect corporate investment." *American Economic Review* 102(6):2381–2409.

Chen, Kaiji and Yi Wen. 2017. "The Great Housing Boom of China." *American Economic Journal: Macroeconomics* 9(2):73–114.

Chen, Mingyu. 2020. The Value of US College Education in Global Labor Markets: Experimental Evidence from China. Technical Report 627 Industrial Relations Section Working Paper at Princeton University.

Chen, Ting, Laura Liu, Wei Xiong and Li-An Zhou. 2017. "Real Estate Boom and Misallocation of Capital in China." *Working Paper, Princeton University* .

Clemens, Michael A. 2014. "Does Development Reduce Migration?" *International Handbook on Migration and Economic Development* p. 152–185. Robert E.B. Lucas (ed.) Cheltenham: Edward Elgar Publishing.

Collins, William J., Kevin H. O'Rourke and Jeffrey Williamson. 1997. Were Trade and Factor Mobility Substitutes in History? NBER Working Papers 6059.

Comin, Diego A, Danial Lashkari and Martí Mestieri. 2019. Structural Change with Long-Run Income and Price Effects. Technical report National Bureau of Economic Research.

de Brauw, Alan and John Giles. 2015. "Migrant Opportunity and the Educational Attainment of Youth in Rural China." *Journal of Human Resources* 52(1):272–311.

Ding, Haiyan and Hui He. 2018. "A Tale of Transition: An Empirical Analysis of Economic Inequality in Urban China, 1986–2009." *Review of Economic Dynamics* 29:106–137.

Dingel, Jonathan I. 2016. "The Determinants of Quality Specialization." *The Review of Economic Studies* 84(4):1551–1582.

Dix-Carneiro, Rafael. 2014. "Trade Liberalization and Labor Market Dynamics." *Econometrica* 82(3).

Eaton, Jonathan and Samuel Kortum. 2018. Trade in Goods and Trade in Services. In *World Trade Evolution*, ed. Lili Ing and Miaojie Yu. Routledge pp. 82–125.

Eckert, Fabian, Sharat Ganapati and Conor Walsh. 2019. "Skilled Tradable Services: The Transformation of US High-Skill Labor Markets." *Available at SSRN 3439118* .

Erten, Bilge and Jessica Leight. 2020. "Exporting out of Agriculture: The Impact of WTO Accession on Structural Transformation in China." *Review of Economics and Statistics* pp. 1–46.

Facchini, Giovanni, Maggie Y Liu, Anna Maria Mayda and Minghai Zhou. 2019. "China's "Great Migration": The Impact of the Reduction in Trade Policy Uncertainty." *Journal of International Economics* 120:126–144.

Fajgelbaum, Pablo, Gene M. Grossman and Elhanan Helpman. 2011. "Income Distribution, Product Quality, and International Trade." *Journal of Political Economy* 119(4):721–765.

Feenstra, Robert, Haiyan Deng, Chang Hong, Philip Luck, Alyson Ma, Hong Ma, Shunli Yao, Greg Wright and Mingzhi Xu. 2018. "Chinese and Hong Kong International Trade Data." *Center for International Data, University of California, Davis* .

Ge, Suqin and Dennis Tao Yang. 2014. "Changes in China's Wage Structure." *Journal of the European Economic Association* 12(2):300–336.

Goldsmith-Pinkham, Paul, Isaac Sorkin and Henry Swift. 2020. Bartik Instruments: What, When, Why, and How. Technical report American Economic Review. Forthcoming.

Handley, Kyle and Nuno Limão. 2017. "Policy Uncertainty, Trade, and Welfare: Theory and Evidence for China and the United States." *American Economic Review* 107(9):2731–83.

Hummels, David, Rasmus Jørgensen, Jakob Munch and Chong Xiang. 2014. "The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data." *American Economic Review* 104(6):1597–1629.

Institute for International Education. 2019. "Open Doors Report on International Education Exchange.".
URL: *http://www.iie.org/opendoors*

Jaeger, David A, Joakim Ruist and Jan Stuhler. 2018. Shift-share Instruments and the Impact of Immigration. Technical report National Bureau of Economic Research.

Khandelwal, Amit K, Peter K Schott and Shang-Jin Wei. 2013. "Trade Liberalization and Embedded Institutional Reform: Evidence from Chinese Exporters." *American Economic Review* 103(6):2169–85.

Kiyotaki, Nobuhiro and John Moore. 1997. "Credit cycles." *Journal of political economy* 105(2):211–248.

Kuka, Elira, Na'ama Shenhav and Kevin Shih. 2020. "Do Human Capital Decisions Respond to the Returns to Education? Evidence from DACA." *American Economic Journal: Economic Policy* 12(1):293–324.

Li, Bingjing. 2018. "Export Expansion, Skill Acquisition and Industry Specialization: Evidence from China." *Journal of International Economics* 114:346–361.

Linder, Staffan Burenstam. 1961. *An Essay on Trade and Transformation.* Stockholm: Almqvist & Wiksell.

Liu, Chang and Wei Xiong. 2018. China's Real Estate Market. Technical report National Bureau of Economic Research.

Liu, Maggie Y. 2017. "How Does Globalization Affect Educational Attainment? Evidence from China.".

Manova, Khalina and Zhiyuan Zhang. 2012. "Export Prices across Firms and Destinations." *Quarterly Journal of Economics* 127(1):379–436.

Matsuyama, Kiminori. 1992. "Agricultural Productivity, Comparative Advantage, and Economic Growth." *Journal of Economic Theory* 58(2):317–334.

McKenzie, David and Hillel Rapoport. 2011. "Can Migration Reduce Educational Attainment? Evidence from Mexico." *Journal of Population Economics* 24(4):1331–1358.

Nunn, Nathan. 2007. "Relationship-Specificity, Incomplete Contracts, and the Pattern of Trade." *The Quarterly Journal of Economics* 122(2):569–600.

Parsons, Christopher and Pierre-Louis Vézina. 2018. "Migrant Networks and Trade: The Vietnamese Boat People as a Natural Experiment." *The Economic Journal* 128(612):F210–F234.

Pierce, Justin R and Peter K Schott. 2016. "The Surprisingly Swift Decline of US Manufacturing Employment." *American Economic Review* 106(7):1632–62.

PIIE. 2020. "US-China Trade War Tariffs: An Up-to-Date Chart.".
URL: *https://www.piie.com/research/piie-charts/us-china-trade-war-tariffs-date-chart*

Piketty, Thomas, Li Yang and Gabriel Zucman. 2019. "Capital Accumulation, Private Property, and Rising Inequality in China, 1978–2015." *American Economic Review* 109(7):2469–96.

Potlogea, Andrei, Wenya Cheng et al. 2017. Trade Liberalization and Economic Development: Evidence from China's WTO Accession. In *2017 Meeting Papers*. Number 1648 Society for Economic Dynamics.

Pregelj, Vladimir N. 2001. Most-Favored-Nation Status of the People's Republic of China. In *Most-Favored-Nation Status of the People's Republic of China*. Congressional Research Service, Library of Congress.

Rampell, Catherine. 2018. "One of America's Most Successful Exports Is in Trouble." *The Washington Post* .

Rosenzweig, Mark. 2006. "Global Wage Differences and International Student Flows." *Brookings Trade Forum* pp. 57–86.

Shih, Kevin. 2016. "Labor Market Openness, H-1B Visa Policy, and the Scale of International Student Enrollment in the United States." *Economic Inquiry* 54(1):121–138.

Shih, Kevin. 2017. "Do International Students Crowd-Out or Cross-Subsidize Americans in Higher Education?" *Journal of Public Economics* 156:170–184.

Simonovska, Ina and Michael E. Waugh. 2014. "The Elasticity of Trade: Estimates and Evidence." *Journal of International Economics* 92(1):34–50.

Sun, Stephen T and Constantine Yannelis. 2016. "Credit Constraints and Demand for Higher Education: Evidence from Financial Deregulation." *Review of Economics and Statistics* 98(1):12–24.

Tombe, Trevor and Xiaodong Zhu. 2019. "Trade, Migration, and Productivity: A Quantitative Analysis of China." *American Economic Review* 109(5):1843–72.

Topalova, Petia. 2010. "Factor Immobility and Regional Impacts of Trade Liberalization: Evidence of Poverty from India." *American Economic Journal: Applied* 2:1–41.

Venables, Anthony. 1999. Trade liberalisation and Factor Mobility: An Overview. In *China's Growing Role in World Trade*, ed. Riccardo C. Faini, Jaime de Melo and Klaus Zimmermann. Cambridge University Press pp. 23–47.

Wang, Jin. 2013. "The Economic Impact of Special Economic Zones: Evidence from Chinese Municipalities." *Journal of Development Economics* 101:133–147.

Wang, Zhi, Shang-Jin Wei, Xinding Yu and Kunfu Zhu. 2018. Re-Examining the Effects of Trading with China on Local Labor Markets: A Supply Chain Perspective. Working Paper 24886 National Bureau of Economic Research.

Yang, Dennis Tao. 1999. "Urban-Biased Policies and Rising Income Inequality in China." *American Economic Review* 89(2):306–310.

Yu, Miaojie. 2015. "Processing Trade, Tariff Reductions and Firm Productivity: Evidence from Chinese Firms." *The Economic Journal* 125(585):943–988.

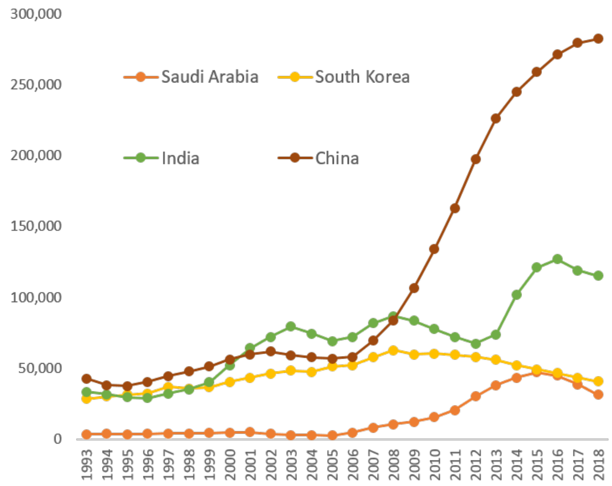
Zhu, Xiaodong. 2012. "Understanding China's Growth: Past, Present, and Future." *Journal of Economic Perspectives* 26(4):103–24.

Zivin, Joshua S Graff, Yingquan Song, Qu Tang and Peng Zhang. 2018. Temperature and High-stakes Cognitive Performance: Evidence from the National College Entrance Examination in China. Technical report National Bureau of Economic Research.

Tables & Figures

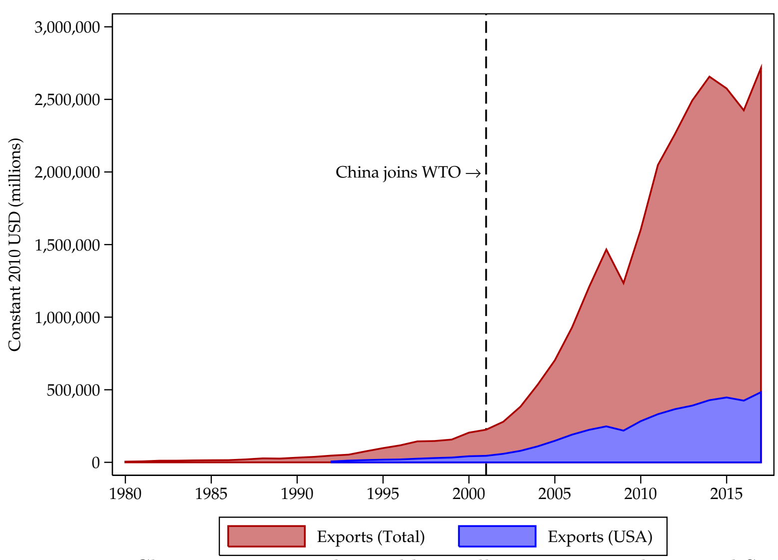
7.1 Descriptive Figures

Figure 1: Number of International Students in the United States by Country of Origin



Notes: Open Doors, Institute for International Education, 1992-2018. Includes graduate and undergraduate students.

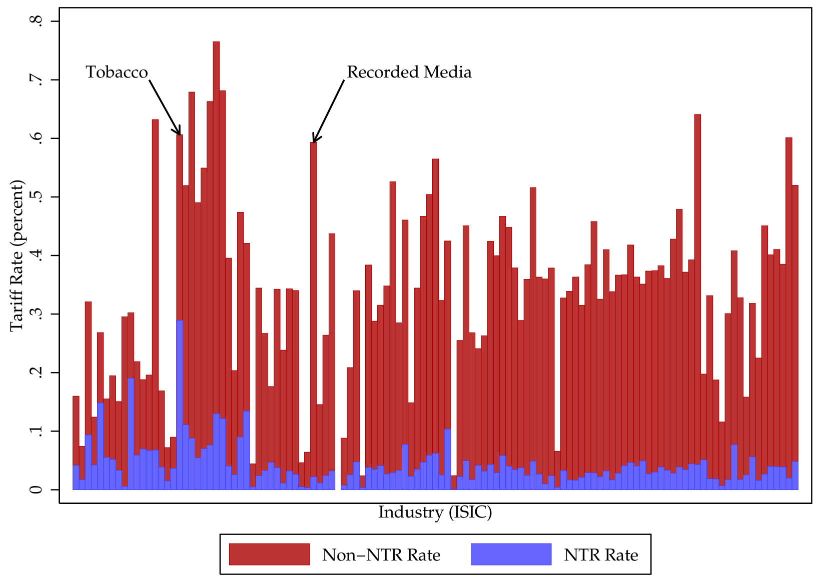
Figure 2: Chinese Exports, 1980-2017



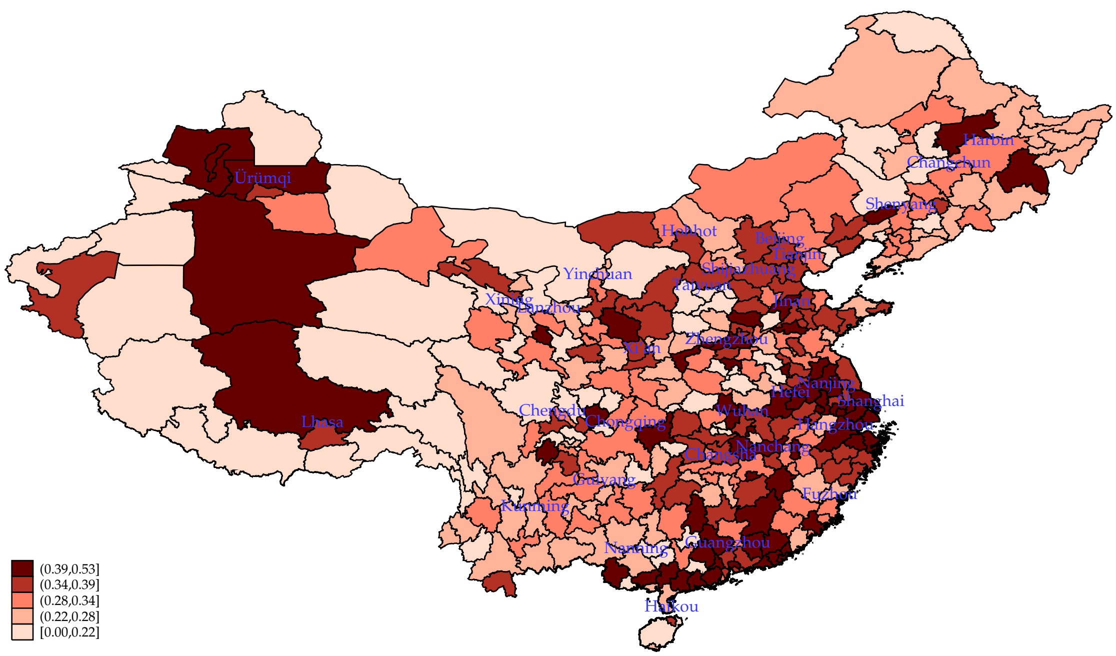
Notes: This figure presents Chinese exports to the world as well as exports to the United States only. Data for exports to the United States are from Comtrade. Exports to the world are sourced from the World Bank. Both reflect exports in 2010 prices using the US GDP deflator for that year.

7.2 PNTR Variation

Figure 3: Variation in PNTR Exposure



(a) NTR and non-NTR rates across industries



(b) PNTR exposure across Chinese prefecture cities

Notes: Figure 3a shows the NTR and non-NTR rates for each 4-digit ISIC industry. The NTR gap is the difference between the two and is plotted in Figure A.2. Figure 3b shows a map of prefecture cities used in the sample, with shading representing the intensity of weighted NTR gaps. We measure city-level exposure as a weighted average of industry-level NTR gaps, weighted by each city's existing activity, as detailed in equation (3). Data on NTR and non-NTR rates by industry are from Pierce and Schott (2016).

7.3 Summary Stats

Table 1: Summary Statistics

	2004	2013
Population (thousands)	1,239	1,463
	(1,510)	(1,845)
GDP (10,000 RMB)	3,320,868	13,178,523
	(6,808,102)	(25,694,406)
GDP per capita (RMB)	21,401	72,090
	(18,703)	(53,655)
Exports (10,000 RMB)	91,836	451,080
	(250,154)	(1,501,816)
Students entering US higher education	39	357
	(168)	(1,372)
Academic level shares:		
Associate	0.03	0.05
	(0.10)	(0.04)
Bachelor	0.05	0.27
	(0.10)	(0.10)
Master	0.31	0.38
	(0.19)	(0.11)
Doctorate	0.56	0.12
	(0.24)	(0.07)
Other	0.05	0.18
	(0.09)	(0.09)
Field of study shares:		
STEM	0.63	0.35
	(0.23)	(0.11)
Social science	0.29	0.43
	(0.21)	(0.10)
Arts/humanities	0.09	0.23
	(0.14)	(0.10)
University selectivity shares:		
Tier 1	0.18	0.18
	(0.15)	(0.07)
Tier 2	0.26	0.22
	(0.20)	(0.07)
Tier 3	0.22	0.20
	(0.19)	(0.06)
Tier 4	0.33	0.40
	(0.21)	(0.10)
Scholarship funding shares:		
Received funding	0.62	0.22
	(0.23)	(0.09)
No funding	0.38	0.78
	(0.23)	(0.09)
Number of cities	274	274

Notes: Calculations from SEVIS individual-level data on student flows, majors of study, and destination universities. 'Students entering US higher education' are measured as a fraction of one million residents in the city. STEM degrees include degrees in Science, Technology, Engineering, and Mathematics. Social sciences degrees also include business-related degrees. University selectivity shares based on admissions rates are from IPEDS data. Universities are categorized into four tiers based on quartiles of the admissions rate. Population and GDP numbers are from the China City Statistics Yearbook.

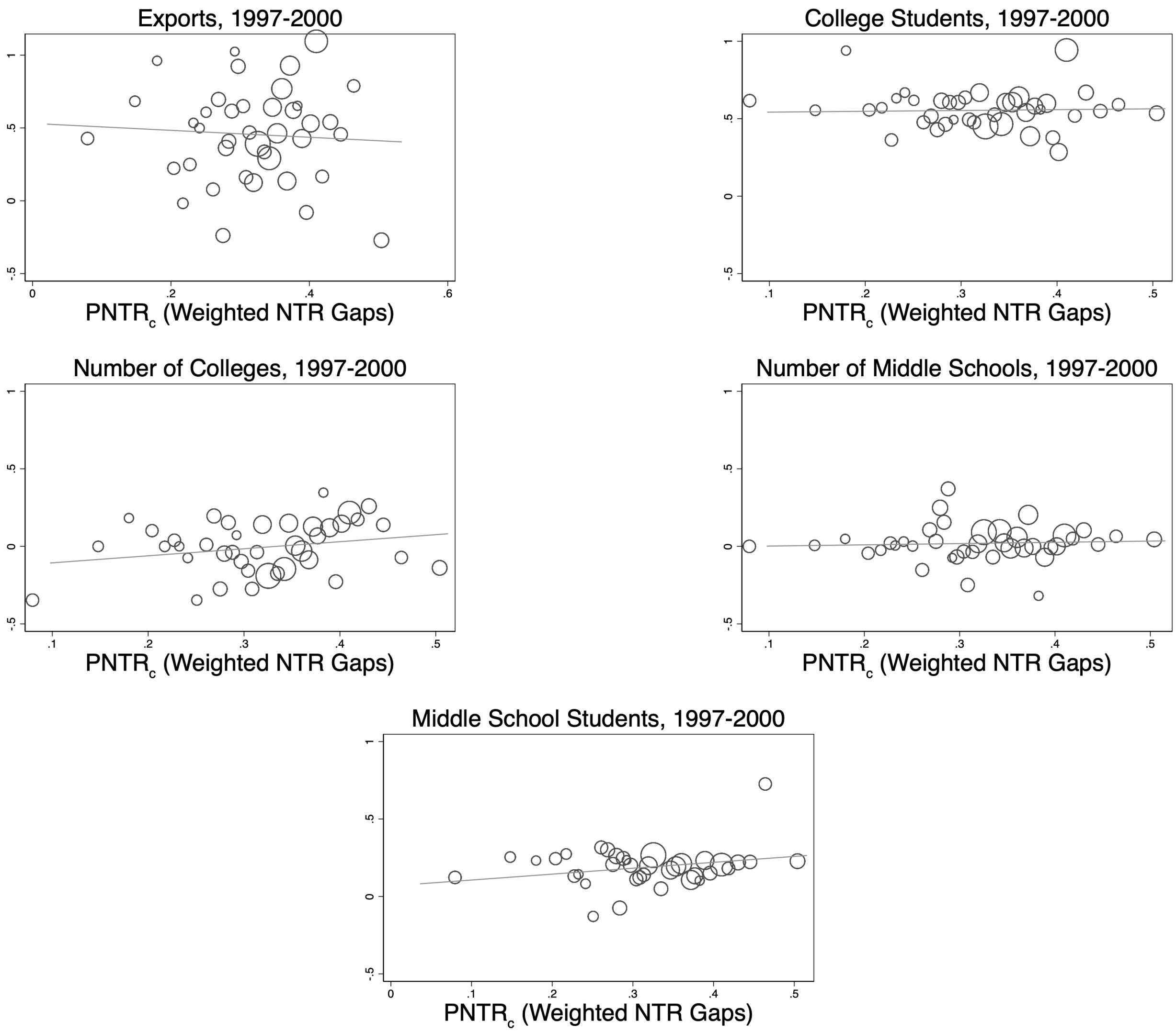
7.4 Identification Checks

Table 2: Identification Checks

	1997-2000					2000-13
	(1) College students	(2) Number of colleges	(3) Middle school students	(4) Number of middle schools	(5) Exports	(6) Exports
A: No controls						
$PNTR_c$	0.053	0.455	0.152	0.081	-0.236	3.984***
	(0.349)	(0.397)	(0.154)	(0.136)	(0.641)	(0.788)
B: w/ controls						
$PNTR_c$	-0.025	0.400	0.778	-0.050	0.419	2.881***
	(0.390)	(0.473)	(0.649)	(0.174)	(0.775)	(0.834)
Contract intensity	-0.054	0.548	2.667*	0.442*	2.562*	1.740*
	(0.434)	(0.464)	(1.486)	(0.254)	(1.339)	(0.981)
Import tariffs	0.201	0.010	-0.380	-0.074	-2.727**	3.116*
	(0.341)	(0.464)	(1.070)	(0.264)	(1.107)	(1.670)
Input tariffs	0.412	-0.619	2.490*	1.563	2.536	1.568
	(1.420)	(1.749)	(1.484)	(1.096)	(3.641)	(3.881)
Export license	0.189	-0.401	-3.431	-0.148	-3.660*	-0.998
	(0.984)	(0.976)	(2.261)	(0.378)	(2.148)	(1.713)
Observations	182	184	246	219	275	275

Notes: City-level regression results showing baseline checks (columns (1) - (5)), and the 'first-stage' relationship (column (6)), on how the NTR gap affects export growth between 2000 and 2013. Columns (1) - (4) examine pre-trends in education-related outcomes, where outcomes are defined as the city-level log change between 1997 and 2000. Education-related outcomes are sourced from the China City Statistics Yearbook. City exports are from the China Customs Database, provided by the UC Davis Center for International Data (Feenstra et al., 2018). We report heteroskedasticity-consistent standard errors (in parentheses) at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Figure 4: Correlation between PNTR Exposure and Pre-Trends



Notes: Binned scatter plots of the relationship between the weighted NTR gap (PNTR) and pre-trends in outcomes. The plots show 40 equal-size bins, weighted by population size in each bin. Pre-trend outcomes are measured as the city-level log change between 1997 and 2000. Data on exports come from the China Customs Database. Data on college and middle school students come from the China City Statistical Yearbook. Coefficients and standard errors are reported in Table 2.

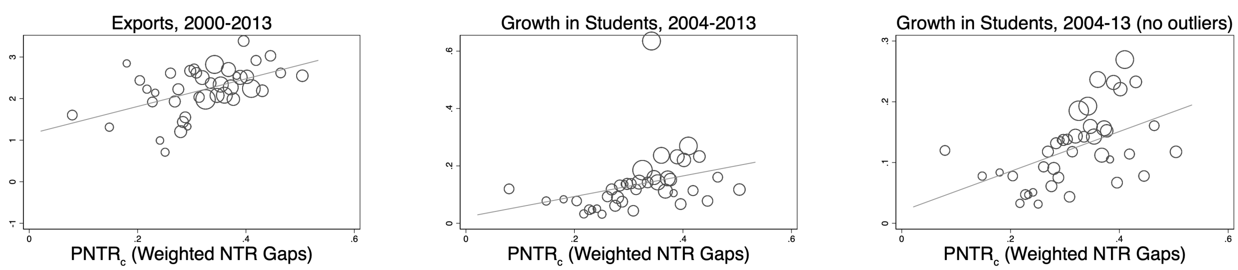
7.5 Main Results

Table 3: Effect on Enrollment, 2004-13

	(1) No controls	(2) +Control for contract intensity	(3) +Control for import tariffs	(4) +Control for input tariffs	(5) +Control for export licenses
$PNTR_c$	0.358***	0.300***	0.368***	0.380***	0.324***
	(0.104)	(0.104)	(0.106)	(0.105)	(0.106)
Contract intensity		0.315*	0.337*	0.321*	0.258
		(0.188)	(0.194)	(0.187)	(0.177)
Import tariffs			-0.265*	-0.111	-0.071
			(0.137)	(0.125)	(0.122)
Input tariffs				-0.982***	-0.882**
				(0.354)	(0.352)
Export license					0.361**
					(0.178)
Interquartile effect:					
Δ Students per 1m Pop.	41	34	42	43	37
Mean dep. var.	0.138	0.138	0.138	0.138	0.138
Obs.	275	275	275	275	275
R2	0.023	0.037	0.043	0.054	0.059

Notes: City-level regressions showing the effect of PNTR exposure on Chinese student enrollment growth between 2004 and 2013, per thousand city residents. Rows below the coefficients scale up the effect size in terms of students per million residents, for a change in the PNTR that traverses its interquartile range (≈10 p.p.). In each column we iteratively include controls, with details on controls in section 4. All controls are at the city-level, constructed by taking weighted averages of ISIC industries in the same way as our PNTR measure. Contract intensity refers to the Nunn (2007) measure of the proportion of intermediate inputs employed by a firm that require relationship-specific investments. Output tariffs are for the year 2000 (from World Integrated Trade Solution (WITS)), while input tariffs are constructed using WITS tariff data and the 2002 input-output table for China. Export licenses refers to the Bai, Krishna and Ma (2017) measure of the fraction of export revenues licensed to export directly. We report heteroskedasticity-consistent standard errors (in parentheses) at the city level.. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Figure 5: Correlation between PNTR Exposure and Growth in Outcomes post WTO



Notes: Binned scatter plots of the relationship between the weighted NTR gap (PNTR) and post-treatment growth in outcomes. The plots show 40 equal-size bins, weighted by population size in each bin. The right panel drops the two cities with the largest student growth (Beijing and Shenzhen) to check for sensitivity to outliers. Export growth is measured as the log change from 2000 to 2013, using data from the China Customs Database. Student growth is measured as the change in students from 2004 to 2013, divided by initial city population (only non-agricultural hukou) in 2004. Data on Chinese students by city of origin are from SEVIS. Coefficients and standard errors are reported in Table 2, column 6 (Exports) and Table 3 column 1, and Table 4 column 2.

Table 4: Effect on Enrollment, 2004-13, Robustness Checks

	(1) Total	(2) Drop 4 largest cities	(3) Drop capital/coasts	(4) Region FE	(5) All population
$PNTR_c$	0.324***	0.276***	0.290***	0.194*	0.152**
	(0.106)	(0.100)	(0.091)	(0.108)	(0.067)
Contract intensity	0.258	0.217	0.194	0.267	0.181
	(0.177)	(0.168)	(0.168)	(0.172)	(0.138)
Import tariffs	-0.071	-0.042	-0.087	-0.076	-0.091
	(0.122)	(0.116)	(0.114)	(0.126)	(0.085)
Input tariffs	-0.882**	-0.695**	-0.804**	-0.889***	-0.659**
	(0.352)	(0.306)	(0.312)	(0.310)	(0.254)
Export license	0.361**	0.353**	0.215	0.432**	0.205
	(0.178)	(0.175)	(0.162)	(0.219)	(0.136)
Interquartile effect:					
Δ *Students per 1m Pop.*	37	31	33	22	17
Obs.	275	271	237	275	274
R2	0.059	0.054	0.048	0.100	0.036

Notes: City-level regressions showing the effect of PNTR exposure on Chinese student enrollment growth between 2004 and 2013, per thousand city residents. The rows below the coefficients scale up the effect size in terms of students per million residents, for a change in the PNTR that traverses its interquartile range (≈10 p.p.). We include all main controls. Column (1) reproduces our main estimates from column (5) in Table 3. Column (2) drops the four largest cities from the sample. Column (3) drops province capitals and coastal cities. Column (4) includes region-level fixed effects, where the region is the first (of four) digit in the prefecture code. Column (5) uses a slightly different outcome measure: we normalize the change in the number of students by the *total* population, including the surrounding agricultural areas. We report heteroskedasticity-consistent standard errors (in parentheses) at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5: Effect on Enrollment, 2004-13, Bartik Checks and Alternative Instruments

	(1)	(2)	(3)	(4)	(5)	(6)
$PNTR_c$	0.324***					
	(0.106)					
1990 employment weights		0.748***				
		(0.243)				
Remove high Rotemberg weights			0.420***			
			(0.150)			
World Import Demand IV				0.113***		
				(0.027)		
MFA quotas IV					0.151***	
					(0.056)	
AKM shift-share method						0.358***
Conventional SE						(0.104)
AKM0 SE						(0.138)
AKM SE						(0.110)
Controls	Yes	Yes	Yes	Yes	Yes	–
Interquartile effect:						
Δ *Students per 1m Pop.*	37	42	27	47	40	41
Obs.	275	265	269	275	275	275
R2	0.059	0.085	0.059	0.110	0.060	0.023

Notes: City-level regressions showing the effect of trade shocks on Chinese student enrollment growth between 2004 and 2013, per thousand city residents. We include all main controls. Column (1) reproduces our main estimates from column (5) in Table 3. The rows below the coefficients scale up the effect size in terms of students per million residents, for a change in the PNTR that traverses its interquartile range ($\approx$ 10 p.p.). Column (2) uses the 1990 employment shares as weights in constructing the city-level NTR gaps. Column (3) removes the top five Rotemberg weight industries, as in Goldsmith-Pinkham, Sorkin and Swift (2020). Column (4) uses the World Import Demand instrument, as in Autor, Dorn and Hanson (2013). Column (5) leverages the expiration of the Multifiber Agreement quotas by using the quota fill rate by industry in 2001 (from Khandelwal, Schott and Wei (2013)). For columns (1) to (5), we report heteroskedasticity-consistent standard errors (in parentheses) at the city level. In column (6), we report standard errors as outlined by (Adao, Kolesar and Morales, 2019). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

7.6 Migration Elasticities by Sub-group and Composition Changes

Table 6: Migration Elasticities and Compositional Changes, 2004-13

	(1)	(2)	(3)	(4)	(5)	(6)
A: Level of study	Total	Associate	Bachelor's	Master's	Doctorate	Other
$PNTR_c$	0.324***	0.019***	0.130***	0.102***	0.008	0.065***
	(0.106)	(0.005)	(0.042)	(0.036)	(0.005)	(0.024)
Effect as proportion of total		.06	.4	.31	.02	.2
Student proportions in 2004		.03	.07	.37	.47	.07
Change in proportions		.03	.33	-.06	-.45	.13
B: Field of study	Total	STEM	Arts	Social sci.	Social sci.: business	
$PNTR_c$	0.324***	0.089***	0.089***	0.146***	0.102***	
	(0.106)	(0.033)	(0.031)	(0.045)	(0.031)	
Effect as proportion of total		.28	.27	.45	.31	
Student proportions in 2004		.55	.1	.35	.21	
Change in proportions		-.27	.17	.1	.1	
C: University quality	Total	1st quartile	2nd quartile	3rd quartile	4th quartile	
$PNTR_c$	0.324***	0.079***	0.075***	0.055***	0.116***	
	(0.106)	(0.024)	(0.023)	(0.020)	(0.042)	
Effect as proportion of total		.24	.23	.17	.36	
Student proportions in 2004		.24	.22	.23	.31	
Change in proportions		0	.01	-.06	.05	
D: Funding	Total	Has funding	No funding			
$PNTR_c$	0.324***	0.038***	0.286***			
	(0.106)	(0.014)	(0.093)			
Effect as proportion of total		0.12	0.88			
Student proportions in 2004		0.57	0.43			
Change in proportions		-0.45	0.45			
E: Personal funds:	Total	1st quartile	2nd quartile	3rd quartile	4th quartile	
$PNTR_c$	0.324***	0.009	0.065***	0.114***	0.136***	
	(0.106)	(0.007)	(0.022)	(0.037)	(0.044)	
Effect as proportion of total		0.03	0.20	0.35	0.42	
Student proportions in 2004		0.58	0.26	0.09	0.07	
Change in proportions		-0.55	-0.06	0.26	0.35	
F: Human capital, U.S. CZ	Total	1st quartile	2nd quartile	3rd quartile	4th quartile	
$PNTR_c$	0.324***	0.069***	0.102***	0.071***	0.082***	
	(0.106)	(0.022)	(0.032)	(0.023)	(0.030)	
Effect as proportion of total		.21	.32	.22	.25	
Student proportions in 2004		.26	.27	.22	.24	
Change in proportions		-.05	.05	0	.01	

Notes: City-level regressions showing the effect of weighted NTR gaps on Chinese student enrollment growth between 2004 and 2013, per thousand city residents. We include all main controls. Column (1) reproduces our main estimates from column (5) in Table 3. The first row below the coefficients documents the effect as a fraction of the total effect in column (1). The second row shows the fraction of students of each type in 2004. The final row takes the difference between these two rows, and illustrates how the proportional inflow of students attributable to PNTR exposure has changed since the initial proportions in 2004. In panel B, STEM degrees include degrees in science, technology, engineering and mathematics. Social sciences also includes business-related degrees, and we separately report effects for business only. In panel C, we use the IPEDS data to create four quartiles of university selectivity based on admissions rates. In panel D, 'Has funding' refers to students who reported receiving scholarship funding from the university or other agency, whereas 'No funding' refers to students who finance their education only using personal funds. In panel E, we divide the students by quartiles of personal funds reported used to fund the education, where the fourth quartile uses more personal funds than the first quartile. In panel F, we distinguish US commuting zones based on human capital, that is, the fraction of persons over age 25 with a college education (from the 1990 decennial census), and then link students to commuting zones based on the address of the US university. We then construct four different outcomes: the change in the number of students (relative to the urban population size) going abroad in each Chinese city, *only* to a US CZ in a specific human capital quartile. In all panels, coefficients for the specific categories sum to the total (0.324). We report heteroskedasticity-consistent standard errors (in parentheses) at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. CZ = commuting zone

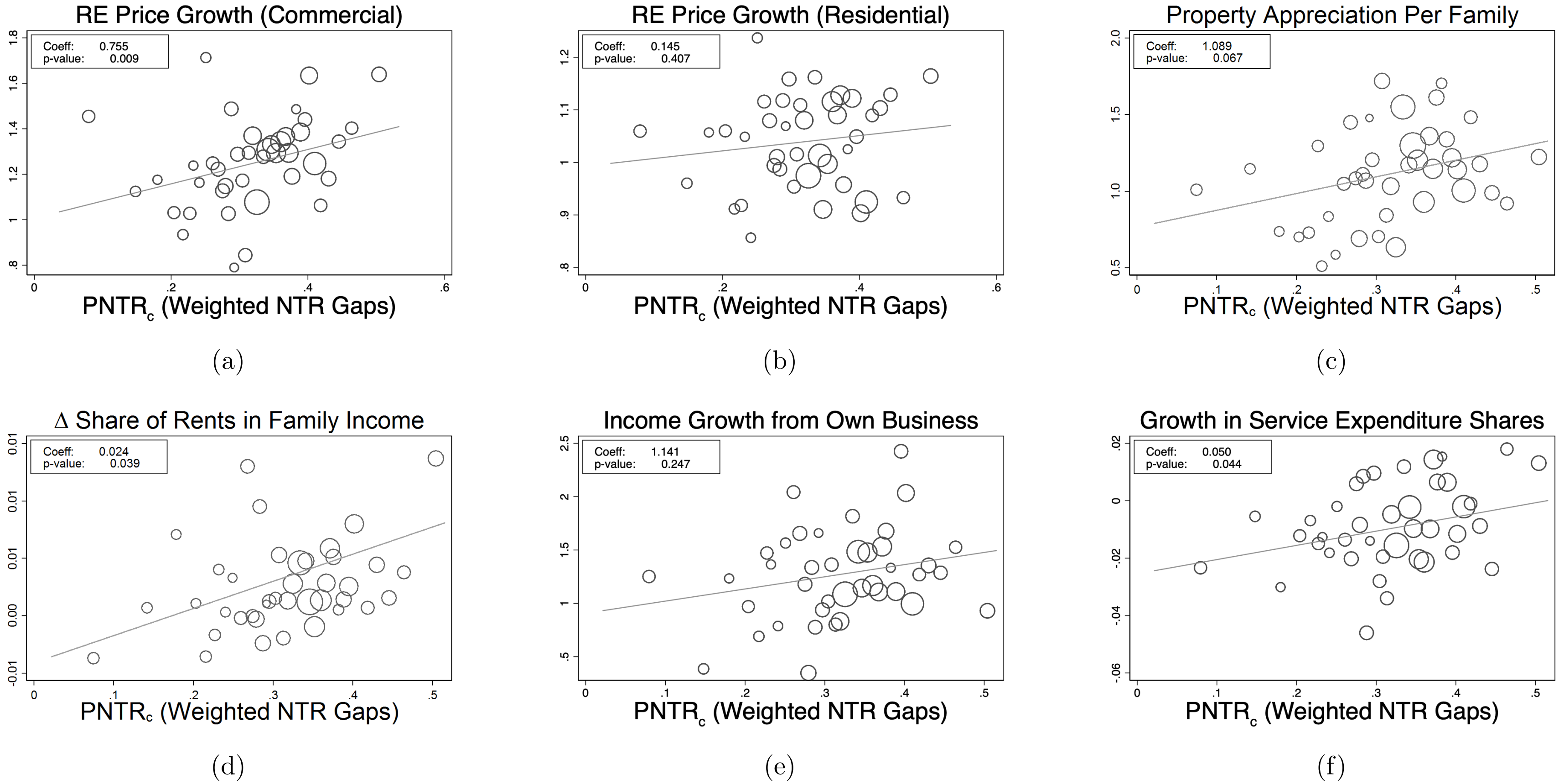
7.7 Mechanisms - GDP and Housing Wealth

Table 7: Log GDP and Population

	GDP		Population		GDP per capita	
	(1)	(2)	(3)	(4)	(5)	(6)
$PNTR_c$	0.504**	0.541**	0.285	0.251	0.219	0.289
	(0.238)	(0.255)	(0.242)	(0.230)	(0.222)	(0.246)
Controls		x		x		x
Obs.	274	274	274	274	274	274

Notes: City-level regressions showing the effect of weighted NTR gaps on logged values of GDP, population, and GDP per capita. Even-numbered columns include the main controls: contract intensity, import tariffs, input tariffs, and export licenses. We report heteroskedasticity-consistent standard errors (in parentheses) at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Figure 6: Wealth Shocks



Notes: Binned scatter plots of the relationship between the weighted NTR gap (PNTR) and post-treatment growth in outcomes. The plots show 40 equal-size bins, weighted by population size in each bin. The real estate data (plots (a) and (b)) are from WINDBANK. Real estate data from WINDBANK are available from 2002 to 2013 for commercial properties and from 2005 to 2013 for residential properties. Household income outcomes (plots (c)-(e)) and average services expenditures (last plot) are obtained from the Urban Households Survey, with the outcomes being changes from 2002 to 2007. Service expenditure shares are total service expenditures over household expenditure. Income growth is in log changes while the shares are long differences. For each plot we report the coefficient, and its associated p-value given heteroskedasticity-consistent standard errors, of a regression of the outcome on the PNTR measure in the underlying data.

7.8 Mechanisms: Returns to Education

Table 8: Effect of Skill-Specific Shocks on Student Flows

	(1) China skill shares	(2) Indonesian skill shares
Skilled NTR CHN	0.033	
	(0.161)	
Unskilled NTR CHN	0.265***	
	(0.100)	
Skilled NTR IND		-0.186
		(0.182)
Unskilled NTR IND		0.264**
		(0.110)
Obs.	275	275
R2	.062	.085

Notes: City-level regressions showing the effect of PNTR exposure on Chinese student enrollment growth between 2004 and 2013, per thousand city residents. Column (1) splits the PNTR exposure measure into one based on high skill intensive industries and another based on low skill intensive industries, using China-specific skill shares of industries. Column (2) repeats this exercise using Indonesia-specific skill shares from Amiti and Freund (2010). All regressions include the full set of controls: contract intensity, import tariffs, input tariffs and export licenses. We report heteroskedasticity-consistent standard errors (in parentheses) at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7.9 Mechanisms - Information

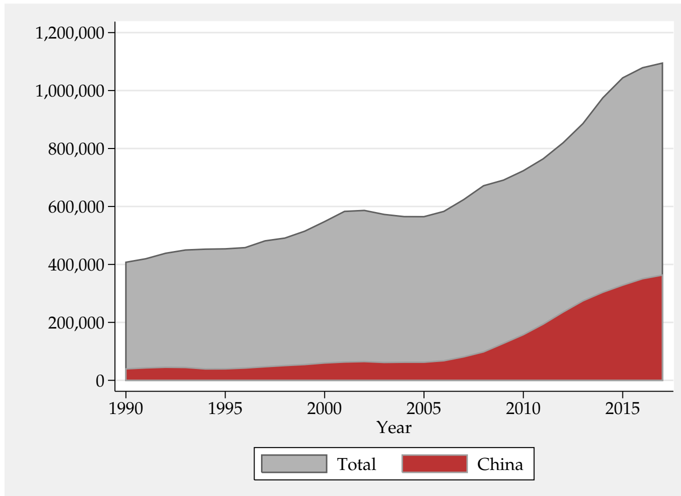
Table 9: Testing Information Flows between China and the United States

	(1) Reduced form	(2) First stage	(3) 2SLS	(4) 2SLS	(5) 2SLS
$PNTR_c$	0.324***	2.881***			
	(0.106)	(0.834)			
$\Delta \ln(X^{00-13})$			0.113**		
			(0.049)		
$\Delta \ln(X^{00-13}_{nonUSA})$				0.108**	0.092**
				(0.047)	(0.044)
F-stat			11.95	12.64	12.26
Obs.	275	275	275	275	275
Controls	x	x	x	x	x

Notes: City-level regressions showing the effect of PNTR exposure on Chinese student enrollment growth between 2004 and 2013, per thousand city residents. Column (1) reproduces our main estimates from column (5) in Table 3. All regressions include the following controls: contract intensity, import tariffs, input tariffs, and export licenses. Column (2) shows the first stage, where the outcome of interest is the log change in exports between 2000 and 2013. Column (3) shows the 2SLS effect of export growth on student flows, using PNTR exposure as an instrument. Column (4) reproduces the 2SLS result, but after excluding all exports to the United States in the export growth variable. Column (5) once again excludes all exports to the United States in the explanatory variable and also the PNTR exposure measure (instrument). We report heteroskedasticity-consistent standard errors (in parentheses) at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A Appendix Tables and Figures

Figure A.1: International and Chinese Enrollment Trends



Source: Open Doors, Institute for International Education, various years. Total flows include flows from China. Numbers include the sum of graduate and undergraduate students.

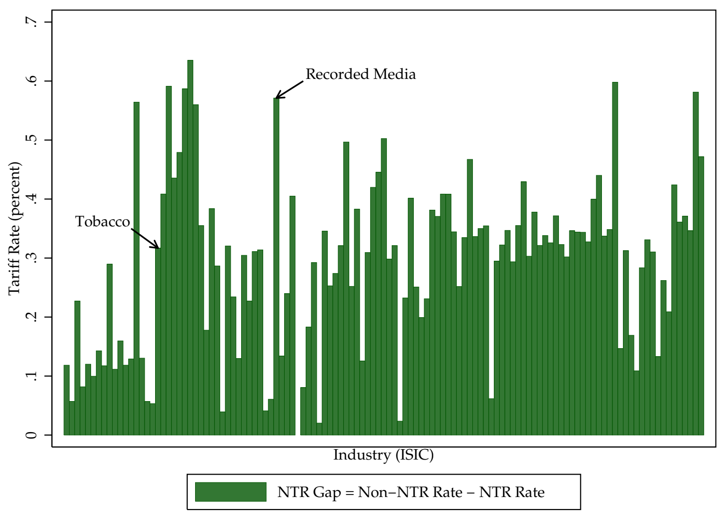
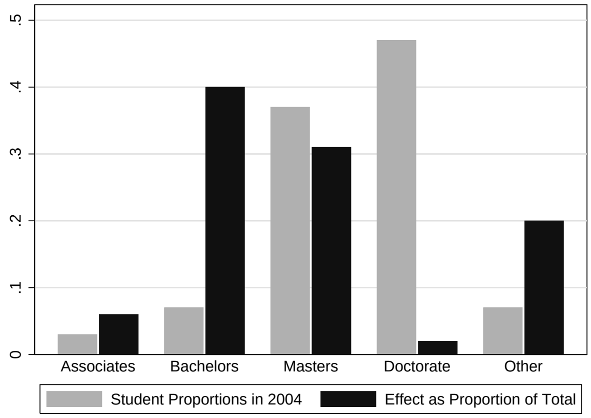


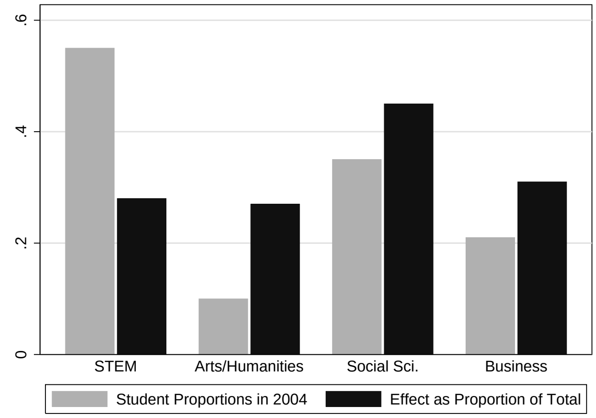
Figure A.2: NTR Gaps

Notes: The figure shows the NTR gaps for each industry. Green bars plot the difference in NTR and non-NTR tariffs shown in Figure 3a. Data on NTR and non-NTR tariff rates by industry are from Pierce and Schott (2016).

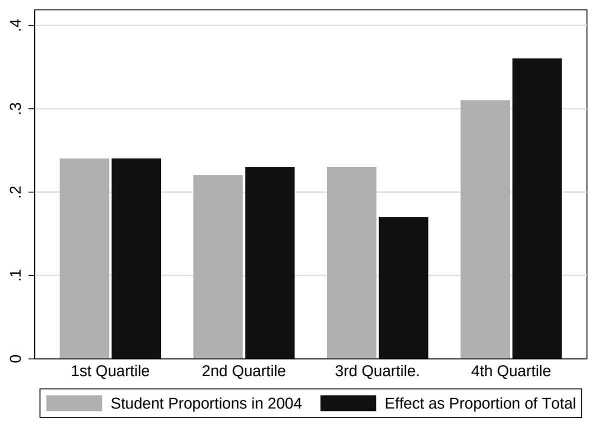
Figure A.3: Changes in the Composition of Chinese Students Attributable to PNTR



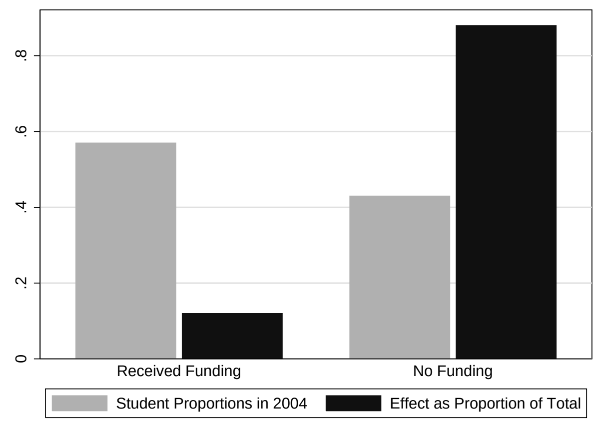
(a) Academic level



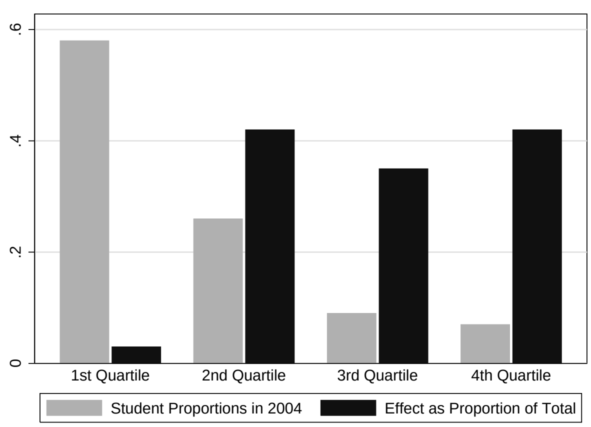
(b) Field of study



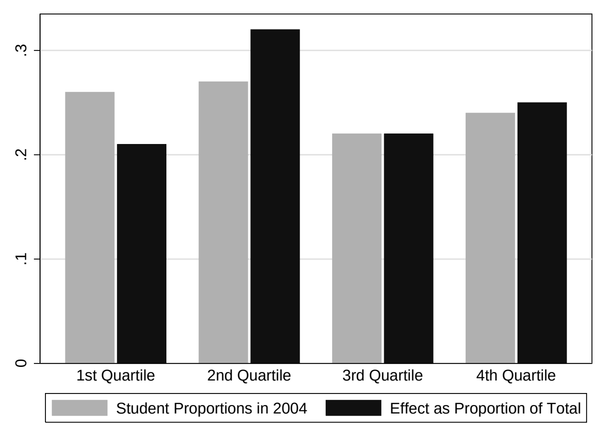
(c) University selectivity (admissions rate)



(d) Scholarship funding



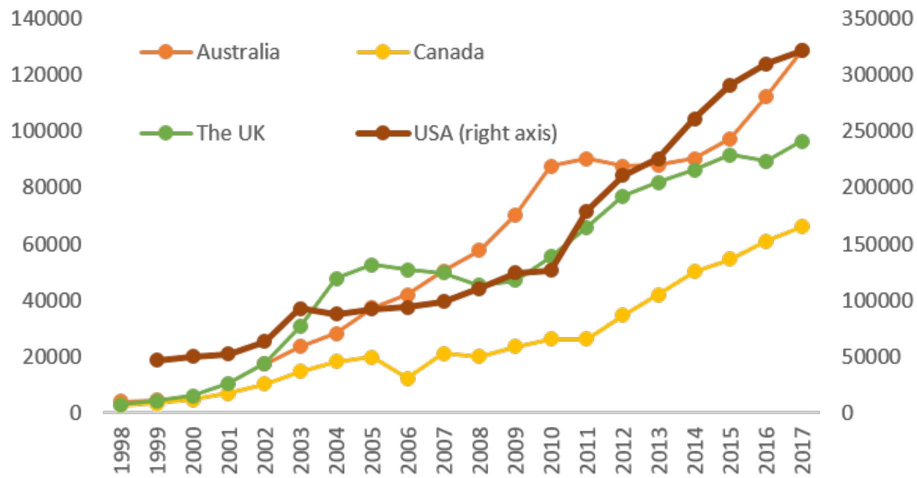
(e) Personal funding



(f) Human capital, US commuting zones

Notes: The figure displays estimates from Table 6. The lighter bar shows the proportion of incoming Chinese students in each category in 2004. The darker bar shows the proportional effect, that is, the coefficient on student growth in each category divided by the total effect on student growth. Hence, the proportional effect measures the proportion of the inflow of Chinese students in each category, attributable to PNTR exposure. Comparing the proportional effect to the proportions in 2004 gives a sense of the compositional changes in inflows induced by PNTR exposure. For full information on point estimates and standard errors, see Table 6.

Figure A.4: International Students from China in Top Four Destination Countries



Notes: The figure shows the growth in the number of Chinese students at the top destinations, as measured in 2017, using UNESCO data. The United Kingdom includes Great Britain and Northern Ireland. Students at all levels and degree types are aggregated here. US enrollment is on the right-axis.

Table A.1: Compositional Changes by Degree Level, 2004-13

	(1) STEM	(2) Arts	(3) Social sci.	(4) Social sci. business
A: Associate's				
$PNTR_c$	0.002*	0.007***	0.010***	0.009***
	(0.001)	(0.002)	(0.003)	(0.003)
Effect as proportion of total	0.09	0.36	0.55	0.50
Student proportions in 2004	0.16	0.14	0.70	0.37
Change in proportions	-0.07	0.22	-0.15	0.13
B: Bachelor's				
$PNTR_c$	0.040***	0.024***	0.066***	0.046***
	(0.014)	(0.007)	(0.022)	(0.016)
Effect as proportion of total	0.31	0.18	0.51	0.35
Student proportions in 2004	0.22	0.15	0.64	0.47
Change in proportions	0.09	0.03	-0.13	-0.12
C: Master's				
$PNTR_c$	0.042***	0.003	0.056***	0.041***
	(0.016)	(0.002)	(0.019)	(0.013)
Effect as proportion of total	0.42	0.03	0.55	0.40
Student proportions in 2004	0.40	0.09	0.51	0.39
Change in proportions	0.02	-0.06	0.04	0.01
D: Doctorate				
$PNTR_c$	0.004	0.001	0.003*	-0.000
	(0.005)	(0.001)	(0.002)	(0.001)
Effect as proportion of total	0.49	0.13	0.38	-0.05
Student proportions in 2004	0.81	0.04	0.14	0.04
Change in proportions	-0.32	0.09	0.24	-0.09
E: Other				
$PNTR_c$	0.001	0.054**	0.010***	0.005***
	(0.001)	(0.021)	(0.003)	(0.001)
Effect as proportion of total	0.01	0.83	0.16	0.08
Student proportions in 2004	0.06	0.49	0.46	0.12
Change in proportions	-0.05	0.34	-0.30	-0.04

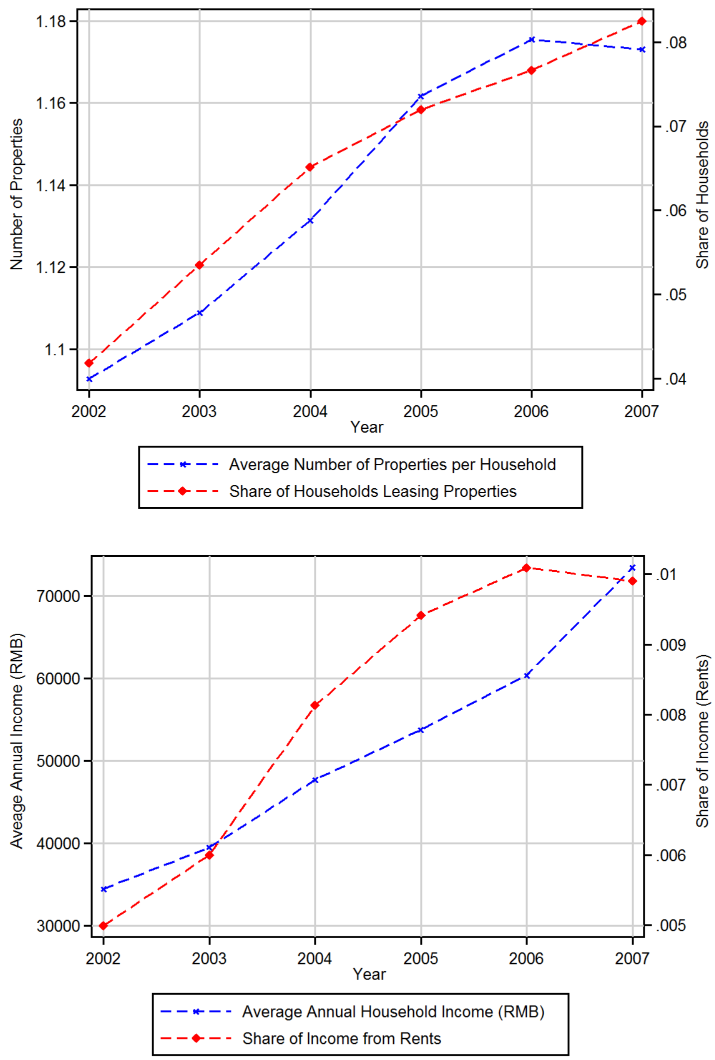
Notes: City-level regressions showing the effect of weighted NTR gaps on Chinese student enrollment growth between 2004 and 2013. We include all the main controls. The first row below the coefficients documents the effect as a fraction of the total effect in column (1). The second row shows the fraction of students of each type in 2004. The final row takes the difference between these two rows, and illustrates how the proportional inflow of students attributable to PNTR exposure has changed since the initial proportions in 2004. STEM degrees include degrees in science, technology, engineering and mathematics. Social sciences includes Business-related degrees.

Table A.2: Short-, Medium-, and Long-Run Impacts

	(1) 2004-07	(2) 2008-10	(3) 2011-13
$PNTR_c$	0.024**	0.074***	0.138***
	(0.012)	(0.025)	(0.046)
Contract intensity	0.016	0.044	0.121
	(0.013)	(0.039)	(0.086)
Import tariffs	-0.008	-0.025	-0.026
	(0.016)	(0.030)	(0.057)
Input tariffs	-0.044	-0.128	-0.347**
	(0.035)	(0.088)	(0.157)
Export license	0.026	0.099**	0.143
	(0.016)	(0.039)	(0.091)
Mean dep. var.	0.012	0.030	0.060
Obs.	275	275	275
R2	0.029	0.051	0.049

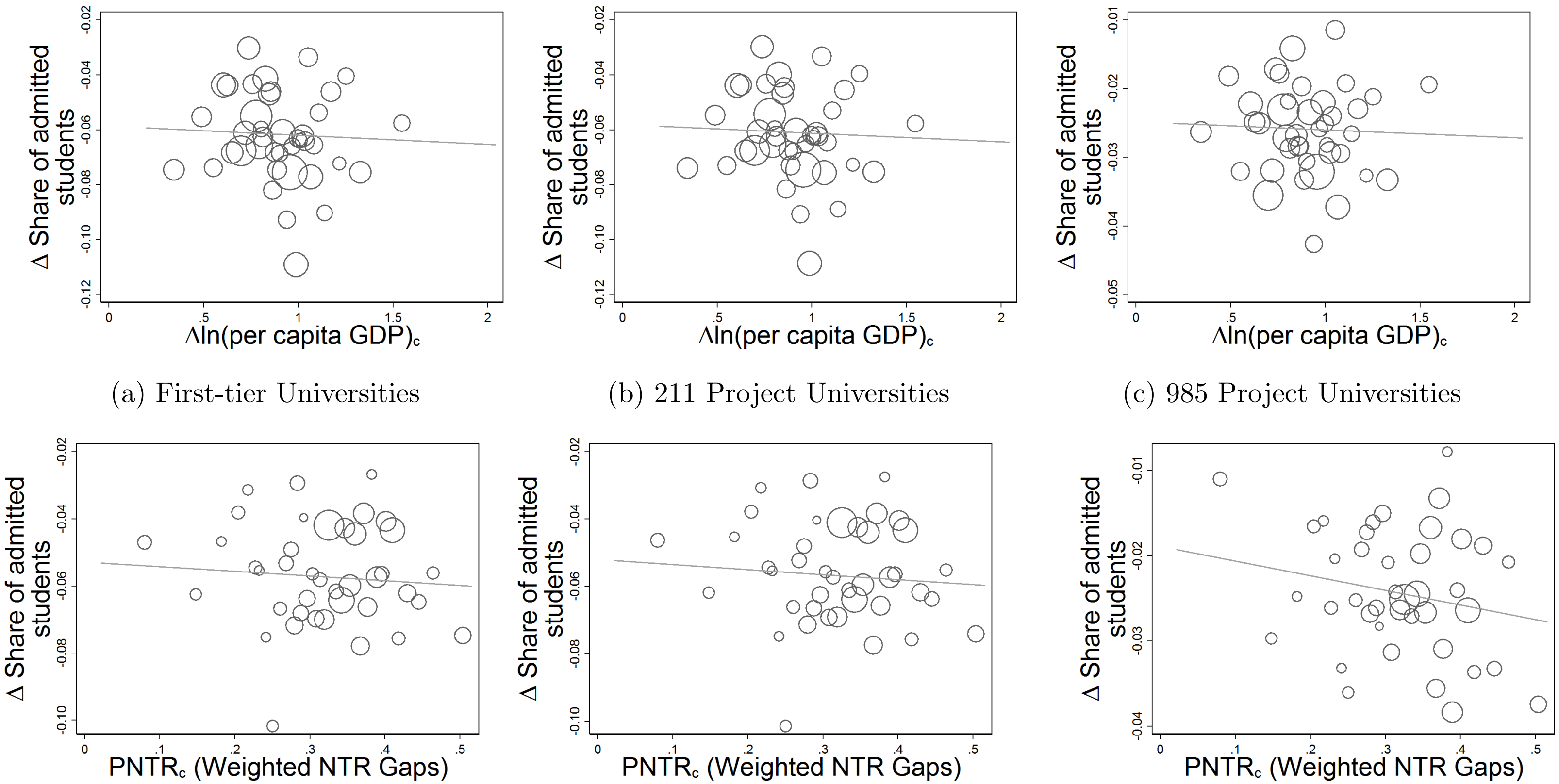
Notes: City-level regressions showing the effect of weighted NTR gaps on Chinese student enrollment growth, per thousand city residents, over different time periods. We examine a shorter-run time frame in column (1), 2004-07. Column (2) examines a medium-run time frame, which covers the Great Recession and recovery, 2008-10. Column (3) examines student growth over the longer-run period, 2011-13. We include all the main controls. We report heteroskedasticity-consistent standard errors (in parentheses) at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Figure A.5: Property Leasing and Share of Income from Rents



Notes: The figure displays information about rental properties in China using micro data from UHS. For each, we take the average across all households. The top figure shows the average number of properties per household along with the share of households that lease properties. The bottom figure show the average share of income that comes rents (which is zero for the vast majority of households), along with the rise in household income by year.

Figure A.6: Admissions to Elite Universities, per Capita GDP, and PNTR Gaps



(a) First-tier Universities

(b) 211 Project Universities

(c) 985 Project Universities

(d) First-tier Universities

(e) 211 Project Universities

(f) 985 Project Universities

Notes: The figure shows the correlation between the change in the share of admitted students by elite universities and (a) top row: per capita GDP growth rate by city, and (b) bottom row: PNTR gap. Per capita GDP and college shares are computed as the difference between 2005 and 2011. City population in 2005 is used as the weight. The aggregate number of students admitted by universities in each city is computed from the National College Entrance Examination data provided by the China Institute for Educational Finance Research at Peking University, between 2005 and 2011. We aggregate the micro-level data to obtain the number of admitted students by student's city of origin, university and year, based on which we calculate the year-city-specific share of admitted students by elite universities.

Table A.3: Trade Shocks and the Difficulty of Entering Elite Chinese Universities

Dep. var: Δ Share of admitted college students (05-11)	First-tier		211-Project		985-Project	
	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE
$PNTR_c$	-0.014	0.028	-0.015	0.027	-0.017	-0.001
	(0.033)	(0.033)	(0.032)	(0.033)	(0.013)	(0.014)
Region FE	-	Y	-	Y	-	Y
Observations	239	239	239	239	239	239
R-squared	0.001	0.153	0.001	0.153	0.007	0.156
	First-tier		211-Project		985-Project	
	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE
$\Delta \ln(\text{GDP})_{c,05-11}$	-0.012	-0.000	-0.011	-0.000	-0.001	0.003
	(0.010)	(0.009)	(0.010)	(0.009)	(0.005)	(0.004)
Region FE	-	Y	-	Y	-	Y
Observations	208	208	208	208	208	208
R-squared	0.005	0.328	0.005	0.318	0.000	0.233
	First-tier		211-Project		985-Project	
	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE
$\Delta \ln(\text{GDP/Pop})_{c,05-11}$	-0.003	-0.000	-0.003	-0.000	-0.001	0.003
	(0.008)	(0.009)	(0.008)	(0.009)	(0.004)	(0.004)
Region FE	-	Y	-	Y	-	Y
Observations	208	208	208	208	208	208
R-squared	0.001	0.328	0.000	0.318	0.000	0.233

Notes: City-level regressions show the effect of PNTR gaps (top row), GDP growth (middle row) and GDP per capita growth (bottom row) on the growth in the share of admissions in top universities, between 2005 and 2011. The aggregate number of students admitted by universities in each city is computed from the National College Entrance Examination data provided by the China Institute for Educational Finance Research at Peking University, between 2005 and 2011. We aggregate the micro-level data to obtain the number of admitted students by student's city of origin, university, and year, based on which we calculate the year-city-specific share of admitted students by elite universities.

B Theoretical Framework: Education as an Investment Good

This simple theoretical framework highlights a few basic points: if education is an investment rather than a consumption good, then a response to income shocks must mean households have borrowing constraints to fund their education (in this case, their education abroad). Indeed, as Bound et al. (2020) discuss, almost all the educational expenditures for international students from China are paid by their families, rather than via scholarships or loans. Our model also shows that the difference in prices (home versus foreign tuition) determines the magnitude of the educational response to income shocks.

In our setup, households choose where to get education when young. If they choose to go to college abroad, then $s = 1$; if they stay at home in China, then $s = 0$. They also choose how much to borrow from the future $\bar{b}$. They maximize their two-period utility: $u(c_1) + \beta u(c_2)$, where $\beta \leq 1$ is a discount factor.

Period 1 consumption depends on wealth Y, the price of education at home p_o, the price abroad p_d, and how much they can borrow b from period 2. Period 2 consumption depends on earnings and paying back the period 1 debt with interest R:

$$\begin{aligned} c_1 &= Y - p_o(1-s) - p_d s + b \\ c_2 &= w(s) - Rb \ , \end{aligned} \tag{4}$$

where $w(s)$ is a location-specific wage profile. A fraction of households are credit constrained: $b \leq \bar{b}$, where $0 \leq \bar{b} \leq \infty$. For households reaching the binding constraint, $b = \bar{b}$, the first-order condition with respect to s is:

$$p\ u'(Y - ps + b) = \beta w'_{od}(s)\ u'(w_{od}(s) - Rb) \tag{5}$$

For reasonable assumptions on $u(.)$ and w (for instance, if $u(c) = \log\ c$, and $w(s)$ is linear in s), schooling will respond to income shocks, in the manner $\Delta s = \frac{\beta}{(1+\beta)(p_d - p_o)} \Delta Y$, for credit constrained households. For non-constrained households, the education decision does not depend on Y.[49]

[49] In this setup, the only role that changing returns to education (via changes to $w(s)$) plays for borrowing-constrained households is in relaxing borrowing constraints. If borrowing is strictly prohibited, $\bar{b} = 0$, then a change in returns does not affect education for borrowing-constrained households.

C World Import Demand and MFA Exposure

Industry-level exposure to MFA liberalization is based on fill rates by industry that are provided by Brambilla, Khandelwal and Schott (2010). We use the 2001 fill rates to measure the exposure to the phasing out of the reforms through 2005, and once again concord the Harmonized System (HS) level data to International Standard Industrial Classification industries.

To construct the world import demand as our second set of policy treatments, we use the data on world trade flows covering 2000 to 2014. The data are provided by the International Trade Statistics Database of UN Comtrade, and each trade flow reports the corresponding importer, exporter, HS 6-digit code, and total values. We create total imports for each HS 6-digit product at the world level, netting out any trade (exports or imports) that involves the United States.

We predict Chinese export growth based on world demand for imports from China that excludes US imports. To construct the instrumental variable based on the change in total world demand, we first calculate the total imports (or exports) of a product at the world level, netting out any trade (exports or imports) that involves the United States or China. To do so, we aggregate the imports where all other countries (excluding the United States and China) are reported and "World" is the source. We then calculate the total exports where all other countries (excluding the United States and China) are reported and "World" is the destinations. Then we net out the total imports from the parts exported by the United States and China.[50]

$WorldM_{it}$ is the sum of total imports (or exports) of a product i at the world level, in year t, after netting out any transactions with the United States. The industry weights are built using past city-level exports as weights.

$$XD'_{pt} = \sum_i \lambda_{pi} \frac{WorldM_{it}}{WorldM_i^{2004}}, \;\; \lambda_{pi} = \frac{X_{pi}^{1998-2000}}{\sum_j X_{pj}^{1998-2000}} \;\;, \tag{6}$$

where λ_{pi} is such that the weights now depend on city exports prior to China's accession to the World Trade Organization. The end result is a yearly prediction of how Chinese exports should have evolved if it exactly followed world demand.

[50]In case we obtain a negative value, we redo the same procedure but from the 'supply' perspective, by calculating the aggregate exports in the same way we calculate the total imports as above. We replace the negative value for the industries where the total adjusted imports (excluding trade with the United States and China) with the corresponding value obtained from the adjusted exports.

D Rotemberg Weights

We follow Goldsmith-Pinkham, Sorkin and Swift (2020) and construct Rotemberg weights to get a sense of which industries drive the variation in Normal Trade Relations gaps across cities. Table D.4 details the top 30 industries along with the International Standard Industrial Classification industry name. Not surprisingly, the top industries are textiles and apparels. However, outside the top three there are also chemicals, food, and other miscellaneous industries.

Table D.4: Rotemberg Weights by Industry, Top 30

ISIC	Industry description	Rotemberg weight
1810	Manufacture of wearing apparel, except fur apparel	0.53
1711	Preparation and spinning of textile fibers; weaving of textiles	0.25
1721	Manufacture of made-up textile articles, except apparel	0.16
2423	Manufacture of pharmaceuticals, medicinal chemicals and botanical products	0.15
1551	Distilling, rectifying and blending of spirits: ethyl alcohol production from ferment	0.14
2691	Manufacture of non-structural non-refractory ceramic ware	0.08
3699	Other manufacturing n.e.c.	0.07
1920	Manufacture of footwear	0.07
3694	Manufacture of games and toys	0.05
2429	Manufacture of other chemical products n.e.c.	0.05
1730	Manufacture of knitted and crocheted fabrics and articles	0.05
2029	Manufacture of other products of wood; manufacture of articles of cork, straw and pla	0.05
2520	Manufacture of plastic products	0.04
1513	Processing and preserving of fruit and vegetables	0.04
1912	Manufacture of luggage, handbags and the like, saddlery and harness	0.03
3210	Manufacture of electronic valves and tubes and other electronic components	0.03
3140	Manufacture of accumulators, primary cells and primary batteries	0.03
2421	Manufacture of pesticides and other agro-chemical products	0.03
3230	Manufacture of television and radio receivers, sound or video recording or reproduci	0.03
2899	Manufacture of other fabricated metal products n.e.c.	0.02
2893	Manufacture of cutlery, hand tools and general hardware	0.02
2022	Manufacture of builders' carpentry and joinery	0.02
3591	Manufacture of motorcycles	0.02
2610	Manufacture of glass and glass products	0.02
1542	Manufacture of sugar	0.02
2925	Manufacture of machinery for food, beverage and tobacco processing	0.02
3150	Manufacture of electric lamps and lighting equipment	0.02
3110	Manufacture of electric motors, generators and transformers	0.02
3693	Manufacture of sports goods	0.02

E Other Data

Firm Survey Data

The annual city-industry-specific employment is sourced from the Annual Survey of Industrial Production (ASIP) conducted by the National Bureau of Statistics (NBS) of China (1998 to 2013). The dataset surveys all types of firms (state-owned / non-state owned) whose revenue is more than five million RMB each year in the manufacturing sector. The sample size varies from 165,119 in 1998 to 336,768 in 2007. ASIP provides us with employment at the firm level, and we aggregate it to obtain total employment at the city-industry level. Notably, the ASIP industry classification uses the China Standard Industrial Classification (GB/T4754-1994 and GB/T4754-2002) at the 4-digit level. To be consistent with the tariff and trade data, we concord the China Standard Industrial Classification to the International Standard Industrial Classification Revision 3 at the 4-digit level using the crosswalk provided by the NBS of China.

College Students Admissions Data

The aggregate number of students admitted by universities in each city is computed from the National College Entrance Examination (NCEE) data provided by the China Institute for Educational Finance Research at Peking University. The data covers the universe of students enrolled in Chinese universities and colleges between 2005 and 2011.[51] We aggregate the micro-level data to obtain the number of admitted students by student's city of origin, university and year, based on which we calculate the year-city-specific share of admitted students by elite universities.

We measure the eliteness of a university according to its membership in the first-tier class, 211-Project, and 985-Project.[52] In terms of eliteness, 985-Project universities are typically considered better than the 211-Project universities, followed by the first-tier universities.

Background: The National College Entrance Examination

The NCEE (i.e., *Gao Kao* in Chinese) is so far the most important channel for higher education admissions in China. In practice, the same subjects are tested in every province, while the testing contents may vary. Each university assigns a predetermined admissions quota to each province before the test, and will admit applicants from the highest to the lowest scores until the provincial quota is filled. Students compete within a province based on the total score to be admitted to a university, and they do not compete across provinces. Therefore, students from different prefecture cities within a province will be faced with the same NCEE policy.

[51] The detailed data information and the background of the NCEE are discussed in Zivin et al. (2018).

[52] Regular colleges and universities can be classified into three tiers according to the admissions process. The first-tier universities are generally considered as the elite or key universities, whose admissions process takes place before the second- and third-tier universities (first-tier universities also require higher cut-off scores for admission). The 211-Project refers to the proposal to "enhance the quality of 100 colleges in the 21st century." In 1998, the Chinese government launched a program to increase financial support for elite universities, and this program is referred to as the 985-Project. The universities in the 985-Project lists are typically considered better than the ones in 211-Project lists. In 2011, there were 39 universities in the 985-Project list, and 112 in the 211-Project list.