# Trade Liberalization and Chinese Students in US Higher Education*

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**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 how the trade deficit in goods cycles back as a surplus in US exports of education services. Focusing on China's accession to the World Trade Organization, we show that Chinese cities more exposed to trade liberalization sent more students to US universities. Growth in housing income/wealth 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 trends in regional inequality. Our estimates suggest that recent trade wars could cost US universities around $1.6 bn in tuition revenue.

*JEL:* F16, I25, J24, J61

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# 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 show that trade-driven growth raised wealth among upper-income Chinese families, generating demand for US services, and higher education in particular. As such, a trade deficit in goods can partially cycle back as services exports in the developed country. This provides 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).

US higher education has been transformed by marked increases in international enrollment since 2005, driven by Chinese students whose enrollment grew 400% over this period (Figure 1a). Full-fare paying foreign students generated much needed revenue for universities, often used to the advantage of domestic students (Bound et al., 2020; Shih, 2017).[1] In the same 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 expanded the size of college-ready, high-school graduate cohorts. A major driver of this structural change was 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 services from the US.

Detailed, sub-national examination of services trade has been severely constrained due to data limitations. We utilize a novel database of US education exports to international students, obtained through a Freedom of Information Act (FOIA) request, detailing students' city of origin, degree-level, university, field of study, and financial support. This allows us to exploit variation across Chinese prefecture cities 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) tariffs on Chinese imports. Failure to renew would result in a sudden increase to high non-NTR rates. In 2001, the US made NTR tariff rates permanent. Gaps between NTR and non-NTR tariffs across products help measure the reduction in uncertainty following the conferral of permanent NTR (PNTR) rates. Eliminating tariff uncertainty

[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.

increased commerce between the US and China, and induced export-driven growth in Chinese cities (Figure 1b) (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 us to compare student flows across cities more and less intensely affected by the conferral of PNTR rates.

We find a significant and positive association between trade liberalization and student flows – an 10 percentage point (p.p.) increase in PNTR exposure led to growth in Chinese student enrollment in the US of around 32 students per million city residents.[3] Our effects account for 25% of the total number of Chinese students matriculating in US higher education during this period. As such, the WTO accession induced substantial student flows externally, and not just internal migration as shown previously (Facchini et al., 2019; Tian, 2020).

Our results inform the consequences of the 2018 US-China trade war. A counterfactual exercise indicates that tariff increases of 20 p.p. could cost US universities up to 40,000 Chinese students over the next 10 years – equivalent to a loss of $1.15-$1.60 billion in tuition revenue, or 10% of educational services exports to China, at a time that universities are increasingly reliant on revenue from China (Bound et al., 2020). This estimated loss to universities is a lower bound, as it does not account for spillovers on surrounding localities.[4]

Our findings are representative of broader implications. While our unique data allows us to focus specifically on education exports, rising services demand as a response to trade liberalization apply to other sectors, such as information and financial services. Although the US goods deficit dominates its services surplus, the global growth of services trade implies that services will soon be sizable to shift trade balances (McKinsey Global Institute, 2019).

Alongside increases in scale, we observe changes in the composition of Chinese students. Chinese students traditionally enrolled in Doctoral programs, which typically provide funding for students. Trade liberalization induced a shift towards undergraduate studies, which generally provide little funding, and often require full-sticker price tuition payments. As such, we find that PNTR exposure dramatically increased the share of students financing their education through personal funds, rather than through scholarships/fellowships.

These findings inform potential mechanisms. Consistent with compositional changes, we show that trade liberalization increased global demand for Chinese manufactured goods and subsequently the wealth of city residents. First, PNTR exposure led to an increase in exports of 25% to 34% at the city level. Given the relatively high average cost of US tuition, about

[3] Our units of analyses are Chinese prefecture-level cities. In the text, we use the terms cities and prefectures interchangeably. We use prefectures, as they determine an individual's *hukou*. Even if individuals move within their *hukou* jurisdiction, we assign them to their correct prefecture.

[4] 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.

$40,000 per year, we focus on sources of wealth/income growth pertinent to the top of the income distribution, namely real estate appreciation and rental/own-business income.[5] Given limited investment opportunities in China, a meaningful fraction of wealth expansion occurred 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 (Cheng and Potlogea, 2017), and wage growth (Erten and Leight, 2020). Expanding wealth allowed families with means to finance the large cost of paying for housing and tuition in the United States. Although wealth/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.

We also inform distributional impacts in US higher education and growing regional inequality. While Chinese students initially tended towards STEM (science, technology, engineering and mathematics) majors, trade liberalization induced large responses in social sciences and business-related fields. Trade liberalization also increased the share of students at less selective universities, and raised student flows in equal proportion at universities in localities with low and high levels of human capital. Subsequent spillovers to areas surrounding universities may help countervail the negative labor market impacts Chinese imports. 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. Our findings suggest that educational services exports may help dampen the widening trends in regional labor-market inequality (Eckert, Ganapati and Walsh, 2019).

We perform 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 find no evidence of differential trends in student flows, and other economic and education indicators prior to 2001. Our estimates are robust to the exclusion of large, coastal cities and industries with high Rotemberg weights, to controls for internal migration during our sample period, and to inference corrections for correlation across cities in baseline industry shares. The sizes and patterns of the estimates are remarkably similar when utilizing 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). Together these bolster our confidence that trade liberalization helped increase Chinese enrollments in the US.

We contribute to two strands of the trade literature: the importance of labor reallocation, and the role of demand in driving trade patterns. Although the detrimental impacts from Chinese goods imports are well documented (Autor, Dorn and Hanson, 2013; Pierce

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

and Schott, 2016), less is known about services trade, which now accounts for over a third of US trade activity (Eaton and Kortum, 2018).[6] We exploit detailed data on exports of education services to show that trade-driven income growth in China generated strong demand for US higher education, complementing recent findings that trade with China raised non-manufacturing employment (Wang et al., 2018; Bloom et al., 2019; Caliendo, Dvorkin and Parro, 2019). While trade dynamics are driven by relative production costs in previous studies, the operating channel in our empirical findings is an increase in the *demand* for services through greater wealth abroad, consistent with theoretical studies on non-homotheticity in demand (Matsuyama, 1992; Foellmi, Hepenstrick and Josef, 2017; Dingel, 2016; Fajgelbaum, Grossman and Helpman, 2011). As such, our findings indicate that a trade deficit in goods partly cycled back to the US as a surplus in educational services.

We also add to two strands of the migration literature on the 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.[7] These migration costs are quantifiable for international students as standard tuition and living expenses at US higher education institutions. In contrast, canonical models also show that greater income may also raise the opportunity cost of emigrating (Angelucci, 2015; Bazzi, 2017). As many international students view study in the US as a pathway to join the US labor market (Bound et al., 2015; Shih, 2016), better income opportunities at home may lower the option value of a US degree. 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.

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.

[6] 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).

[7] 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.

[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.

Finally, we speak to recent work on trade and education (Liu, 2017; Li, 2018). While they analyze human capital decisions stemming from changes in the returns to education (Greenland and Lopresti, 2016; Atkin, 2016; Blanchard and Olney, 2017), we highlight the role of trade induced wealth generation in helping overcome financial barriers to study abroad.

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, importantly converting the uncertain Most Favored Nation (MFN) tariff regime to a permanent NTR tariff regime. Beginning in 1980, the US granted low MFN tariffs to China–subject to yearly Congressional renewal–despite it not having MFN status.[9] The need for annual renewal generated uncertainty over the low-tariff regime's longevity, which inhibited the expansion of commerce between the US and China (Pierce and Schott, 2016; Handley and Limão, 2017). Termination of MFN status would have increased tariffs facing US importers over eight-fold, from an average tariff of 4% (under MFN status) to 35% (Facchini et al., 2019), and affected over 95% of US imports from China (Pregelj, 2001), with the possibility of further retaliation.

The NTR regime made the low MFN tariffs permanent and no longer required Congressional renewal. This did not change actual tariffs, but reduced the uncertainty facing Chinese exporters and US importers, with substantial impacts on trade. China's exports to the US grew by 57% within a year, and by 177% within the first five years of PNTR conferral.[10]

We derive plausibly-exogenous variation in PNTR exposure across Chinese prefecture cities (henceforth, cities).[11] We utilize the potential spike in tariffs under loss of MFN status – the gap between NTR and non-NTR tariff rates (henceforth, NTR gap) – to quantify 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.

[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).

[10] Calculations based on US imports from China reported by the Census Bureau (December, 2020): https://www.census.gov/foreign-trade/balance/c5700.html. Although NTR tariffs apply only to trade with the US, this accounts for a meaningful one-fifth of all Chinese exports (Cheng and Potlogea, 2017).

[11] We describe the administrative definitions of prefecture cities and the reasoning for using this geographical unit of analysis in section 4.

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.

Notably, the conferral of PNTR affected internal "non-*hukou*" migration in China (Facchini et al., 2019). The *hukou* system ties an individual's access to schooling to their prefecture city of birth, making it difficult for youth to attend schools outside of their hukou city. An advantage of our student-level data is that contains permanent addresses, which are likely to reflect an individual's *hukou* prefecture city. This limits the potential for endogenous internal migration in our estimation. We further augment our analysis with micro-data from Chinese Censuses to explore in detail how internal migration affects our estimates.

# 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 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 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; Cheng and Potlogea, 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 and networks.

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).[12] 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.

If education is considered a consumption good, increases in income/wealth 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? Prior work links PNTR exposure to increased wages at the county level in China (Erten and Leight, 2020), and greater employment and investment growth (Cheng and Potlogea, 2017). Interestingly, Bound et al. (2020) illustrate that almost all education costs for Chinese students in the US are financed using family funds, rather than via scholarships or loans. Given the extraordinarily high cost of a US education–one year of tuition is 40-50 times average Chinese household incomes–we examine sources of wealth generation applicable to the top income groups. Unlike prior work, we explore growth in real estate and business income/wealth in cities exposed to PNTR. Recent work documents the importance of the real estate sector in China, 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).[13]

Other than income and wealth, trade liberalization may have also 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

[12] 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 consider their wealth, the price of education at home and abroad, and how much they can borrow $b$ from period 2. With household first-order conditions, we 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 unconstrained households, education does not depend on wealth.

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

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.[14] Alternatively, this could occur if the returns to college rise alongside an inelastic supply of higher education within China.[15] 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 outmigration 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.

# 4 Empirical Strategy and Data

We describe our empirical strategy and data, with additional data details in Appendix E. 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 prefecture 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 focus on prefecture cities as this geographical administrative unit reflects Hukou status, thus limiting the scope for endogenous internal migration, and as prefectures can be reasonably identified in the available address information

[14] 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.

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

in SEVIS.[16] 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, $\Delta S_c$

We obtain data on Chinese students from the Student Exchange and Visitors Information System (SEVIS) through a Freedom of Information Act (FOIA) request. The data contain records for every foreign student visa by year of matriculation from 2000 to 2013. The information includes the student's permanent address, 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 group subtotals by program/funding characteristics. For each city we calculate the change in the number of students between the latest and initial year of various time frames (pre- and post-WTO). 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.[17] As city population is measured in thousands of persons, our dependent variable measures the change in the number of Chinese students per 1,000 residents.

[16] A three-level system governs official geographical administrative units 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 prefecture city. Because sub-municipality trade data are unavailable in the customs data, we include the 4 municipalities Beijing, Shanghai, Chongqing, and Tianjin in the analysis, and also provide robustness checks where we drop them. For details, see http://xzqh.mca.gov.cn/statistics/2018.html.

[17] 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 Surveys of the National Bureau of Statistics of China. Second, using the total city population, which

### 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).[18] 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 2a 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, *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).[19] We use 1997

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.

[18] 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.

[19] 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

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 $c$ ($\sum_j X_{cj}^{1997}$).[20] 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.[21]

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 2b, 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.[22]

#### 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 productivity in skill-intensive industries, and possibly growth in demand for higher education. Data on contract intensity by industry are from Nunn (2007).[23] 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

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.

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

[21] 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.

[22] 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.

[23] 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.

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.[24] 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 reliable tracking of 275 Chinese prefecture cities over time (see Figure 2b), for which we can measure their exposure to PNTR and growth in the number of students going to the US over 2000-13. 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.[25]

Table 1 shows summary statistics. Between 2000 and 2013, cities experienced sharp growth in economic activity, with more modest growth in population. In contrast, the average number of Chinese students studying abroad in the United States increased over ten-fold. The share of students pursuing undergraduate and master's degrees experienced substantial growth, offset by declines in the share pursuing Doctoral studies. Furthermore, 81% of matriculating students in 2000 pursued STEM degrees, but that share fell to 35% in 2013. The declining share of STEM students was offset by substantial increases in social sciences and arts and humanities. Interestingly, the composition of students by university selectivity, grouped into quartiles by admissions rates, saw large increases in the share of

[24] The input-output table is available for 120 industry groups ("scodes"), of which 70 are manufacturing.

[25] 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.

students entering the least selective (tier 4) universities. Notably, the fraction of students that received scholarship funding decreased from 77% to 22%.

## 4.2 Validating Identifying Assumptions

Causal identification requires PNTR exposure to be exogenous to other determinants of student emigration. We examine whether city-level PNTR exposure correlates with pre-trends in student emigration,[26] and other city-level educational and economic indicators. These include exports, GDP, employment, FDI flows, real-estate investment, students attending college domestically, the number of domestic colleges, domestic students attending secondary schools, and the number of secondary schools.[27]

Figure 3 illustrates the relationship between PNTR exposure and growth in educational and economic outcomes 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 test these relationships by estimating specification (1) and replacing the dependent variable with our pre-trend measures of growth in these variables.[28] Growth is measured in log changes using available data on cities from 1997 to 2000, the period just prior to PNTR conferral.

Tables 2A and 2B display the results of this exercise. In each panel, we show results with and without our full set of controls. Panel A columns (1)-(5) show the growth in our main economic variables in the pre-WTO regime, whereas column (6) shows our first-stage relationship: the growth in exports as a function of PNTR. Panel B shows the pre-trends in our primary outcome (column (1)), and in other domestic education measures. The results show no significant relationship between pre-PNTR growth in outcomes and PNTR exposure. Hence, effects on student emigration are unlikely to be explained by unobserved differences between cities with high and low PNTR exposure.

Importantly, we assess the relationship between PNTR and our two primary variables of interest: exports and student growth. Figure 3 and Table 2A column (5), show that PNTR did not benefit cities on the basis of pre-existing trade patterns – there is no significant relationship between PNTR exposure and export growth from 1997-2000. However, Figure 5 and Table 2A column (6) indicate the policy had a substantial impact on exports after enactment. Moving from a city at the 25th percentile in PNTR exposure to one at the 75th

[26] We measure student pre-WTO emigration in 2000 and 2001, as our SEVIS data begins in 2000.

[27] 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.

[28] We also jointly estimate the significance of pre-trends by regressing our PNTR exposure on all pre-period variables shown in tables 2A and 2B. The F-test fails to reject the null hypothesis that all coefficients are 0 at conventional levels of significance, with a p-value of 0.61.

percentile (roughly 10 p.p.) increased exports by 25-34 p.p. In sum, the intensity of PNTR appeared to be exogenous with respect to initial city characteristics and trends, but had a substantial impact on export growth after conferral.

Next we examine student emigration. The right panel of Figure 4, illustrates the relationship between PNTR exposure and pre/post-WTO student flows.[29] While there was no correlation with student emigration prior to 2001, PNTR exposure is positively associated with student emigration after enactment. We then regress year-on-year changes in student outflows on PNTR exposure, and plot coefficients and 95% confidence intervals in the left panel of Figure 4. Interestingly, much of growth in student flows occurs only after 2004, perhaps as income gains and college-decisions take time to materialize. To be conservative, we will focus on student flows over the 2004-13 period, but also show results using 2000-13.

# 5 Results

## 5.1 Student Flows to US Universities

Figures 4 and 5 revealed a strong positive association between exports, and growth in the number of students studying in the US. We now formally quantify and test the relationship between post-WTO student migration and PNTR exposure, by estimating our benchmark equation 1 in Table 3. Column (1) excludes controls and shows that PNTR exposure is positively and significantly associated with student emigration. Since we measure long differences in student migration (2004-13), time-invariant city characteristics and time-varying national trends are accounted for in the estimation. Remaining threats to identification include 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 controls for initial city-level factors that might determine future access to foreign markets. Column (2) of Table 3 adds the control for initial contract intensity. Columns (3) and (4) add the controls for initial import tariffs and input tariffs, respectively. Finally, column (5) fully saturates the model, including the control for the initial share of revenue in export licenses. Column (6) shows the relationship for the longer 2000-13 period.

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

[29] The pre-period student flow is measured between 2000-01. The post-period student flow is the average yearly growth–the change between 2000-13 divided by 13. Figure A.3 shows the long-difference (2000-13), rather than the average yearly change.

(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 PNTR exposure 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.

The effect of PNTR exposure on out-migration to the US also increases over time, as shown in the left panel of Figure 4 and Tables A.1 and A.2. In examining the growth over all years of our student data (i.e., 2000-13), the relationships are both larger and more precisely estimated. When we analyze initial (2004-2007), intermediate (2008-2010), and later (2011-2013) growth, magnitudes grow each period. This is consistent with gradual accumulation of wealth/income as a predominant mechanism, which we explore in section 6.

## 5.2 Robustness of PNTR Exposure

We provide a variety of sensitivity checks. We begin with sample refinements. In column (2) of Table 4 we remove the cities under the direct administration of the central government – Beijing, Shanghai, Chongqing, and Tianjin.[30] Column (3) excludes capital and coastal cities to ensure that results are not driven by particularly large influential cities, or places with stronger access to foreign markets.

We then include region fixed effects in column (4), to account for any differences in policy, culture, or institutions that vary across regions. The magnitude decreases size due to a loss in variation – there are now only about 45 cities per region – but remains significant. The last column includes an additional control for time-varying changes in tariffs – the difference between average city-level tariffs in 2013 and 2004. Results remain virtually unchanged compared to our preferred estimates, reprinted in column (1).

[30] As government policies can favor municipalities more than other prefecture cities (Wang, 2013), we exclude the four municipalities for robustness.

### 5.2.1 Internal Migration

We assess whether our findings could simply reflect population changes from in-migration to cities experiencing trade-induced growth. While cities exposed to trade shocks enacted migrant-friendly policies (Tian, 2020) and sustained in-migration, we note that these inflows were primarily low-skilled, non-*hukou* migrants (Facchini et al., 2019). Limited access to local services meant non-*hukou* migrants could not attend schools and it was extremely difficult to obtain *hukou* residency in destination cities. Our data contain permanent addresses, which likely reflect their *hukou* city and helps guard against endogenous in-migration. In addition, as most children must attend high-school in their *hukou* city, for students applying to undergraduate degrees, their stated address is their *hukou* city.

Nonetheless, we examine whether our results are robust to internal migration in Panel B of Table 4. In the first three columns, our findings remain robust and stable when controlling for concomitant changes of in- and out-migration rates for both skilled and unskilled workers.[31] In column (4) we use the entire prefecture population (both rural and urban) as the denominator of our outcome variable to account for potential rural to urban migration within-prefecture. Results remain robust, and the slight attenuation of the estimate is expected as the denominator is larger. In column (5) we divide student growth by the 2013 population as it allows our outcome to reflect internal migration over our period. The result, though slightly attenuated, indicate that internal migration alone cannot account for our findings. Finally, our results are unchanged when excluding large cities that are more likely to attract in-migrants in Panel A of Table 4.

### 5.2.2 Sensitivity of the Shift-Share Approach

Our measure of PNTR exposure falls under the broad 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

[31] We use microdata on skilled and unskilled migration from the Chinese Population Census in 2000 and 2015. For both skilled and unskilled workers, we compute the probability of out-migration and in-migration from each city, and then calculate the change from 2000-2015. For details on the Chinese Population Census and the internal migration measures, see Appendix E.

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. Correlation between lagged shares and unobserved determinants of future student emigration renders the shift-share approach invalid (Goldsmith-Pinkham, Sorkin and 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.[32] 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 is 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 another check, introduced by Goldsmith-Pinkham, Sorkin and Swift (2020), that examines the weights that different initial shares play in estimation. We use our initial PNTR measure, and calculate Rotemberg weights for each industry's export share.[33] Appendix Table D.5 shows the top 30 industry weights. Removing the five industries with the largest Rotemberg weights from our PNTR measure–shown in the third row in Table 5–does not affect our findings. Finally, in column (6), we report standard errors using an adjustment outlined by Adao, Kolesar and Morales (2019), which accounts for the correlation

[32]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 earliest available data on city-level exports by industry is 1997, using current city codes (severely limited data are available for earlier periods).

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

across cities in industrial shares, and find that our results are still precisely estimated.

### 5.2.3 Alternative Sources of Variation

We complement our main analysis with two additional sources of variation that do not rely on the PNTR policy.[34] 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 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.[35]

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

## 5.3 Migration Elasticities by Type and Compositional Changes

Table 6 examines whether PNTR exposure affected the composition of students. We study how migration elasticities differed by the level and field of study, sources and amounts of funding, and quality of US institution attended. Changes to the composition of students help inform mechanisms that we examine in section 6. For instance, full-tuition-paying undergraduate students are more responsive to PNTR shocks than subsidized doctoral students, suggesting that income/wealth growth could underlie our main results.

We estimate specification 1, altering the dependent variable to reflect enrollment growth by academic level. Results are shown in Table 6, panel A. We reprint our main estimates again in column (1). The subsequent columns (2)-(5) reflect how total growth is distributed across academic levels. Results indicate that all levels, except doctoral programs, saw significant growth in Chinese students. In the second row, below the coefficient estimates, we report the effect for each academic level as a proportion of the total effect, by dividing the academic level coefficients for by the coefficient for total students (column 1). The overall

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

[35] 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.

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.

We then compare the proportions of students in 2004, reported in row 3, with the proportion of the effect for each academic level, in row 2. The difference in these proportions is shown in row 4.[36] Although only 7% of Chinese students entering in 2004 matriculated in bachelor's 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. Since PNTR exposure induced no significant change in doctoral students, the change in proportions 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 a slight compositional shift toward students in other academic levels, which mainly include non-degree-granting programs.

Panel B of Table 6 examines compositional changes by field of study, separately assessing STEM, arts and humanities, and social sciences in columns (2), (3), and (4), respectively. As they comprise a large fraction of international students, business majors are separately shown in column (5). While all fields saw growth in Chinese students, PNTR exposure shifted the composition away from STEM and towards arts and social sciences. Compared to the baseline proportions, our 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 science major among international students, also sustained a large increase in Chinese students. This again may reflect underlying income/wealth accumulation, as STEM degrees are more likely to receive outside funding, whereas business students rely on their own funds.[37]

In panel C, we examine changes in the composition of students by the quality of the US university they attend, grouped into quartiles based on admissions rates – the 1st quartile represents the most selective schools and the 4th quartile comprises the least selective.[38] Results indicate that changes in composition mainly occurred in the least selective institutions. The share of Chinese students grew slightly in the 4th quartile and shrank slightly in the 3rd quartile, indicating potential movement from less selective to the least selective institutions.

In Table 6, panel D and E, we assess whether PNTR exposure affected the composition of students in terms of the type and amount of funds to finance higher education in the US. Panel D examines the number of students who were funded by scholarships, grants, or other institutional resources ("Has funding") and the number of students who primarily used

[36]For visual clarity, Figure A.4 is bar graph that compares the proportional effect for each student type with the proportion of students in 2004.

[37]In Appendix Table A.3, we add detail by showing the composition of the field of study by level of study.

[38]Data on admissions rates come from the Integrated Postsecondary Educational Data System (IPEDS).

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. Estimates indicate that PNTR exposure induced a large shift in student composition toward unfunded students. Panel E assesses growth in the number of students by quartile of their reported personal funds in 2004. Results indicate compositional shifts among those with substantial personal funds in the 3rd and 4th quartiles. Taken together, this evidence is again consistent with the hypothesis that rising income/wealth helped more students go abroad.

## 5.4 US Regional Inequality

We also investigate whether PNTR exposure induced Chinese students to move to high or low human capital localities in the US.[39] 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 Panel F of Table 6, we separately examine changes in the number of Chinese students, by the human capital of their *destination* city. We match US universities to their respective commuting zones.[40] For each commuting zone, we calculate the share of college educated of adults. Panel F displays the results, with the outcome split into four quartiles based on the college educated share. 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 university quality in Panel C, this suggests that the reallocation to educational services has dampened the growing 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.

## 5.5 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 US departed from PNTR rates, and by mid-2019, average tariffs on Chinese goods increased from 3% to over 20%, almost a

[39] There is recent work on rising regional disparities in labor markets (Eckert, Ganapati and Walsh, 2019).

[40] There are more than 3,000 cities, aggregated into about 700 commuting zones. we calculate the fraction of adults that have completed college education using the 1990 decennial census

20p.p. rise (PIIE, 2020).[41] An agreement in January 2020 (i.e., the phase I deal) modestly reduced tariffs imposed on Chinese goods in exchange for concessions, yet tariff uncertainty remains significant – tariff increases can be levied if China is deemed to be reneging.

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 a 20 p.p. rise in tariffs – the approximate increase in tariffs on Chinese products in 2020. 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 32-55 fewer students per million city residents over a 9- and 13-year period.[42] The 20 p.p. increase in tariffs would reduce enrollment by 700-840 students over a 10-year period, normalizing by the same number of years, in cities that have a population of 10 million. Given China's urban population (the denominator in our outcome) this implies about 32,000-40,000 fewer students over 10 years.

Assuming average tuition of $40,000 per year implies that, over 10 years, US institutions would lose $1.15-$1.60 billion in tuition revenue. That is up to a 4% reduction in educational services exports and 10% reduction in education exports to China, excluding general equilibrium multiplier effects that reverberate across local economies (Acemoglu et al., 2016).[43]

Our focus on educational services is partly due to the novel feature of our data which identifies the city of the 'importer,' and thus lends itself to a reliable identification strategy. Even though educational exports relate to just one industry, they contributed $44bn in export revenue in 2019, being about as big as the combined exports of soybeans, corn and textiles (BEA, 2020). Still, the mechanism highlighted here likely has broader implications for the services trade. For instance, "skilled scalable services" identified by Eckert, Ganapati and Walsh (2019) as accounting for most of the wage growth in the US, make up 35% of service exports (up from 21% in 2001) and are plausibly subject to the same demand-driven growth.[44] In this sense, our paper speaks to implications beyond the education sector.[45]

[41]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.

[42]The first-stage and 2SLS results in Table 9A, 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 2.5% over a 13 year period, while 2SLS implies an elasticity of student flows to exports of 0.113 over this period. A trade elasticity of 2.5 (with an upper bound of 3.4 in all specifications) is close to that found in the trade literature (Simonovska and Waugh, 2014).

[43]The 4% number does not depend on the exact tuition cost, but on the fact that the US loses 4% of its total international students in the upper bound of this counterfactual (relative to the number if tariffs were to stay at their pre-trade war level). Similarly, the loss of Chinese students represents 10% of the current stock. Appendix Figure A.1 displays the numbers of international and Chinese students enrolled over time.

[44]Eckert, Ganapati and Walsh (2019) identify 4 "skilled scalable service" sectors: information, financial and insurance, professional services, and management of companies. For the export data we cite above, see BEA table: BEA International Transactions, Table 2.1.

[45]In fact, the phase one trade deal signed in 2020 between the US and China explicitly mentions the

# 6 Mechanisms

We explore several explanations for why trade liberalization induced large numbers of students to migrate to the US. In section 3, we outlined possible channels. Here, we focus on the possible changes over time across Chinese cities, rather than shocks to the US that should affect all Chinese cities in an equal manner.[46] We examine whether increased student flows to US universities due to PNTR exposure is consistent with (1) income/wealth generation, (2) changing returns to education, and/or (3) information flows and networks.

## 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. Cheng and Potlogea (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.[47]

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.[48]

To start, we confirm some of the results on economic growth found in the previous literature.[49] The first two columns in Table 7 show that cities with the most exposure to

liberalization of financial and information (through IP protection) services, which underscores the importance of these sectors for US exports at-large. See What's in the US-China 'phase one' trade deal?, published in *Financial Times*, 15 January 2020.

[46] For instance, changes to visa policies, or recessions in the US increased the demand from US universities for all international students, regardless of origin city (Bound et al., 2020).

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

[48] 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.

[49] We should note that the strong negative effect of import tariffs seen across our results (Table 3) also

exports experienced relatively larger GDP growth, and this effect was large.[50] However, as in Cheng and Potlogea (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 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 23% in 2000 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.[51] 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.[52] Plots (c)-(e) of Figure 6 report

support the income channel.

[50] 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.

[51] We use data on average residential housing prices (Chinese yuan per square meter) from Wind-Economic Database. Part of the reason for differences in results may be data coverage. Commercial prices start in 2002, and residential house prices in 2005. We can track between 196 and 204 of the 275 cities in our sample.

[52] 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

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.6, 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, 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.

Growth in wealth can also lead to a general reallocation of consumption toward services, as 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 in total household expenditure. We find that higher PNTR exposure is associated with a reallocation of expenditure toward services.[53] Although suggestive, these results confirm that households in cities with greater liberalization behave in ways consistent with rising wealth.[54]

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

data in the last few years of our student sample.

[53]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.

[54]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.

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.7, we see no meaningful positive relationship between city-level income growth and admissions of city residents to top universities, nor between PNTR exposure and admissions (the exact numbers are in Table A.4 and details of the data are in Appendix E).[55] 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.[56]

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.[57] 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.5) 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 does not

[55]Details of the data, including the province level quota used in admissions, are included in Appendix E. The detailed results in Table A.4 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.

[56]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.

[57]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).

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.[58] 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.

## 6.3 Information

Finally, out-migration might occur due to greater information flows and knowledge of US educational opportunities. While directly measuring information flows is empirically difficult, we assess this in two ways. First, we examine how student migration responded to different types of trade flows (i.e. by destination) that cities experienced after the conferral of PNTR. Second, prospective students might choose universities that have established networks with their city, so we check whether student flows in 2000 help predict future trade-induced flows.

In the first procedure, we perform empirical checks of the relationship between student migration and city-level exports, using a country-specific 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 US 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 US.

These results are reported in Table 9A. Column (1) reprints 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. 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 to the estimate in Column (4), which *excludes* exports to the US in the PNTR exposure measure. The effect on student migration remain strong even when excluding exports from the PNTR exposure measure.[59] Results in column (5), which also removes US exports from city-level export growth, remain robust. We do not observe a weaker relationship between student flows and trade with non-US destinations, which is what would be expected if information flows a dominant mechanism.[60]

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

[59] 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.

[60] 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

The finding that expansions in non-US exports also encouraged student emigration is 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.5, 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.

The second way we examine information flows is to include an interaction of $PNTR_c$ with the student flows from city $c$ to the US in both 2000, and between 2000-2003. If network effects are important, cities with relatively more student flows to the US before the large influx should continue to see relatively large flows in the 2004-2013 period. From the two separate columns in Table 9B, there is no evidence of this.

While evidence indicates that information flows are unlikely to drive our findings, it is possible that this mechanism interacts with the wealth push. Although we find it most plausible that the large outflow of students since 2004 was triggered by gains in wealth, we cannot rule out that future students did not trace the path of initial migrants.

# 7 Conclusion

International student flows are a function of home and destination country education and labor markets. Several factors drive such flows. US universities suffering secular declines in government appropriations have turned to foreign students (Bound et al., 2020; Shih, 2017) to provide much needed tuition revenue. Home country demographics or constraints in high-quality education may drive students abroad. The option value of joining the US labor market after obtaining a US degree serves as an attractive incentive. Finally, the capacity to pay for higher education abroad constrains student flows. Our research finds that relaxing financial constraints explains a substantial portion of student flows from China to the US.

In recent years, however, there has been a dramatic deceleration in international student flows. Yearly growth of Chinese students in the US averaged about 22% between 2007 and 2013, but has since fallen to under 5% per year. Given the various determinants of student flows, this reflects a few important global changes, including the growth in universities and labor markets across China, political tensions, and the uncertainty in US job prospects.

Local income growth in sending countries generates an important tradeoff for migrants: forego rising local opportunities or leverage income growth to emigrate. We show that for Chinese students, the latter was the predominant driving force. Recent downturns 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.

flows suggest that the former may have become an important factor as well.

Such declines in international students 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. Education exports added about $44 billion to the US current account; about as large as the combined total exports of soybeans, coal, and natural gas (Rampell, 2018; BEA, 2020). Although much of the conversation on trade with China has focused on the goods 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.

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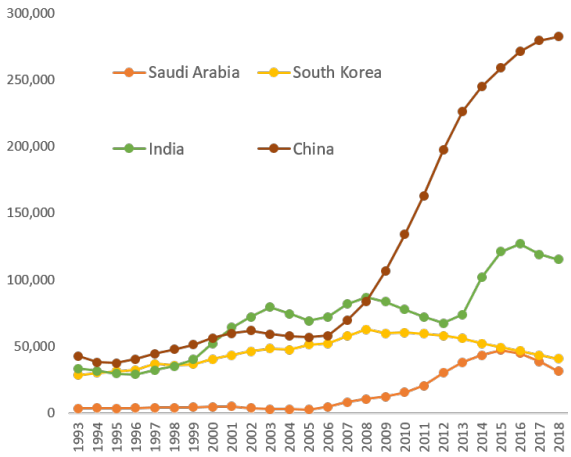
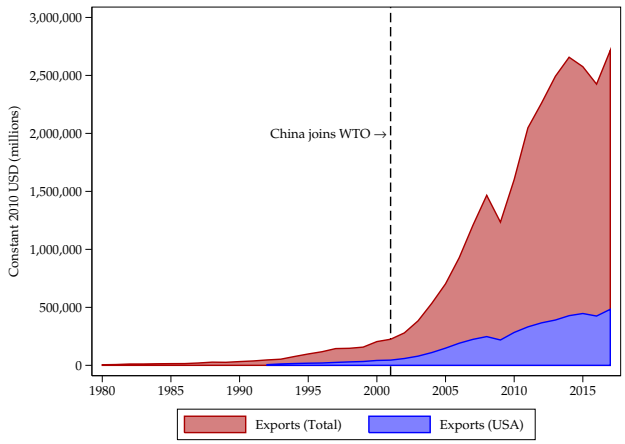
# 8 Tables & Figures

## 8.1 Descriptive Figures and PNTR Variation

Figure 1: Growth in International Students and Exports



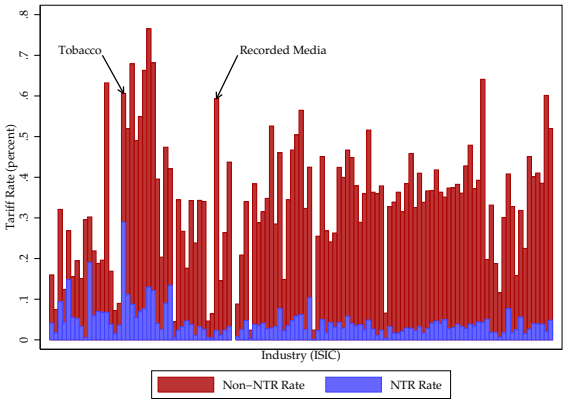

(a) Number of International Students in the United States by Country of Origin



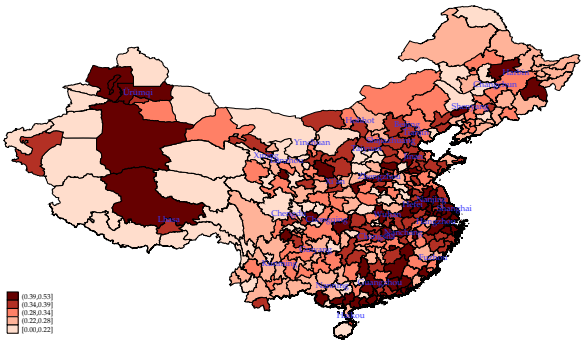

(b) Chinese Exports, 1980-2017

Notes: Figure 1a source is Open Doors, Institute for International Education, 1992-2018. Includes graduate and undergraduate students. Figure 1b 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.

Figure 2: Variation in PNTR Exposure




(a) NTR and non-NTR rates across industries



(b) PNTR exposure across Chinese prefectures

Notes: Figure 2a 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 2b 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).

## 8.2 Summary Stats

Table 1: Summary Statistics

| | (1) 2000 | (2) 2013 |
|---|---|---|
| Population (in 000s) | 1,093 | 1,460 |
| | (1,334) | (1,843) |
| GDP (in 10,000 RMB) | 1,852,178 | 13,133,248 |
| | (3,777,893) | (25,658,250) |
| GDP per capita (in RMB) | 14,537 | 71,877 |
| | (13,033) | (53,672) |
| Exports (in 10,000 RMB) | 39,910 | 449,441 |
| | (99,197) | (1,499,319) |
| Students Entering US Higher Ed Per 1M City Residents | 22 | 356 |
| | (84) | (1,369) |
| *Academic Level:* | | |
| Associates | 0.00 | 0.05 |
| | (0.01) | (0.04) |
| Bachelors | 0.02 | 0.27 |
| | (0.04) | (0.10) |
| Masters | 0.11 | 0.38 |
| | (0.16) | (0.11) |
| Doctorate | 0.86 | 0.12 |
| | (0.17) | (0.07) |
| Other | 0.01 | 0.18 |
| | (0.03) | (0.09) |
| *Field of Study:* | | |
| STEM | 0.81 | 0.35 |
| | (0.20) | (0.11) |
| Social Science | 0.14 | 0.43 |
| | (0.17) | (0.10) |
| Arts/Humanities | 0.05 | 0.23 |
| | (0.14) | (0.10) |
| *University Admissions Rate:* | | |
| Tier 1 - 1st Quartile | 0.28 | 0.18 |
| | (0.22) | (0.07) |
| Tier 2 - 2nd Quartile | 0.26 | 0.22 |
| | (0.25) | (0.07) |
| Tier 3 - 3rd Quartile | 0.23 | 0.20 |
| | (0.20) | (0.06) |
| Tier 4 - 4th Quartile | 0.23 | 0.40 |
| | (0.21) | (0.10) |
| *Scholarship Funding:* | | |
| Received Funding | 0.77 | 0.22 |
| | (0.23) | (0.09) |
| No Funding | 0.23 | 0.78 |
| | (0.23) | (0.09) |
| Number of Cities | 275 | 275 |

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.

## 8.3 Identification Checks

Table 2A: Identification Checks–Economic Indicators

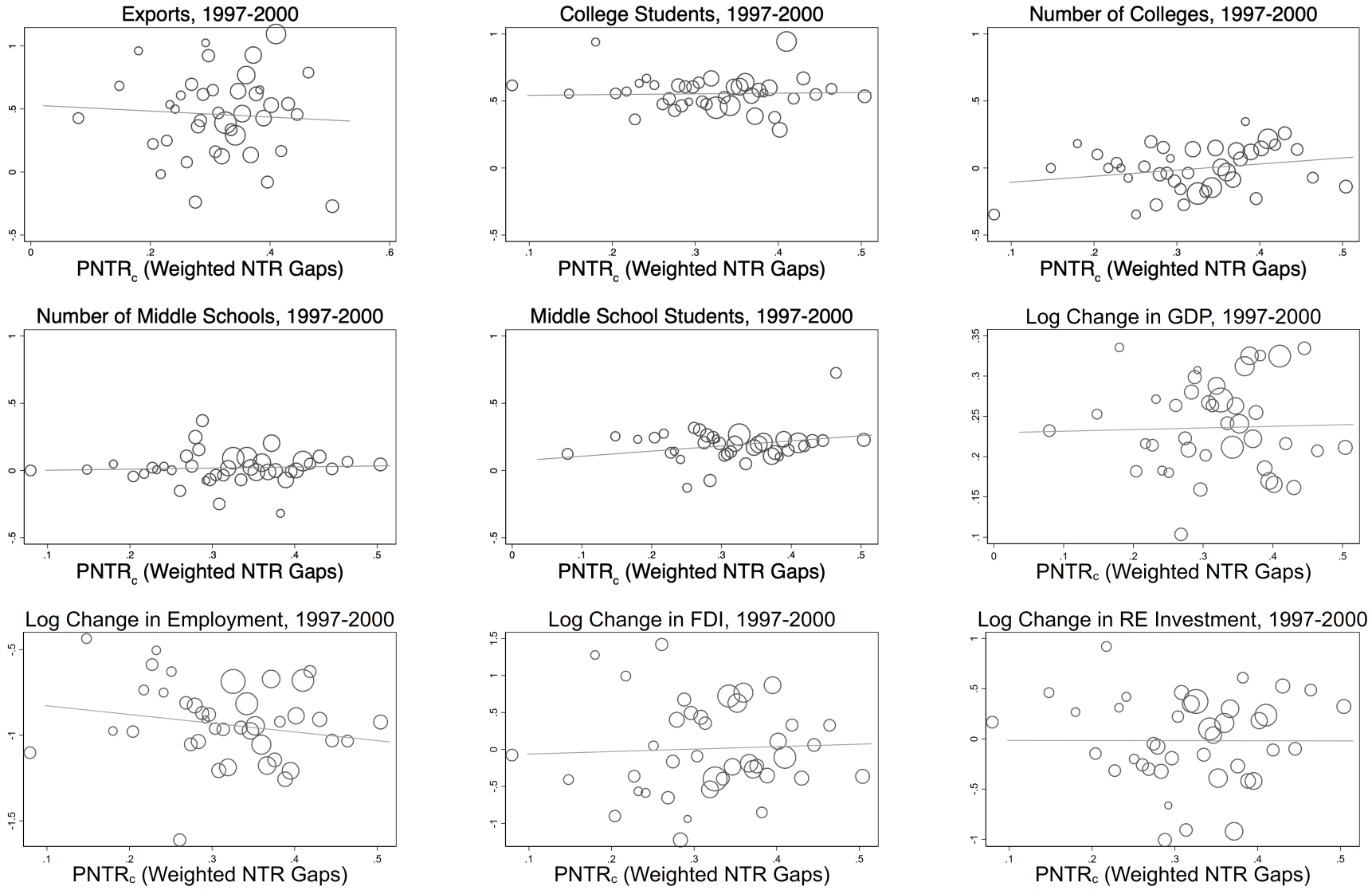
| | 1997-2000 | | | | | 2000-2013 |
|---|---|---|---|---|---|---|
| | (1) GDP | (2) Employment | (3) FDI | (4) Real Estate Investment | (5) Exports | (6) Exports |
| *No Controls* | | | | | | |
| $PNTR_c$ | 0.020 | -0.509 | 0.334 | -0.004 | -0.189 | 3.425*** |
| | (0.144) | (0.499) | (1.006) | (0.883) | (0.643) | (0.792) |
| *With Controls* | | | | | | |
| $PNTR_c$ | -0.038 | -0.089 | 0.475 | -0.112 | 0.477 | 2.497*** |
| | (0.146) | (0.569) | (1.418) | (1.031) | (0.841) | (0.864) |
| Mean Dep Var. | 0.24 | -0.94 | 0.02 | -0.02 | 0.46 | 2.19 |
| Obs. | 246 | 219 | 190 | 216 | 313 | 313 |
| R2 | 0.01 | 0.03 | 0.04 | 0.00 | 0.02 | 0.13 |

Table 2B: Identification Checks–Education Indicators

| | 2000-2001 | 1997-2000 | | | |
|---|---|---|---|---|---|
| | (1) Chinese Students in the US | (2) College Students | (3) Number of Colleges | (4) Middle School Students | (5) Number of Middle Schools |
| *No Controls* | | | | | |
| $PNTR_c$ | 0.005 | 0.053 | 0.455 | 0.152 | 0.081 |
| | (0.005) | (0.349) | (0.397) | (0.154) | (0.136) |
| *With Controls* | | | | | |
| $PNTR_c$ | 0.005 | -0.025 | 0.400 | 0.004 | -0.050 |
| | (0.006) | (0.390) | (0.473) | (0.161) | (0.174) |
| Mean Dep Var. | 0.01 | 0.56 | 0.00 | 0.18 | 0.02 |
| Obs. | 275 | 182 | 184 | 242 | 219 |
| R2 | 0.02 | 0.00 | 0.02 | 0.02 | 0.03 |

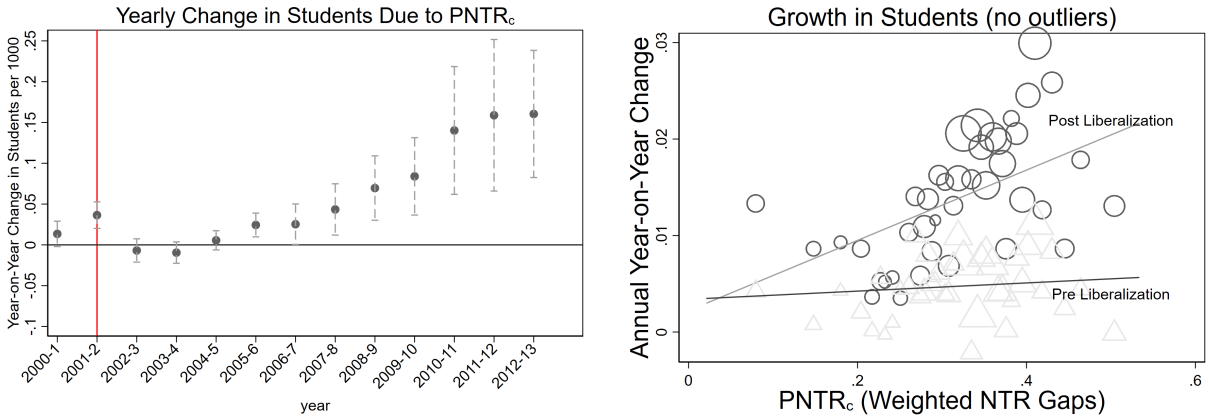
Notes: **Table 2A:** City-level regression results showing baseline checks on pretrends for economic indicators in columns (1)-(5). All outcomes are constructed as the log change between 1997 and 2000. Column (6) shows the 'first-stage' relationship between PNTR exposure and export growth between 2000 and 2013. **Table 2B:** Column (1) examines the change in Chinese students in the US using SEVIS data from 2000-2001, standardized by city population. Columns (2) - (5) examine pre-trends in education-related outcomes within China. 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 3: Correlation between PNTR Exposure and Pre-WTO Trends



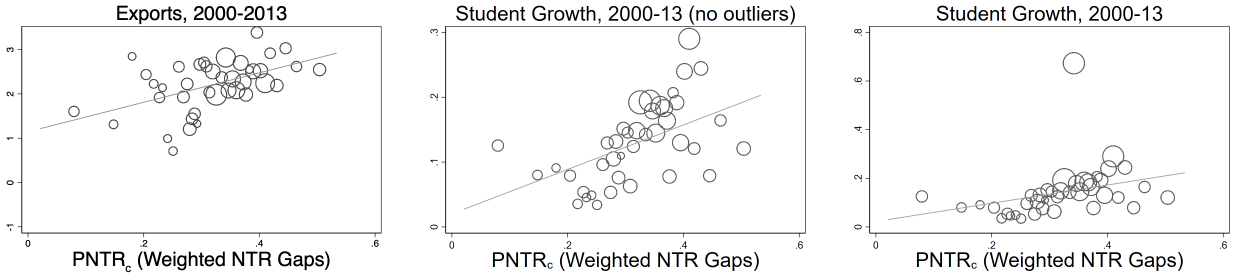

Notes: Binned scatter plots of the relationship between the weighted NTR gap (PNTR) and pre-trends in outcomes. The plots show 40 equal-size bins, weighted by population size in each bin. Specifically, we divide the x-variable (PNTR gap) into 40 bins, such that each bin contains the same number of cities (39 bins of 7 cities and 5 bins of 6 cities). We take the mean outcome (y-axis) value within each bin, weighting the mean by the population of the city. We plot it against the mean PNTR gap (x-axis) again weighting by the population in each city. See Cattaneo et al. (2019) for more on weighted binscatters. Pre-trend outcomes are measured as the city-level 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 2B.

Figure 4: Correlation between PNTR and Year-on-Year Change in Student Outflows




Notes: Left panel shows year-on-year change in the number of students per 1000 residents of a city as a function of the weighted NTR gap ($PNTR_c$). We divide the number of students by initial city population in 2000. Each point is from a distinct regression. For instance, the final point shows the change in students per 1000 residents between 2012 and 2013 as a function of $PNTR_c$. Right panel shows binned scatter plots of the relationship between the weighted NTR gap (PNTR) and annual (year-on-year) growth in students per 1000 residents. The plots show 40 equal-size bins, weighted by population size in each bin. See Figure 3 notes for binscatter details. The right panel drops the two cities with the largest student growth (Beijing and Shenzhen) to check for sensitivity to outliers. Pre-liberalization student growth is measured as change in students between 2000 and 2001, divided by initial city population. Post-liberalization student growth is measured as the change in students from 2004 to 2013 per year (i.e., divided by 9 years), per initial city population. Initial population is non-agricultural hukou (in 1000s) in 2000. Data on Chinese students by city of origin are from SEVIS.

Figure 5: Correlation between $\text{PNTR}_c$ and Long-Differenced Growth in Outcomes post WTO




Notes: Binned scatter plots of the relationship between the weighted NTR gap (PNTR) and post-treatment growth in outcomes, where post-treatment account for the full 2000-2013 sample. The plots show 40 equal-size bins, weighted by population size in each bin. See Figure 3 notes for binscatter details. Export growth (first panel) is measured as the log change from 2000 to 2013, using data from the China Customs Database. Student growth (second two panels) is measured as the change in students from 2000 to 2013, divided by initial city population (only non-agricultural hukou) in 2004. The middle figure drops the two cities with the largest student growth (Beijing and Shenzhen) to check for sensitivity to outliers. Data on Chinese students by city of origin are from SEVIS. Scatterplots showing post- and pre-WTO trends together are shown in Figure A.3.

## 8.4 Main Results

Table 3: Effect on Enrollment

| | 2004-2013 | | | | | 2000-2013 |
|---|---|---|---|---|---|---|
| | (1) No Controls | (2) +Control for Contract Intensity | (3) +Control for Import Tariffs | (4) +Control for Input Tariffs | (5) +Control for Export Licenses | (6) +Control for Export Licenses |
| $PNTR_c$ | 0.358*** | 0.300*** | 0.368*** | 0.380*** | 0.324*** | 0.546*** |
| | (0.104) | (0.104) | (0.106) | (0.105) | (0.106) | (0.194) |
| Contract Intensity | | 0.315* | 0.337* | 0.321* | 0.258 | 0.538 |
| | | (0.188) | (0.194) | (0.187) | (0.177) | (0.347) |
| Import Tariffs | | | -0.265* | -0.111 | -0.071 | 0.126 |
| | | | (0.137) | (0.125) | (0.122) | (0.192) |
| Input Tariffs | | | | -0.982*** | -0.882** | -1.424** |
| | | | | (0.354) | (0.352) | (0.615) |
| Export License | | | | | 0.361** | 0.552* |
| | | | | | (0.178) | (0.298) |
| *Interquartile Effect:* | | | | | | |
| $\Delta$ *Students per 1m Pop.* | 41 | 34 | 42 | 43 | 37 | 62 |
| Mean Dep Var. | 0.138 | 0.138 | 0.138 | 0.138 | 0.138 | 0.201 |
| Obs. | 275 | 275 | 275 | 275 | 275 | 254 |
| R2 | 0.023 | 0.037 | 0.043 | 0.054 | 0.059 | 0.074 |

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.. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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

| | (1) Main Effect Col 5 of Table 3 | (2) Drop 4 Largest Cities | (3) Drop Capital Coastal Cities | (4) Control for Region FE | (5) Control for Changing Tariffs |
|---|---|---|---|---|---|
| *A: Robustness Checks* | | | | | |
| $PNTR_c$ | 0.324*** | 0.276*** | 0.290*** | 0.194* | 0.326*** |
| | (0.106) | (0.100) | (0.091) | (0.108) | (0.104) |
| *Interquartile Effect:* | | | | | |
| $\Delta$ *Students per 1m Pop.* | 37 | 31 | 33 | 22 | 37 |
| Obs. | 275 | 271 | 237 | 275 | 275 |
| R2 | 0.059 | 0.054 | 0.048 | 0.100 | 0.079 |

| | (1) Control for In-Migration | (2) Control for Out-Migration | (3) Control for In- and Out-Migration | (4) Total Population in Denominator | (5) 2013 Population in Denominator |
|---|---|---|---|---|---|
| *B: Internal Migration Checks* | | | | | |
| $PNTR_c$ | 0.294** | 0.237* | 0.306** | 0.152** | 0.234*** |
| | (0.122) | (0.121) | (0.127) | (0.067) | (0.087) |
| *Interquartile Effect:* | | | | | |
| $\Delta$ *Students per 1m Pop.* | 33 | 27 | 35 | 17 | 27 |
| Obs. | 252 | 252 | 252 | 274 | 275 |
| R2 | 0.108 | 0.086 | 0.134 | 0.036 | 0.061 |

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. **Panel A** provides general robustness checks: 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) controls for time-varying changes in tariffs at the city-level. **Panel B** provides checks against endogeneity from internal migration, as Facchini et al. (2019) link PNTR exposure to increases non-hukou in-migration: Column (1) controls for city-level growth in migration rates for skilled and unskilled workers; Column (2) for city-level growth in the share of migrants in the skilled and unskilled population; Column(3) controls for both migration rates and shares; Column (4) normalizes the change in the number of students by the *total* population, including the surrounding agricultural areas; Column (5) normalizes the change in the number of students by the 2013 urban population. 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 Shocks

| | (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:* | | | | | | |
| $\Delta$ *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). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

## 8.5 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

## 8.6 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) |
| Obs. | 274 | 274 | 274 | 274 | 274 | 274 |
| R2 | 0.02 | 0.08 | 0.01 | 0.01 | 0.00 | 0.08 |
| Controls | | x | | x | | x |

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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

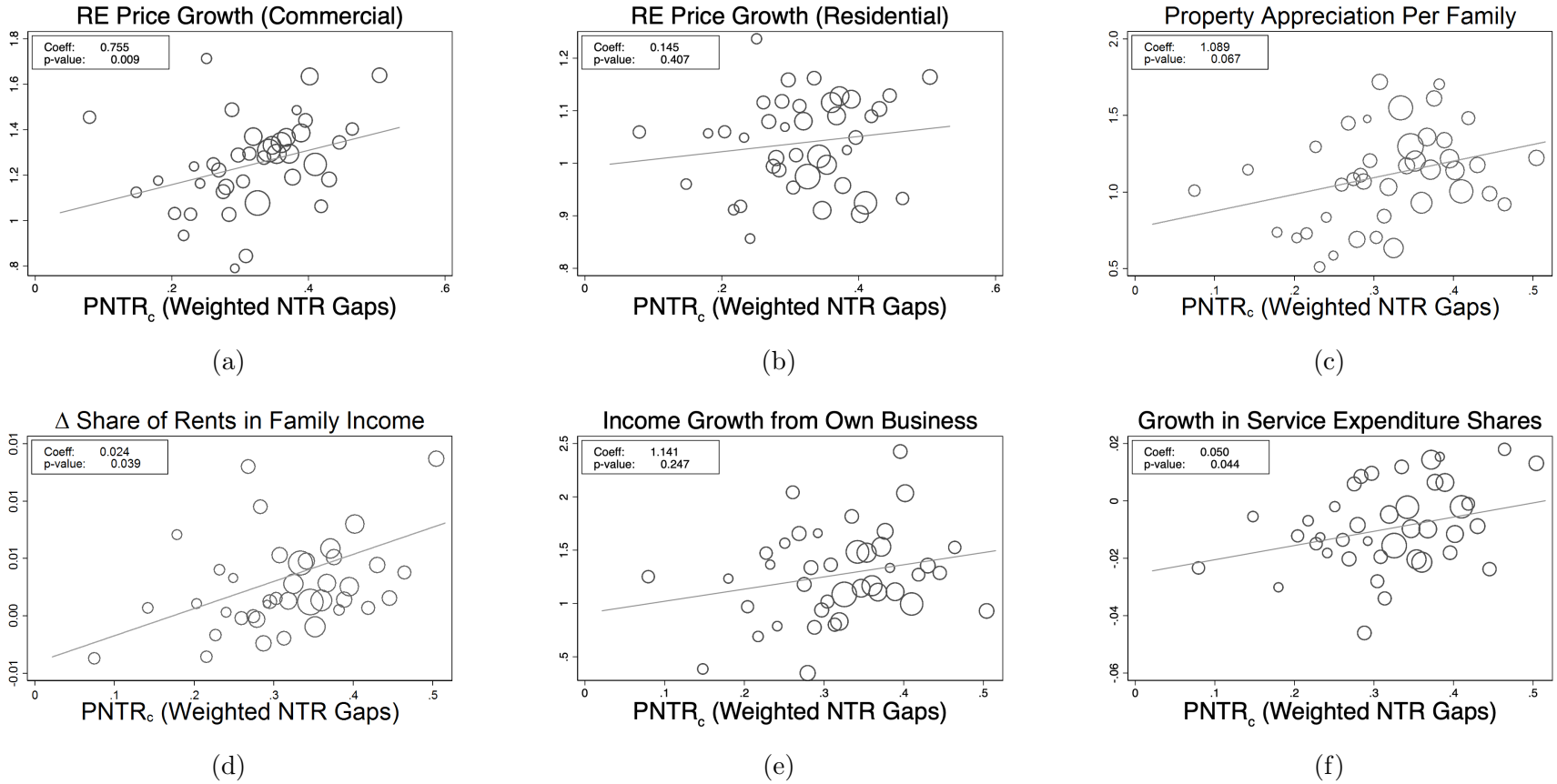
## 8.7 Mechanisms: Returns to Education

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 |
| Controls | 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) 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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Figure 6: Wealth Shocks (post-WTO Changes)




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. See Figure 3 notes for binscatter details. The real estate data (plots (a) and (b)) are from Wind-Economic Database. Real estate data from Wind-Economic Database 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.

## 8.8 Mechanisms - Information and Networks

Table 9A: Test for Information Flows

| | (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 |

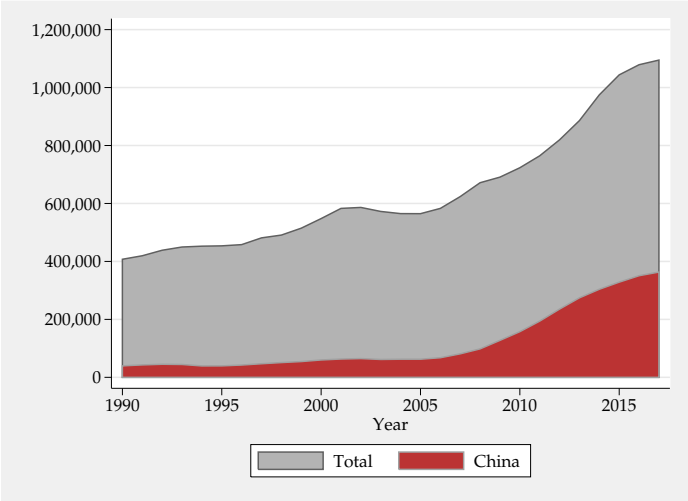
Table 9B: Test for Network Effects

| | (1) Network Defined as Students in 2000 | (2) Network Defined as Total Students from 2000-03 |
|---|---|---|
| $PNTR_c$ | 0.183** | 0.241*** |
| | (0.084) | (0.085) |
| $PNTR_c$ X Students in 2000 | 0.003 | |
| | (0.006) | |
| Students in 2000 | 0.000 | |
| | (0.002) | |
| $PNTR_c$ X Students in 2000-03 | | -0.001 |
| | | (0.001) |
| Students in 2000-03 | | 0.000 |
| | | (0.000) |
| *Interquartile Effect:* | | |
| $\Delta$ *Students per 1m Pop.* | 21 | 27 |
| Mean Dep Var. | 0.138 | 0.138 |
| Obs. | 275 | 275 |
| R2 | 0.364 | 0.398 |
| Controls | 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. All regressions include the following controls: contract intensity, import tariffs, input tariffs, and export licenses. **Table 9A:** Column (1) reproduces our main estimates from column (5) in Table 3. 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). **Table 9B:** Column (1) defines the city-level network as the number of students matriculating in the US in 2000, while Column (2) uses the total students matriculating in 2000-03. We interact this with PNTR. 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.

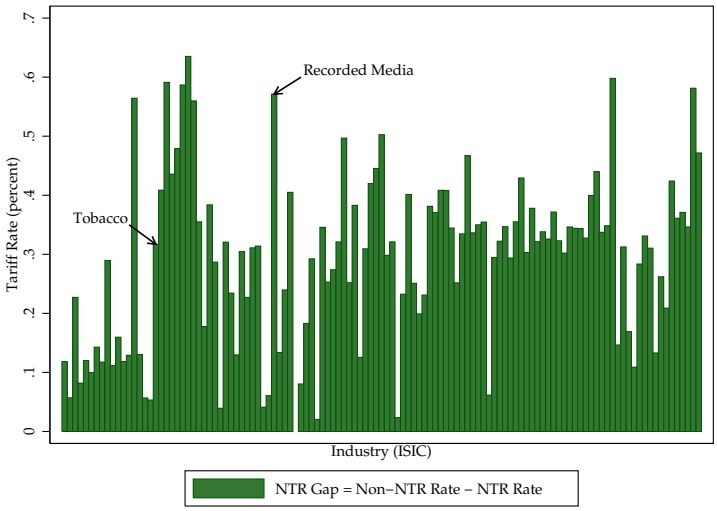
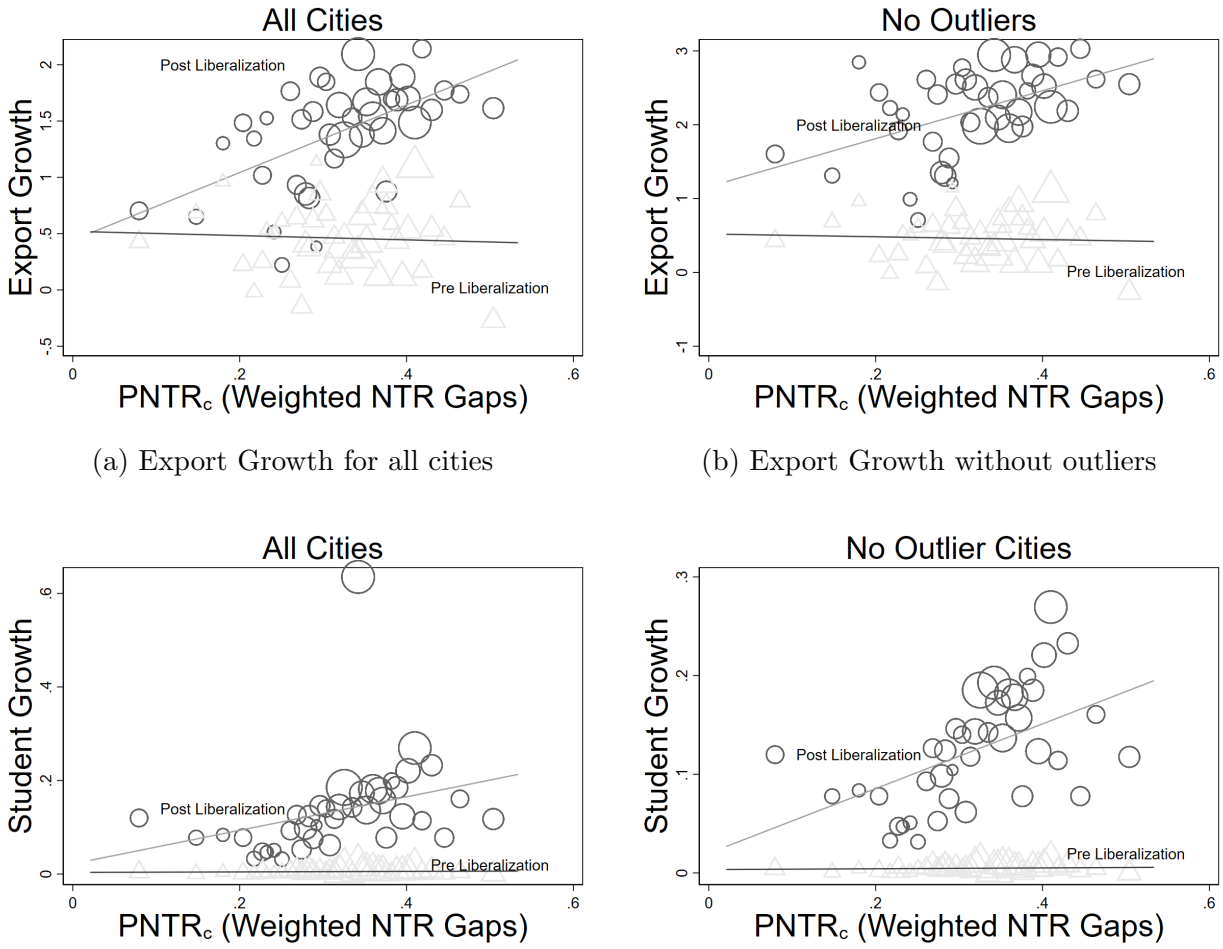



Figure A.2: NTR Gaps

Notes: The figure shows the NTR gaps for each industry. Green bars plot the difference in NTR and non-NTR tariffs shown in Figure 2a. Data on NTR and non-NTR tariff rates by industry are from Pierce and Schott (2016).

Figure A.3: Export and Student Growth as a Function of $PNTR_c$




(a) Export Growth for all cities

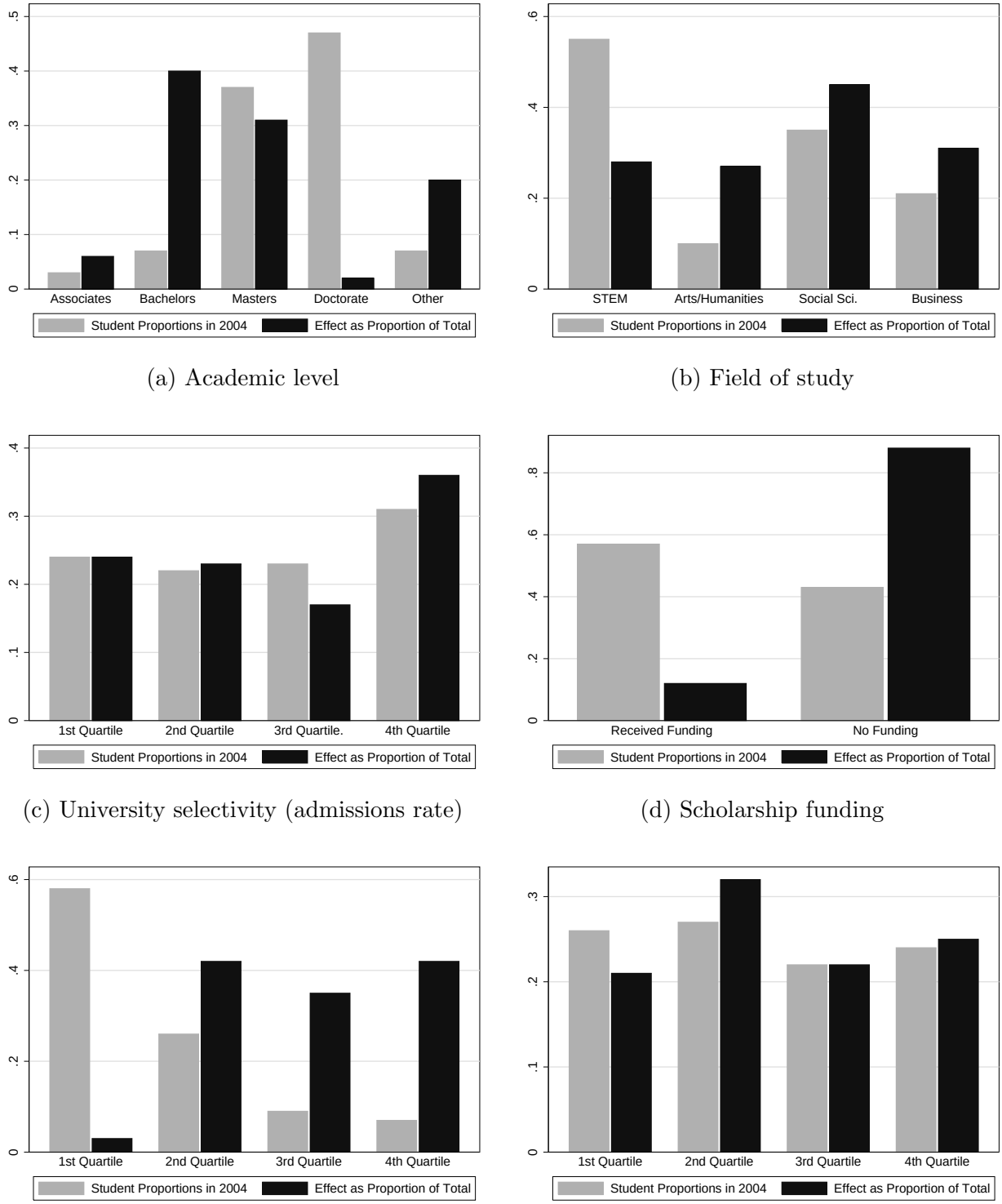
(b) Export Growth without outliers

(c) Student Growth for all cities

(d) Student Growth without outliers

Notes: Notes: Binned scatter plots of the relationship between the weighted NTR gap (PNTR) and growth in outcomes. Unlike Figure 4, we show the long-differenced growth (for instance, the total change in students between 2004 and 2013). The plots show 40 equal-size bins, weighted by population size in each bin. See Figure 3 notes for binscatter details. The right panels drop two cities with the largest student growth (Beijing and Shenzhen) to check for sensitivity to outliers. Post-liberalization export growth is measured as the log change from 2000 to 2013, using data from the China Customs Database; whereas pre-liberalization export growth is measured as the change from 1997-2000. Post-liberalization student growth is measured as the change in students from 2004 to 2013, divided by initial city population (only non-agricultural hukou) in 2004. Pre-liberalization growth is from 2000-1. Data on Chinese students by city of origin are from SEVIS. Coefficients and standard errors are reported in Table 2A, column 6 (Exports) and Table 3 column 1, and Table 4 column 2.

Figure A.4: Changes in the Composition of Chinese Students Attributable to PNTR




(a) Academic level

(b) Field of study

(c) University selectivity (admissions rate)

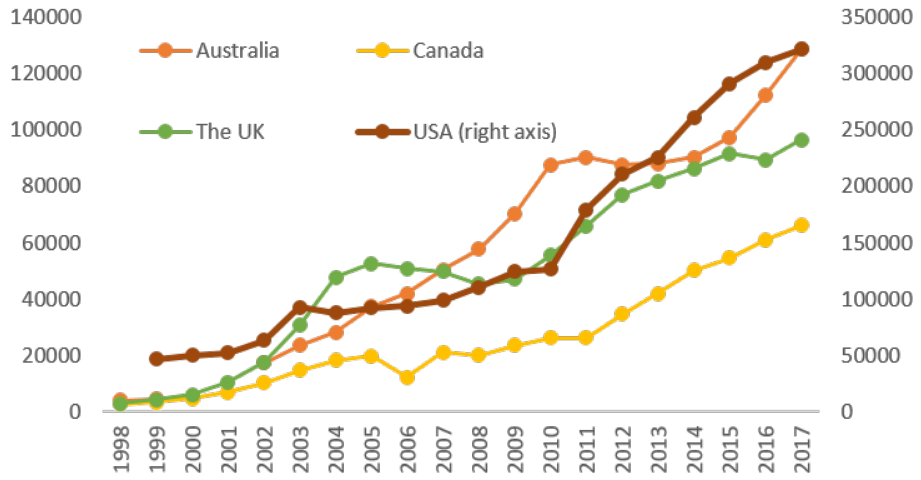
(d) Scholarship funding

(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.5: 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: Effect on Enrollment, 2000-2013

| | (1) No Controls | (2) +Control for Contract Intensity | (3) +Control for Import Tariffs | (4) +Control for Input Tariffs | (5) +Control for Export Licenses |
|---|---|---|---|---|---|
| $PNTR_c$ | 0.745*** | 0.567*** | 0.618*** | 0.643*** | 0.546*** |
| | (0.193) | (0.194) | (0.189) | (0.192) | (0.194) |
| Contract Intensity | | 0.692* | 0.701* | 0.636* | 0.538 |
| | | (0.364) | (0.370) | (0.362) | (0.347) |
| Import Tariffs | | | -0.185 | 0.051 | 0.126 |
| | | | (0.204) | (0.200) | (0.192) |
| Input Tariffs | | | | -1.545** | -1.424** |
| | | | | (0.605) | (0.615) |
| Export License | | | | | 0.552* |
| | | | | | (0.298) |
| *Interquartile Effect:* | | | | | |
| $\Delta$ *Students per 1m Pop.* | 85 | 64 | 70 | 73 | 62 |
| Mean Dep Var. | 0.201 | 0.201 | 0.201 | 0.201 | 0.201 |
| Obs. | 254 | 254 | 254 | 254 | 254 |
| R2 | 0.036 | 0.059 | 0.060 | 0.069 | 0.074 |

Notes: City-level regressions showing the effect of PNTR exposure on Chinese student enrollment growth between 2000 and 2013, per thousand city residents in 2000. 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. We report heteroskedasticity-consistent standard errors (in parentheses) at the city level.. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

## 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 |

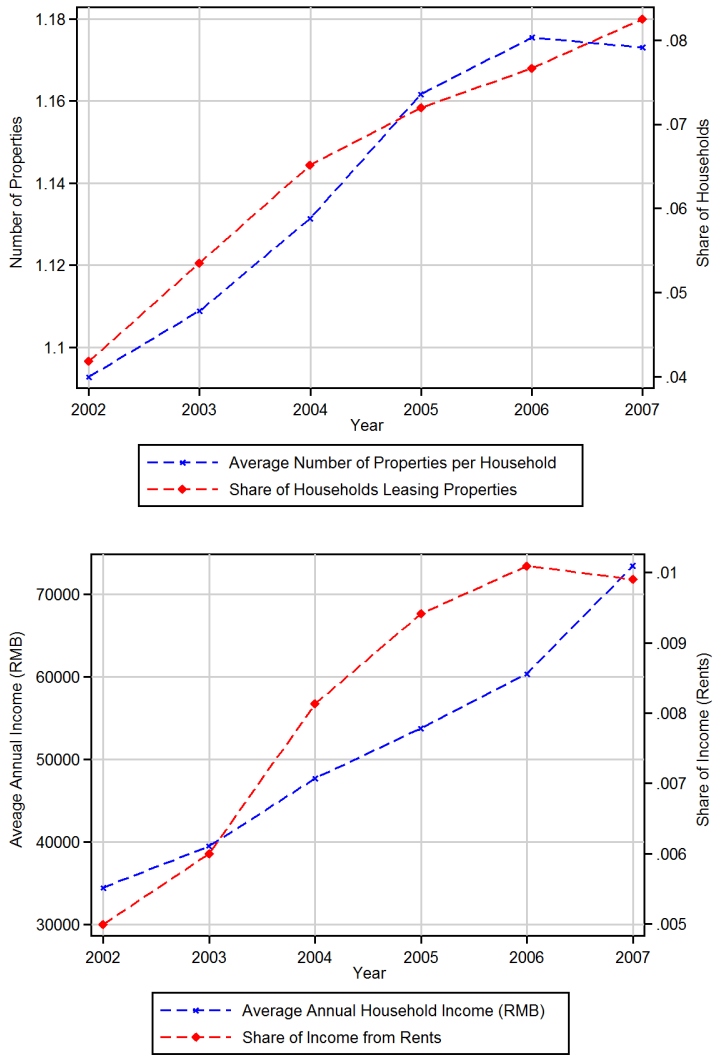
Notes: City-level regressions showing the effect of weighted NTR gaps on Chinese student enrollment growth, per thousand city residents, over different time periods. We examine a shorter-run time frame in column (1), 2004-07. Column (2) examines a medium-run time frame, which covers the Great Recession 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. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.3: 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 |

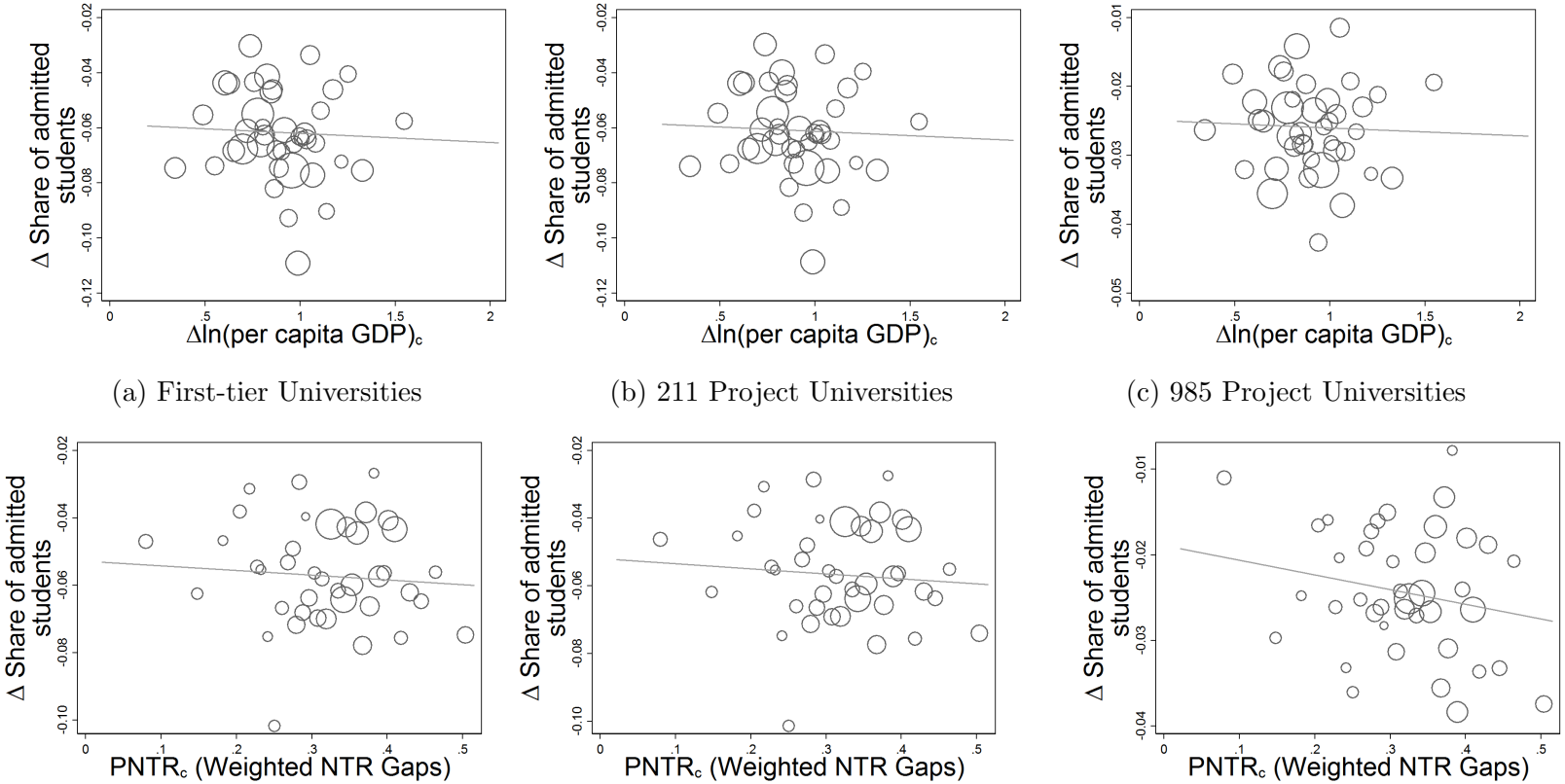
Notes: City-level regressions showing the effect of weighted NTR gaps on Chinese student enrollment growth between 2004 and 2013. We include all the main controls. The first row below the coefficients documents the effect as a fraction of the total effect in column (1). The second row shows the fraction 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.

Figure A.6: 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.7: 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. See Figure 3 notes for binscatter details.

Table A.4: 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 $Y$.[61]

[61] 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.[62]

$WorldM_{it}$ 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.

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

where $\lambda_{pi}$ 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.

[62] 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.5 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.5: 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 Data Appendix

## USCIS International Students Data

Our primary outcome data comes from an individual-level file of F-1 visa recipients obtained from the U.S. Immigration and Customs Enforcement group of the Department of Homeland Security through a Freedom of Information (FOIA) Request, covering the period 2000 to 2013. These data identify each student's intended degree, subject of study, post-secondary institution in the U.S., city and country of origin, along with variables indicating cost of attendance, financial support, and the period of study.

These data are stored by the Student and Exchange Visitor Program (SEVP), which is a part of the National Security Investigations Division and acts as a bridge for government organizations that have an interest in information on nonimmigrants whose primary reason for coming to the United States is to be students. SEVP maintains the Student Exchange and Visitors Information System (SEVIS).

SEVP requires that students provide their permanent address, which helps determine their prefecture city of origin. 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.

## China Customs Database and Tariff Data

The tariff data comes from the Trade Analysis and Information System (TRAINS) database, which is maintained by the United Nations Conference on Trade and Development (UNCTAD). The raw tariff data is withdrawn with the simple average at the level of country-HS 6-digit.

Information of city exports and imports are derived from the China Customs Database, which covers the universe of Chinese exports and imports, and were harmonized and generously provided by the University of California, Davis, Center for International Data (Feenstra et al., 2018). The data reports the annual trade information on values, quantities, and partner countries at the HS 8-digit level for all Chinese cities in the period under investigation (i.e., 1997 to 2014). As the industry classifications used in tariffs and the China Customs Database (i.e., HS 6-digit) are different between the one in the ASIP (i.e., Chinese Standard Industrial Classification 4-digit), we correspond them to the International Standard Industrial Classification (ISIC) revision three at the 4-digit level to construct various trade shock measures in practice.

## 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.

## Local 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. Other details on the data and the background of the NCEE are discussed in Zivin et al. (2018). 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.[63] 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.

## Urban Household Survey Data

The Urban Household Survey (UHS) is conducted by the National Bureau of Statistics of China (NBS), which is similar to the Current Population Surveys in the United States and adopts a stratified and multi-stage probabilistic sampling scheme. The data is a rotating panel where the full sample is changed every three years. The UHS reports household information and economic characteristics, such as the household income of different types. The data have been widely used, and detailed information on the UHS is provided by Han, Liu and Zhang (2012) and 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 making changes in the city's average outcome between 2002 and 2007. This constitutes more than 30,000

[63] 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.

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.

## China Population Census Data

We use China's One-Percent Population Census data of 2000 and 2015 to trace migration flows across Chinese cities. Notably, the 2015 census is the latest data with restricted public access. The census provides detailed information on individuals' demographic and economic characteristics, such as the education levels, employment status, hukou location, and current residential city. Skilled individuals refer to those with a college degree or above, and the rest would be unskilled. We construct two measures to control for internal migrations, namely: (1) the probability of out-migration; and (2) the inflow of migrants as a share of a city's total population. Both measures are based on five-year period metrics and for both skilled and unskilled individuals. Specifically, let $L^S_{od,10-15}$ and $L^U_{od,10-15}$ denote the skilled ($S$) and unskilled ($U$) migration flows from city $o$ to city $d$ during the period 2010-2015, respectively. The probability of out-migration for skilled and unskilled workers are computed as

$$OUT^T_{o,10-15} = \frac{\sum_{\forall d \neq o} L^T_{od,10-15}}{\sum_{d'} L^T_{od',10-15}}, \quad T \in \{S, U\} \tag{7}$$

The inflow of migrants as a share of a city's total population is computed as

$$IN^T_{d,10-15} = \frac{\sum_{\forall o \neq d} L^T_{od,10-15}}{\sum_{o'} L^T_{o'd,10-15}}, \quad T \in \{S, U\} \tag{8}$$

where migration flows $L^S_{od,10-15}$ and $L^U_{od,10-15}$ are calculated as the aggregate outcome of decisions made by individuals in the 2015 Census. Likewise, we use the 2000 Census to compute $OUT^T_{o,95-00}$ and $IN^T_{o,95-00}$ for $T \in \{S, U\}$.

## China City Statistical Yearbooks

The data on city GDP, population, education, investment, foreign direct investment, government spending, government income, and other economic indicators in the analysis come from the City Statistical Yearbook of China (various issues from 1997 to 2014). The City Statistical Yearbook of China is compiled by the National Bureau of Statistics of China and has been widely used for studying social and economic development at the prefecture city level.

## Wind-Economic Database

The data on average house prices (Chinese yuan per square meter) are from the Wind-Economic Database. The commercial housing prices start in 2002, and residential housing prices in 2005. We can track house prices between 196 and 204 of the 275 cities in our study. The Wind-Economic Database is one of the most comprehensive databases on China's macroeconomy. The Wind data reports over 1.3 million macroeconomic and industry time-series data points sourcing from various government agencies, such as the National Bureau of Statistics, and provincial and municipal Bureaus of Statistics.