Trade Liberalization and Chinese Students in US Higher Education*

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Abstract

We investigate whether trade liberalization encourages Chinese student enrollment in US universities. We focus on China's accession to the World Trade Organization and show that Chinese cities more exposed to this trade liberalization episode sent more students to US universities. Results indicate that growth in housing income/wealth was an important channel that allowed many Chinese families to afford US tuition, consistent with large growth in the share of Chinese students that finance their studies primarily using personal funds. Other potential 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 induced increases in the share of Chinese students studying non-STEM fields, at the Bachelors level, and also at less-selective US universities. Student inflows were similar in both low and high human capital areas in the US, indicating that educational exports do not exacerbate regional inequality. An important conclusion of our work is that the trade deficit in goods partially cycles back as a surplus in education exports to China.

JEL: F16, I25, J24, J61

Keywords: International Students, Trade Liberalization, China, Migration

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1 Introduction

US higher education has been transformed by a marked increase in international enrollment since 2005, largely driven by students from China. Enrollment from China grew by 400% over this period (Figure 1), generating much needed revenue for universities often to the advantage of domestic students (Bound et al., 2019; Shih, 2017). Concurrently, in the decade after 2005, China's GDP per capita quintipled from $1500 to over $7500 per capita.[1] Rapid economic growth in China not only increased the affordability of US higher education, but also expanded the size of college-ready high-school graduate cohorts. A major driver of this structural change was increased demand for Chinese commodity exports following China's accession to the World Trade Organization (WTO) in 2001 (Zhu, 2012). In this paper we demonstrate how this episode of trade liberalization was a crucial determinant of Chinese imports of higher education from the United States.

Openness to trade has been shown to generate economic growth (Frankel and Romer, 1999), which in turn can effect both human capital accumulation and migration (Goldin and Katz, 2009; Clemens, 2014; Bazzi, 2017). We propose a new channel through which openness to trade leads to human capital accumulation and migration in a developing country. We show that trade-driven income growth in China generated increased demand for educational services produced by the United States. This relationship implies that a trade deficit in goods can cycle back as a service export in the developed country.

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

We find a significant and positive association between trade liberalization and student out-migration – a 10 percentage point increase in PNTR exposure led an increase in Chinese

[1] Source: World Bank OECD National Accounts.

student enrollment in the US on the order of around 37 students per 1 million city residents. The implied total number of students emigrating due to trade liberalization alone accounts for a quarter of the total number of Chinese students that went to study in the US during this period. Therefore, the WTO accession induced substantial student out-migration, and not just internal migration as shown previously (Facchini et al., 2018). Our results inform the consequences of the 2018 US-China trade war – a counterfactual exercise using our estimates indicates that the 20 percentage point increase in tariffs in 2018 could cost US universities around 30,000 Chinese students in the next ten years, a loss of $1.15 billion in tuition revenue, or 8% of education service exports to China.[2] This loss is likely an underestimate as it does not account for broader effects on local economies surrounding universities.

Alongside increases in scale, we find changes in the composition of Chinese students. While large shares of Chinese students traditionally enrolled in Doctoral programs, which often have funding for students, trade liberalization induced a shift towards undergraduate studies, which generally have little funding and require foreign students to make full-sticker price tuition payments. Related analysis emphasizes this, showing that PNTR exposure dramatically increased the share of students that finance their education primarily through personal funds, rather than through scholarships or fellowships. These results indicate rising wealth/income in highly affected cities.

We demonstrate that trade liberalization increased global demand for Chinese manufactured goods and subsequently the wealth of city residents. PNTR exposure led to a 29 to 40 percent increase in exports at the city-level. Expanding wealth allowed families with means to finance the large cost of paying for housing and tuition in the US. Given limited investment opportunities in China, a meaningful fraction of this 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 growth (Cheng and Potlogea, 2015) and wage growth (Erten and Leight, 2020). While wealth/income growth are a predominant mechanism behind our reduced form effects, we explore and find a lesser role for other channels such as changing returns to education, and increased information flows.

Our findings also speak to distributional impacts in US higher education, which informs a broader literature on growing US regional inequality. While Chinese students initially tended towards STEM (Science, Technology, Engineering and Math) majors, trade liberalization induced large responses for those in Social Science and Business-related majors. Additionally, trade liberalization increased the share of students in less selective universities. We also find

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

that trade liberalization induced student out-migration in equal proportion to universities in both low and high human capital areas in the US. This carries implications for local labor markets, where public discourse has stressed the negative impacts of rising deficits in commodity imports from China. Different from Bloom et al. (2019), where reallocation leads to regional inequality, raising education exports has the potential to lift all regions, as universities expand nationwide. Given the recent increase in regional labor-market inequality, as high-paying skilled services expand in dense high-paying labor markets (Eckert, Ganapati and Walsh, 2019), an important conclusion from our findings is that the rise of education service exports *dampen* some of this trend.

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

Our findings contribute to the literature on trade and migration. Prior research documents the detrimental impacts of Chinese trade on US manufacturing (Autor, Dorn and Hanson, 2013; Pierce and Schott, 2016).[3] While the US experienced substantial import competition in physical goods, less is known about trade in services, which has grown to account for over a third of US trade activity (Eaton and Kortum, 2018). We elucidate the welfare consequences of trade by exploiting detailed data on trade in *education services*, containing the universe of international students in the US by city of origin, degree, university, field of study, level of program, and detailed information on financial support. We show that trade-driven income growth in China generated strong demand for a particular US service: higher education. We complement recent studies by Wang et al. (2018), Bloom et al. (2019), and Caliendo, Dvorkin and Parro (2019), which emphasize that trade with China raised employment in non-manufacturing industries. We add to the existing channels on changes in relative production costs, by showing that trade dynamics increased the *demand* for services as a result of greater wealth abroad. As such, our findings indicate that a trade deficit in

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

goods cycled back into the US as a trade surplus in education services.

We speak to the migration literature by highlighting how better prospects at home may actually result in *out*-migration as these income gains are used to overcome migration-cost barriers. Canonical models suggest that, while greater income allows individuals the ability to afford migration costs, it also raises the opportunity cost of emigrating (Angelucci, 2015; Bazzi, 2017; Clemens, 2014). These migration costs are quantifiable for international students as standard tuition and living expenses at US higher education institutions. Furthermore, many international students view study in the US as a pathway to join the US labor market. Better income opportunities at home may also lower the option value of a US degree (Bound et al., 2015; Shih, 2016). As such, it is unclear whether economic growth at home, induced by trade liberalization, would lead to more out-migration. We resolve this ambiguity, by showing that income/wealth generation, attributable to trade liberalization, encouraged student flows to the US.[4] Our findings inform related studies on trade and education. Li (2018) finds that export expansion reduces educational attainment within China given its comparative advantage in low-skill sectors, while Liu (2017) finds that high-school completion increases in cities facing larger reductions in tariffs. Atkin (2016) finds that an expansion in less-skilled manufacturing jobs in Mexico leads to more high school dropouts.

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

2 China's Accession to the WTO

On December 11, 2001 China joined the World Trade Organization (WTO). An important facet of this policy change was that it converted the uncertain Most Favored Nation (MFN) tariff regime to a permanent Normal Trade Relations (NTR) tariff regime. Since 1980, the US granted low MFN tariffs to Chinese products, however, this required annual Congressional renewal as China did not have MFN status.[5] This generated uncertainty over the longevity of the low tariff regime, which inhibited further expansion of trade and commerce between the US and China (Pierce and Schott, 2016; Handley and Limão, 2017). Termination of MFN status would have increased tariffs faced by US importers by over 8-fold, from an average tariff of 4% (under MFN status) to 35% (Facchini et al., 2018), and would affect over 95%

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

[5] One exception was in 1998, when Congress extended MFN status for a 3 year duration, expiring in 2001. For an in-depth discussion of the history of China's MFN status, see Pregelj (2001).

of US imports from China (Pregelj, 2001), with the possibility of further retaliation.

Conversion to the NTR regime made the low MFN tariffs permanent, and no longer required Congressional renewal. The conferral of the permanent NTR tariff regime (henceforth PNTR) did not change actual tariff rates, but only altered the uncertainty that Chinese exporters and US importers faced. This reduction in uncertainty had substantial impacts on trade. Within 1 year of receiving PNTR, China's exports to the US grew by 57%, and within the first 5 years it grew by 177%.[6] Although NTR tariffs applied only to trade with the US, this accounts for a meaningful one-fifth of all Chinese exports (Cheng and Potlogea, 2015).

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

The conferral of PNTR had major impacts on structural transformation and internal migration in China (Facchini et al., 2018). Hence, comparisons across Chinese cities must address issues of changing composition due to internal migration. An advantage of examining student emigration, however, is that the reported city of origin is less likely to be impacted by rural-to-urban worker migration. The *hukou* system ties access to schooling to ones city of birth, thereby making it difficult for families to migrate for work with their children.

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

3 Why Exports Affect Student Migration

Our empirical framework estimates reduced form effects of PNTR exposure on Chinese student migration to US higher education. In this section, we delineate and elucidate possible mechanisms underlying this relationship, and use this framework to inform our empirical investigation of mechanisms in section 6. Consistent with recent trade literature, we view

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

PNTR as a trade liberalization shock, which proliferated exports of Chinese manufactured goods. This, in turn, 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, 2015). Similar to the development and migration literature, economic growth may have opposing impacts on student out-migration, such that the net effect is ambiguous (e.g., Clemens, 2014; Angelucci, 2015; Bazzi, 2017). We explore three channels through which export-driven economic development operates: (1) income/wealth generation, (2) changing returns to education and (3) increased information.

First, trade liberalization that creates increased demand for Chinese manufactured products may generate income and wealth. Wealth relaxes financial constraints, increasing the number of households that can afford the cost of US higher education – roughly \$40,000 per year for tuition and board during this time period. We formalize a simple theoretical framework, in appendix Section B, which demonstrates this to be the case either when education is considered an investment good. If education is an investment, then financially constrained households will response to income shocks by funding their education (in this case, their education abroad).[7] The prediction conforms with Sun and Yannelis (2016) that link a causal relationship between credit constraints and the demand for college education. Our model also shows that the difference in prices (home vs. foreign tuition) determine the magnitude of the educational response to income shocks.

When education is considered a consumption good, increases in income/wealth will reallocate expenditures towards 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 education 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 will explore the evolution of the service expenditure share in liberalization-exposed cities.

What are the sources of income/wealth growth attributable to trade liberalization? As

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

Bound et al. (2019) discuss, almost all the educational expenditures for international students from China are from families, rather than via scholarships or loans. Prior literature has linked PNTR exposure to increased wage income at the county-level in China (Erten and Leight, 2020), and greater employment and investment growth (Cheng and Potlogea, 2015). Different from prior literature, we explore possible growth in real estate income and wealth in cities highly exposed to PNTR, as a result of tremendous in-migration of rural workers to fill manufacturing demand (Facchini et al., 2018; Tombe and Zhu, 2019). Recent literature has documented the importance of the real estate sector to China's economy, where, without a developed financial sector, investment growth and capital gains mainly derive from the housing market (Liu and Xiong, 2018; Chen et al., 2017).[8]

Different from income/wealth generation, trade liberalization may have impacted the returns to education by altering the relative demand for particular skills. Changes in the returns to education may either increase or decrease educational investments for migrants (McKenzie and Rapoport, 2011; de Brauw and Giles, 2015; Kuka, Shenhav and Shih, 2020). Growth in the relative demand for unskilled labor might encourage college-ready cohorts to work immediately and forego higher education. Greater outmigration of students would occur if trade shocks raised the return to a US degree in the Chinese labor market.[9] Alternatively, this could occur if the returns to college rise alongside an inelastic supply of higher education within China.[10] 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 regarding opportunities and admission procedures more clear 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 "country-wide" factors likely impacted the enrollment of Chinese students in US universities (e.g. appreciation of the Yuan, US immigration policy). In the next section, we describe our empirical approach, and emphasize that it captures *relative* changes in out-

[8]As of 2016, property related loans make 25% of banking assets.

[9]There is an additional channel when studying student migration, which is that many student 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.

[10]Within the context of the aforementioned model in Appendix B, this represents an increase in the relative price of domestic universities.

migration across Chinese cities based on their exposure to trade shocks. As such, comparing within-city changes abstracts from national shocks that equivalently affect all cities.

4 Empirical Strategy & Data

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

4.1 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 the 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, amounts 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 Chinese Students, ΔS_c

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

We aggregate the individual-level data to obtain total students by year of entry and city of origin, and also group subtotals by the program/funding characteristics listed above. For each city we then calculate the change in students in 2013 relative to 2004. As cities differ greatly in size, we standardize these changes by the 2004 city population of residents with non-agricultural Hukou status, from the China City Statistics Yearbook.[11] As city population is measured in thousands of persons, our dependent variable measures the change in the number of Chinese students per 1,000 city residents.

4.1.2 City-Level PNTR Exposure, $PNTR_c$

City-level differences in PNTR exposure are captured by the industrial structure of the city in 1997. We begin by defining a measure of the size of the PNTR policy treatment for each 4-digit ISIC industry i, as the gap between NTR and non-NTR tariff rates in 1999, using data from Pierce and Schott (2016).[12] Specifically, we define the NTR Gap as:

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

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

Figure 3a illustrates industry-level variation in NTR tariffs (blue) and non-NTR tariffs (red), for each 4-digit ISIC product. Some products had a substantial difference between NTR and non-NTR rates. For instance, Recorded Media faced non-NTR tariffs of nearly 60% compared with a 2% NTR tariff. Hence, PNTR eliminated the risk that Recorded Media exporters might suddenly see tariffs spike by 58 percentage points. 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 are less impacted by PNTR. NTR gaps are shown in Figure A.2, and reveal substantial variation, with some industries facing almost no gap and others having a gap upwards of 60%. The mean NTR gap across all industries is 30%.

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

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

[11] We use the non-agricultural population (i.e., the urban population) for two reasons. First, to be consistent 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 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 than households in non-agricultural residency status. Instead, the two population groups are found to participate mostly in informal labor markets where working conditions are deprived with 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 to our main results.

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

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 UC Davis Center for International Data (Feenstra et al., 2018).[13] We use 1997 as is the earliest base 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 ($\sum_j X_{cj}^{1997}$).[14] Cities with large export shares in high NTR gap industries have both substantial economic activity and exporting knowledge/infrastructure, allowing 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 of China.[15]

As our measure of PNTR exposure is a weighted average of NTR gaps, it is informative about the average reduction in uncertainty or expected tariffs facing each city. We illustrate the variation in our PNTR exposure measure across cities in Figure 3b, with capital cities labeled for reference. The weighted average NTR gap ranges between 0 and 53 percentage points, with the average city facing a 31 p.p. difference between NTR and non-NTR tariffs. There is substantial variation, however, across cities. Cities whose industries would benefit from PNTR include near-coastal cities in the south-east such as Shanghai, Nanjing, 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 had saw very little exposure to PNTR.

4.1.3 City-level Control Variables, Z_c

We control for city specific characteristics that might be correlated with its exposure to PNTR and the volume of students migrating to US universities. First, the quality of contract enforcement has been shown to raise comparative advantage and exports from

[13] We utilize information on the quantity and value of exports classified by the Harmonized System (HS) for all international transactions from China. Exports are categorized by the destination country, 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 within China. Hence, we aggregate city codes in the customs data up to the prefecture level, based on the reported city name. In some regions of China, the exporting location is unspecified in a category called "other". In the end, the original 479 city codes in custom data are aggregated to 275 prefecture cities including four municipalities.

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

[15] 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 us with the employment at the firm level, and we aggregate it up to obtain the total employment at the city-industry level. Notably, the industry classification of ASIP uses 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 International Standard Industrial Classification (ISIC) revision three at the 4-digit level using the crosswalk provided by the National Bureau of Statistics (NBS) of China.

industries requiring relationship-specific investment (Nunn, 2007). Such industries, in turn, often utilize high-tech and skill-intensive labor. We construct a city-level control for contract intensity that helps account for initial city comparative advantage affecting exports and productivity in skill-intensive industries, and possibly also growth in the demand for higher education. Data on contract intensity by industry is provided by Nunn (2007).[16] We then take a weighted average of industry contract intensity measures, using initial city export shares in 1997 as weights.

Second, prior to WTO, Chinese firms required licenses to export directly, with less than half of all firms reported having export licenses in 2000. Bai, Krishna and Ma (2017) show that the ability to directly export had large impacts on productivity growth. We use data on the fraction of exports revenues in total exports within an industry that are licensed to export directly. The time-varying industry data is provided by Bai, Krishna and Ma (2017), and we use only 2000 data to control for the exposure of prefectures to liberalization, as China phases 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 differential initial access of cities 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 both been shown to affect the productivity of Chinese firms (Yu, 2015). Import tariffs are applied tariff rates by China in 2000, averaged across origins, that we source from WITS-TRAINS. We also construct input tariffs using the 2002 input output table for China, combined with output tariffs during that year.[17] 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 us to reliably track 275 Chinese prefecture cities over time (see Figure 3b), for which we can measure their exposure to PNTR and growth in students coming to the US over the 2004-2013 decade. Though 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.[18]

[16]Specifically, contract intensity is measure 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 revision 2 ISIC industries, which we concord to 4-digit revision 3 ISIC industries.

[17]The IO table is available for 120 industry groups ("scode" classification), of which 70 are manufacturing.

[18]We capture all tier 1 cities (e.g. Beijing, Shanghai, Chongqing, Nanjing, etc.) and tier 2 cities (e.g. Xiamen, Kunming, Harbin, etc.). 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.

Table 1 shows summary statistics for our sample in 2004 and 2013. Between 2004 and 2013, cities had seen a sharp growth in economic activity, and a more modest growth in population. In contrast, the average number of Chinese students studying abroad in the US increased by over 10-fold. While all levels of higher education have seen growth over this decade, students pursuing associates and bachelors degrees stand out with substantial growth. Furthermore, while 63% of matriculating students in 2004 pursued STEM degrees, that share fell to 35% in 2013. The declining share of STEM students was offset by increases in both Social Sciences and Arts & Humanities. Interestingly, the composition of students by university selectivity, grouped into quartiles by admissions rates remain roughly similar, with some increase in the share of students in the least selective (tier 4) universities. Notably, the fraction of students that receive scholarship funding decreases from 62% to 22%.

4.2 Validating Identifying Assumptions

The validity of our design depends on whether the exposure of cities to PNTR was exogenous to other determinants of student emigration. We examine whether cities whose industries would see large reductions in expected tariffs, on average, were different in terms of their educational capacity or trends in student enrollment. As SEVIS data only begins in 2004, we cannot assess pre-trends in student emigration. Hence, we utilize data from the City Statistical Yearbook that provide alternative measures of education activity within each city prior to 2001. Specifically, we focus on the number of students attending college domestically, the number of domestic colleges, the number of domestic students attending secondary/middle schools, and the number of secondary/middle schools.[19]

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

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

Columns 1-4 of Table 2 show the results of this exercise. Panel A shows results without any controls. We also report results with the full set of controls in Panel B. This is our

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

preferred specification, which we discuss later. Results show no substantial or statistically significant correlation between the educational trajectory within cities prior to PNTR, and cities' PNTR exposure. Hence, any effects on student emigration are unlikely to be explained by differences between cities with high and low exposure in terms of educational pre-trends.

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

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

5 Results

5.1 Student Flows to US Universities

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

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

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

Across all specifications, the effect of PNTR exposure remains stable, and positive and statistically significant at the 99% level. Coefficient stability to controls lowers the likelihood that there are confounding omitted variables biasing our estimates (Altonji, Elder and Taber, 2005). Our preferred estimates come from the model with the full set of controls in column (5), and indicates that a 10 percentage point increase in PNTR exposure – roughly equal to moving from a city at the 25th percentile to a city at the 75th percentile – increased student emigration to the US by 37 per 1 million city residents. Since the average growth across cities was 138 per 1 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 US. The 2004-2013 time period saw 170,000 more Chinese students at US institutions relative to 2003. In our specification, the average treatment across all cities is equal to 0.316, which implies the average city has 102 students per 1 million residents go abroad (0.324*0.316*1000) as a response to the liberalization. Given the 411 million persons in the non-agricultural population, the elimination of the NTR gap is responsible for a total emigration of 42,080 students to the US. As such, the trade shock alone can explain 25% of the total increase in Chinese international students during this period.

While our primary results focus on growth over the decade between 2004-2013, we also split this period into three sub-periods. In Appendix Table A.2 we analyze short-term growth between 2004-2007, medium-term growth between 2008 and 2010 (also the Great Recession period), and longer-term growth between 2011-13. Results show positive and significant effects on student out-migration in all periods. However, the effect size grows each period – the influence of PNTR exposure grows over time. This result is consistent our exploration of wealth/income growth as a mechanism in Section 6, which did not happen overnight, and took time for households to accumulate.

5.2 Robustness of PNTR Exposure

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

In columns (2) and (3) of Table 4 we make further sample restrictions to assess whether estimates are not driven by highly influential cities or outliers. In column (2) we remove the four cities under the direct administration of the central government – Beijing, Shanghai, Chongqing, and Tianjin.[20] Column (3) removes capitals and coastal cities, to assess whether effects are driven by places with political lobbying power or especially strong access to foreign markets. In column (4) we include region fixed effects. The effect decreases in this case due to the loss in variation – there are now only about 45 cities per region – but remains significant. The last column varies the outcome slightly: we compute the change in the number of students normalized by total population of the city counting its rural areas. Although the coefficient drops by half, notice that "*per 1 million population*" in this case refers to a much larger population – about three times larger.

5.3 Sensitivity of the Shift-share Approach

Our measure of PNTR exposure falls under a broader class of variables that measure local exposure to national policy treatments, often referred to as Bartik or Shift-share instruments. We further examine the strength of our measure of PNTR exposure in light of recent work clarifying identification challenges with Bartik instruments (Goldsmith-Pinkham, Sorkin and Swift, 2020; Borusyak, Hull and Jaravel, 2018; Jaeger, Ruist and Stuhler, 2018; Adao, Kolesar and Morales, 2019). While industry-specific NTR Gaps measure the intensity of treatment, the city-level export shares help appropriately weight treatment intensity to better reflect city-level exposure. We use export shares in 1997, predating PNTR by 4 years. Goldsmith-Pinkham, Sorkin and Swift (2020) clarify that the lagged shares provide a crucial source of identifying variation, and that causality hinges on the exogeneity of lagged shares. Borusyak, Hull and Jaravel (2018) suggest that what we need are 'exogenous' shifters, in this case the NTR gaps. Jaeger, Ruist and Stuhler (2018) propose that we would ideally have a structural break rather than relying on secular trends – in this context, joining the WTO is the break we exploit. Adao, Kolesar and Morales (2019) document a procedure to correct the standard errors for the correlation across cities with similar industrial shares.

We provide several tests that support our research design. A first concern pertains to

[20] The administrative units are currently based on a three-level system in China. The country is first divided into provincial units, including provinces (e.g., Jiangsu Province), autonomous regions (e.g., Tibet), and municipalities directly under the central government (e.g., Beijing, Shanghai, Chongqing, and Tianjin). Prefectural level divisions are the second level of the administrative structure, and most provincial units excepting 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 levels of the administrative structure. In this paper, the unit of analysis is the municipal city (i.e., municipality) and prefecture city. For detail, see http://xzqh.mca.gov.cn/statistics/2018.html. As government policies can favor municipalities more than other prefecture cities (Wang (2013)), we exclude the four municipalities for robustness.

whether past shocks persist over time such that they continue to impact outcomes during the period under study. If lagged shares are correlated with unobserved determinants of future student emigration, the shift-share approach will be invalid (Goldsmith-Pinkham, Sorkin and 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.[21] Specifically, for each city, we interact the share of employment in each industry with the industry specific NTR gaps, and sum over all industries, as in Equation 3. The second row in Table 5 shows the results when using this alternative PNTR exposure measure. The estimated effect is similarly positive and significant at the 1% level. While the coefficient appears over twice as large as our main effect (reported again in the first row), the magnitudes are nearly identical, as the variation in PNTR exposure using 1990 employment shares is on a smaller scale. Moving from a city at the 25th to 75th percentile – roughly 5.7 percentage points for the 1990-weighted PNTR exposure – increases student emigration by 42 per 1 million city residents.

We implement a second check introduced by Goldsmith-Pinkham, Sorkin and Swift (2020), that examines the weight different initial shares play in estimation. We use our initial PNTR exposure measure, that relies on export shares, and calculate Rotemberg weights for each industry's export share.[22] Appendix Table D.4 shows the top 30 industry weights. As a robustness check, we remove the top 5 industries from our PNTR exposure measure and rerun the analysis. Results of this check, shown in the third row of Table 5, are similar to our main findings. Finally, in column (6), we report standard errors using an adjustment outlined by Adao, Kolesar and Morales (2019), which accounts for the correlation across cities in industrial shares, and find that our results are still precisely estimated.

[21] 1997 is the earliest we can get data on city-level exports by industry, at least using current city codes (severely limited data is available for earlier periods.)

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

5.4 Alternative Instruments

We complement our main analysis with two additional sources of variation that do not rely on the PNTR policy.[23] 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 Multi-Fibre Agreement (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 then we aggregate to the city level by weighting industries using 1997 export weights by city and industry. Our MFA instrument is thus a city-level weighted average of quota reductions (which were done gradually through 2005), which captures the importance of textiles and garment industries in the city.[24]

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

5.5 Migration Elasticities by Type and Compositional Changes

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

We estimate specification 1, altering the dependent variable to reflect enrollment growth by academic level. Results for undergraduates, Masters, Doctoral, and other students are shown in columns (2)-(5) of Table 6 panel A. We report our main estimates again in column (1). Subsequent columns reflect how total growth is distributed across academic levels.

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

[24] The MFA instrument and PNTR exposure measure are correlated (equal to 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.

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

To understand changes in student composition attributable to trade shocks, we compare the proportions of students in 2004, reported in row 3, to the proportion of the effect for each academic level, in row 2. For ease, we also provide the difference in these proportions in row 4.[25] While only 7% of Chinese students entering in 2004 matriculated in Bachelor degree-granting programs, 47% of the inflow generated by PNTR exposure occurred at the Bachelors level, an increase of 40 percentage points. In contrast, Doctoral students initially accounted for nearly half of all students matriculating in 2004. Given that they see no statistically significant increase associated with PNTR exposure, the change in proportion attributable to trade is dramatic. While Masters students also saw sizable inflows, these are in line with previous proportions, as is the inflow for Associates students. Finally, there is also a slight trade-induced compositional shift towards students in other academic levels, which mainly include non-degree granting programs.

In panel B of Table 6 we focus on major field of study, separately assessing changes in the number of students in STEM, Arts & Humanities, and Social Sciences in columns 2, 3, and 4, respectively. As Business comprises a large fraction of international students, we separately report Business majors in column 5. While all fields see growth in Chinese students in response to the trade shock, results indicate meaningful shifts in the composition attributable to trade. This trade-induced shift is away from STEM, and toward both Arts and Social Sciences in equal proportion. When comparing to the baseline proportions, the estimates indicate PNTR exposure increased the share of students in Arts and Social Science by 10 pp. Business majors, the most popular Social Science major among international students, sustained an even larger increase in the share of Chinese students. This, perhaps, reflects again the income-mechanism since STEM degrees are more likely to receive other sources of funding, whereas Business students must rely on their own income. In Table A.1 of the appendix we add detail by showing the field of study compositions by levels of study.

In panel C we examine changes in the composition of students by the quality of US universities they attend. We measure quality using admissions rates from the Integrated

[25]For visual clarity, Figure A.3 provide bar graphs that compare the proportional effect for each student type, with the proportion of students in 2004.

Postsecondary Educational Data System (IPEDS). We group US universities into quartiles based on their admissions rate, with the 1st quartile representing the most-selective schools and the 4th quartile comprising of the least-selective institutions. Results indicate that while all universities saw significant increases in Chinese students, changes in composition have 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, thus indicating potential movement from less-selective institutions to the least-selective institutions.

In panel D of Table 6 we focus on whether the rise in Chinese students is driven by those with or without funding. We examine the number of students that are funded by scholarships, grants, or other institutional resources ("Has Funding") and the number of students who primarily use personal and family income to finance their studies ("No Funding"). In 2004, 57% of Chinese students received some form of scholarship, grant, or other financial assistance. The migration elasticities with respect to the trade shock are a lot larger for unfunded students than they are for funded students. This is consistent with elasticities by level of study and our hypothesis that rising wealth is an important mechanism in sending students abroad. The part of the change in the composition of students that depends on trade shocks, substantially shifted the composition away from funded to unfunded students.

In panel E of Table 6 we examine growth in students by the 1st to 4th quartiles of the personal funds distribution in 2004. The export shock explains student migration of those in the upper quartiles of this distribution; those with substantial personal funds.

5.6 US Regional Inequality

We also ask whether PNTR exposure induced Chinese students to high or low human capital localities in the US.[26] The results would speak to whether the rise in educational exports exacerbate or dampen the rise in regional inequality in response to trade-induced labor reallocation. Bloom et al. (2019) find that generally reallocation due to the China shock has raised inequality across regions as large multinationals eliminate jobs in industry and create new service jobs in places with the highest human capital. Our finding also implies that employment in the US reallocates to services. However, raising education exports has the potential to lift all regions, as universities expand nationwide.

In the last panel of Table 6 we split the outcome, changes in students studying abroad, by the human capital of the *destination* city. We match the city of the US university to commuting zones.[27] For each commuting zone we calculate the fraction of adults that have completed a college education using the 1990 decennial census. Panel F displays results

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

[27] There are over 3000 cities, aggregated into about 700 commuting zones.

with the outcome split into four quartiles based on the fraction of persons with a college degree in the destination commuting zone. We find that PNTR exposure induced a rise in service exports *for all types* of commuting zones. This might not be surprising since US universities are geographically dispersed. Yet, along with the results on no selection on university quality, this suggests that the reallocation to educational services dampens the disparities across regions induced by labor reallocation to other types of services. Hurting the market for higher education, as we explore next in the context of a trade war, would imply a further negative shock to localities most exposed to the fall of manufacturing.

5.7 Policy Counterfactuals: Consequences of a Trade War

Our results speak to the consequences of trade wars and uncertainty over tariffs. Since 2017, this uncertainty resurfaced as US-China trade relations soured, and the US government instituted across the board tariffs on goods from China. The US has departed from PNTR rates and by mid-2019, average tariffs on Chinese goods increased to nearly 20% (PIIE, 2020).[28] An agreement in January 2020 (i.e. the phase-I deal) reduced tariffs imposed on Chinese goods in exchange for concessions, yet tariff uncertainty remains significant – tariff increases can be levied if China is deemed to not hold up its end of the deal.

We use our estimates on the effect of uncertainty in tariffs to make simple inferences on possible future changes in international student flows and services exports, if all Chinese industries were to face 20% higher tariffs. Recall our reduced form results on the effect of PNTR exposure on student out-migration (Table 3) indicate that a 10 percentage point increase in tariffs leads to 32 fewer students per million city residents over a ten year period.[29] As the increase in tariffs on Chinese products in 2020 is about 20pp across the board, this suggests that enrollment would decline by 640 students in cities that have a population of 10 million. Given China's urban population (the denominator in our outcome) this implies over 30,000 fewer students over ten years.

Assuming average tuition of $40,000 per year implies that over ten years, US institutions would lose $1.15 billion in tuition revenue. That is a 3% reduction in education service exports, and an 8% reduction in education exports to China, not including general equilibrium multiplier effects that may reverberate across local economies (Acemoglu et al., 2016).[30]

[28]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 US raised tariffs from 10 to 25% on the former set of goods.

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

[30]The 3% number does not depend on the exact tuition cost, but on the fact that the US loses 3% of

6 Mechanisms

We explore several candidate explanations for why and how trade liberalization induce large numbers of Chinese students to migrate to the US. In Section 3 we outlined possible channels by which trade liberalization induced by PNTR exposure could generate student out-migration. We empirically examine whether increased student flows to US higher education due to PNTR exposure is consistent with (1) income/wealth generation, (2) changing returns to education, and/or (3) information flows.

6.1 Income/Wealth Accumulation

Greater income/wealth alleviates credit constraints that families face in financing education abroad. We first investigate whether and how trade liberalization translates to rises in income and wealth. Erten and Leight (2020) find a rise in wages in Chinese counties that experienced high PNTR exposure. Cheng and Potlogea (2015) do not find evidence of changes in wages, but instead find a rise in output, employment and investment growth. They explain 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. (2018) and Tombe and Zhu (2019) showing that cities that benefited the most from PNTR also saw large in-migration of rural workers.[31]

A separate literature has also documented how ensuing economic growth contributed to tremendous asset price appreciation – primarily in real estate. Hence, large increases in wealth may have 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 rose from 350 percent to 700 percent between 1978 and 2015 and that wealth became more concentrated. We view the rise in wealth that includes capital gains, such as housing, the most likely mechanism for student out-migration due to the large costs to finance living and studying in the US. For this reason, we examine real estate price data and also survey data which identifies real estate income.[32]

First, we confirm some of the results on economic growth found in the previous literature. The first two columns in Table 7 and Figure 6 show that cities with the most exposure to

its total international students in this counterfactual (relative to the number if tariffs were to stay at their pre-trade war level). Similarly, the loss of Chinese students represents 8% of the current stock. Appendix Figure A.1 displays the total number of International and Chinese students enrolled over time.

[31] We also find limited gains in average wages, but find increased income that includes capital gains.

[32] In 2017, housing sales were equivalent to 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 land sale revenue, which means that appreciations will have important feedback effects for wealth generated in the local economy.

exports experience relatively larger GDP growth, and this effect is large.[33] However, as in Cheng and Potlogea (2015), we also find that GDP per capita does not increase significantly, likely due to simultaneous population growth in cities highly exposed to PNTR. Although the effect on population growth is not significant, the coefficient implies that cities with a 10 pp larger PNTR exposure experience 2.5% larger population growth, and from the last two columns we see that this is enough to make the relative growth in GDP per capita insignificant. The growth in total GDP combined with population growth would drive up housing wealth, although not necessarily average wages.

To make the case that financial constraints are indeed an important impediment to Chinese coming to the US, we recall results from self-financing of education. Panel D and E of Table 6 imply that students without university funding and those with more personal funds were more likely to respond to trade-shocks. From the summary statistics (Table 1), recall the fraction of students with no funding increased from 38% in 2004 to 78% in 2013.

Given the importance of personal funds in students going abroad, trade liberalization induces migration if it leads to more availability of these funds. We are able to establish two facts: that cities highly exposed to PNTR experienced larger housing price appreciation and saw greater income from real estate transactions. The first four columns in Table 8 report the effect of PNTR exposure on residential housing prices (first two columns, with and without controls) and commercial real estate prices (middle two columns), using price data from the Wind Economic Database.[34] Although these are all positive, it is commercial prices that display a large and significant effect in response to export growth. Figure 6 shows a clear positive relationship between the two types of housing prices and PNTR exposure.[35]

Columns (5) and (6) of Table 8, and the lower row of Figure 6, report the effect of PNTR exposure on income derived from real estate sales. We aggregate individual data on income from real estate transactions from the Urban Household Surveys of the National Bureau of Statistics of China.[36] We calculate the log change in average real estate income

[33]Cities with a 10 pp larger PNTR exposure experience 5.4% larger GDP growth. Outcomes in Table 7 are long differences of log values.

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

[35]These two types of land reflect similar investment purposes. For example, Chen et al. (2017) combine these two into one "commercial" land category.

[36]The Urban Household survey is similar to the Current Population Surveys (CPS) in the US and adopts a stratified and multi-stage probabilistic sampling scheme. The UHS reports household information and economic characteristics such as the household income of different types. The data has been widely used, and detailed information on UHS is provided by Ding and He (2018). The UHS has been used to study wage inequality (Yang, 1999; Ge and Yang, 2014; Ding and He, 2018), the savings rate (Chamon and Prasad, 2010), and trade impact on household income (Han, Liu and Zhang, 2012).

by city during the 2002 to 2008 period, which contains more than 30,000 households and over 120,000 individuals each year. While data constraints only provide 156 cities for the analysis, and we miss asset appreciation for the last 5 years, there is a clear positive effect on real estate income in cities more exposed to trade liberalization. The coefficients in the last two columns of Table 8 implies that a 10 pp rise in PNTR exposure raises income from housing sales by 36 to 39 pps.

The discussion in Section 3 also postulates that growth in wealth can lead to a general reallocation of consumption towards services because the income elasticity of services is greater than other goods. The UHS data above allows us to construct total services consumption by households, which we aggregate to the city level. In the last two columns of Table 8 and the last plot of Figure 6 the outcome is the change in the share of service expenditure to household income. We find that higher PNTR exposure is associated with a reallocation of expenditure towards services.[37] Although suggestive, these results confirm that households in cities with greater liberalization behave in ways consistent with rising wealth.[38]

Overall these results help corroborate the idea that export growth led to income expansions in cities that were strongly treated by China's accession to the WTO. This is especially important for the most wealthy, whom likely had substantial wealth in housing assets prior to 2001. As a result, over the long run, more families at 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 is if trade liberalization increased the returns to higher education. If capacity constrained Chinese universities were unable to meet the increased demand, students would migrate overseas. Alternatively, in the absence of capacity constraints at Chinese universities, trade liberalization could specifically have raised the return to a US degree. We explore the likelihood of these scenarios.

First, we examine whether rising incomes in cities affected capacity-constrained local universities, and as such 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 admission. In Figure 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 (exact numbers in Table A.3 and details of the

[37] The share is defined as total services expenditure relative to household income, though a similar result is obtained using total expenditure as the denominator. The average service share is about 0.18. The data also decomposes services into specific types. The share spent on educational services increases significantly. We also find that the expenditure share on recreational and "self care" increases.

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

data are in Appendix E).[39] The lack of this relationship suggests that it is unlikely that (a) local returns to education are rising, and (b) local top universities are being crowded.[40]

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 can explain student migration. To do so, 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.[41] Table 9 reports results comparable to our benchmark specification, where the NTR gap is constructed using a subset of industries defined above. In the first column we split industries using a skill intensity measure based on Chinese industries, while in the second column, for robustness, we use a measure produced for Indonesian industries from Amiti and Freund (2010). PNTR exposure in *non-skill* intensive industries can explain nearly all of 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 above and the previous literature on education in China. The Rotemberg weights summarized in Section 5 found that textile production – which is not skill intensive – accounts for the most exposed industries. For instance, industries with the three highest Rotemberg weights (Table D.4) are all more than one standard deviation below the mean in skill intensity. Therefore, the industries expanding due to trade liberalization are of lower skill, so that trade liberalization in itself does not necessarily raise the 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) which found that educational attainment in China declined due to export expansion.[42] Additionally, while increases in the return to the US-degree could occur, recent evidence from Chen (2020) show that, all else equal, job applicants with a US degree receive less call-back rates than Chinese degree holders.

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

[40] This doesn't mean there is no relationship between city income and city's share of students at top universities – we do in fact find a positive relationship in 2005 – however there is no relationship between changes in income and changes in the share of students.

[41] We label industries as skill intensive if they are above the median in the ISIC industry data. The skill share is the industry employment share of skilled workers, based on the Annual Survey of Industry Production (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).

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

6.3 Information

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

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

Results of this exercise are reported in Table 10. Column (1) repeats our main results on the reduced form effect of PNTR exposure on student flows, and column (2) displays the first stage results using PNTR exposure to predict actual export growth, comparable to column (6) in Table 2. Column (3) reports the 2SLS estimate with PNTR exposure as an instrument for city-level export growth between 2000 and 2013. We then compare this 2SLS result with the case where exports to the US *are excluded* from the city-level export growth and the export shares used to create PNTR exposure. Column (4) shows that in fact the effect on student migration holds even when we exclude exports to the US from total city export growth.[43] Column (5) also removes US exports from both city-level export growth and the export shares used to construct PNTR exposure.

Intuitively, if information flows were a dominant mechanism, we would expect to see less of a relationship between student emigration and trade with non-US destinations. This evidence indicates that information flows are unlikely to drive our findings.[44]

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

[43] We have 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 lead to student migration to the US.

[44] On the other hand, one might ask why our instrument is a strong predictor of exports to non-US destinations. For example, the EU 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 produce to other destinations as well. Notice that the World Import Demand (WID) instrument, which captures demand from the rest of the world, predicted similar changes in student emigration. It is beyond the scope of this paper to link uncertainty with the US to the overall growth in Chinese exports, but we point out that the rise in wealth reflects the fact that China expanded globally.

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

7 Conclusion

International student flows are a function of both home and destination country education and labor markets. At least a few important factors drive such flows. First, is the growing need for international students from US universities suffering large adverse shocks to non-tuition sources of revenues (Bound et al., 2019; Shih, 2017). Second, is the extent to which home country universities are constrained in the availability of high-quality higher education. Third, is the option value of joining the US labor market after obtaining a US degree. And finally, the capacity to pay for, and the number of high-school graduates prepared for a US university. Our research finds that this final strand explains a substantial portion of flows in students from China to the US.

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

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

Foreign tuition revenues are a crucial aspect of US service exports. The US Commerce Department estimates that in 2017 educational exports added about $34bn to the US current account, which is about as large as the combined total exports of soybeans, coal and natural gas (Rampell, 2018). While much of the conversation on trade with China has focused on the trade-deficit with respect to goods, 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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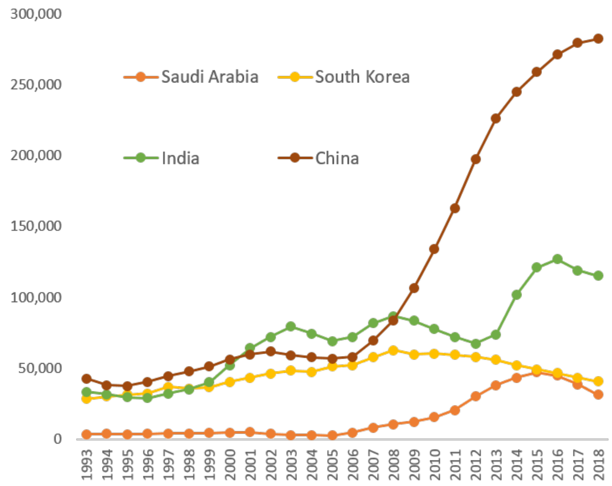
Tables & Figures

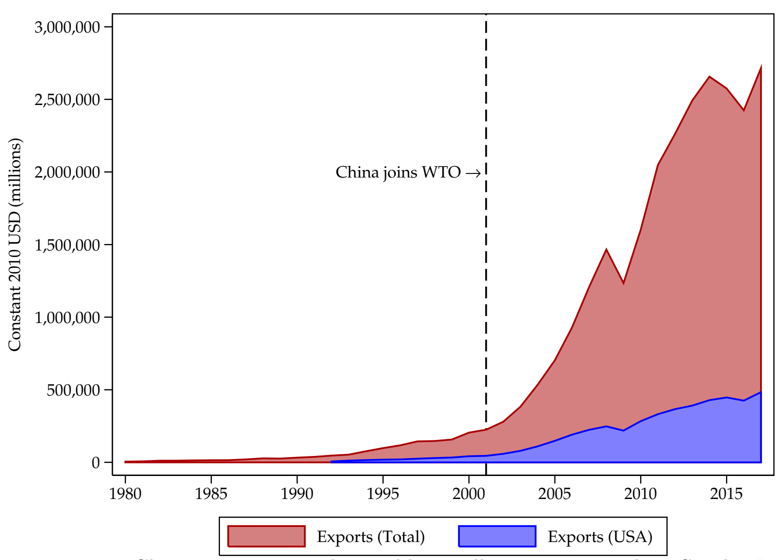
7.1 Descriptive Figures

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



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

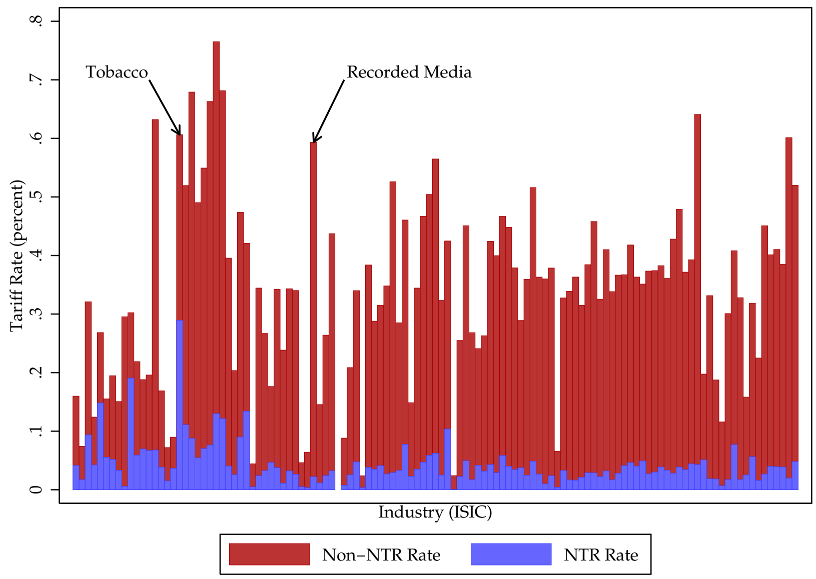
Figure 2: Chinese Exports, 1980-2017



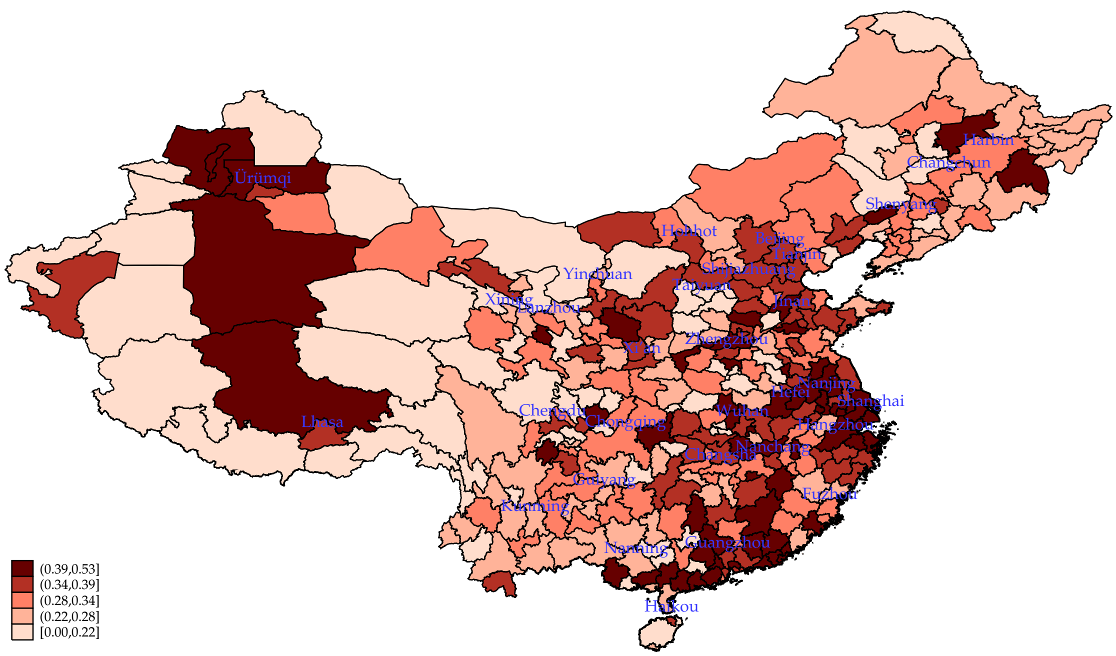
Notes: This figure presents Chinese exports to the world as well as exports to the US only. Data for exports to the US are from Comtrade. Exports to the world are sourced from the World Bank. Both reflect exports in 2010 prices using the US GDP deflator for that year.

7.2 PNTR Variation

Figure 3: Variation in PNTR Exposure



(a) NTR and Non-NTR Rates across Industries



(b) PNTR exposure across Chinese Prefecture Cities

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

7.3 Summary Stats

Table 1: Summary Statistics

	2004	2013
Population (in 000s)	1,239	1,463
	(1,510)	(1,845)
GDP (in 10,000 RMB)	3,320,868	13,178,523
	(6,808,102)	(25,694,406)
GDP per capita (in RMB)	21,401	72,090
	(18,703)	(53,655)
Exports (in 10,000 RMB)	91,836	451,080
	(250,154)	(1,501,816)
Students Entering US Higher Ed	39	357
	(168)	(1,372)
Academic Level Shares:		
Associates	0.03	0.05
	(0.10)	(0.04)
Bachelors	0.05	0.27
	(0.10)	(0.10)
Masters	0.31	0.38
	(0.19)	(0.11)
Doctorate	0.56	0.12
	(0.24)	(0.07)
Other	0.05	0.18
	(0.09)	(0.09)
Field of Study Shares:		
STEM	0.63	0.35
	(0.23)	(0.11)
Social Science	0.29	0.43
	(0.21)	(0.10)
Arts/Humanities	0.09	0.23
	(0.14)	(0.10)
University Selectivity Shares:		
Tier 1	0.18	0.18
	(0.15)	(0.07)
Tier 2	0.26	0.22
	(0.20)	(0.07)
Tier 3	0.22	0.20
	(0.19)	(0.06)
Tier 4	0.33	0.40
	(0.21)	(0.10)
Scholarship Funding Shares:		
Received Funding	0.62	0.22
	(0.23)	(0.09)
No Funding	0.38	0.78
	(0.23)	(0.09)
Number of Cities	274	274

Notes: Calculations from SEVIS individual level data on student flows, majors of study and destination universities. 'Students Entering US Higher Ed' are measured as a fraction of 1 million residents in the city. STEM degrees include degrees in Science, Technology, Engineering and Mathematics. Social Science degrees also include Business-related degrees. University selectivity shares based on admission rates from IPEDS data. Universities are categorized into 4 tiers based on quartiles of the admissions rate. Population and GDP numbers from the China City Statistics Yearbook.

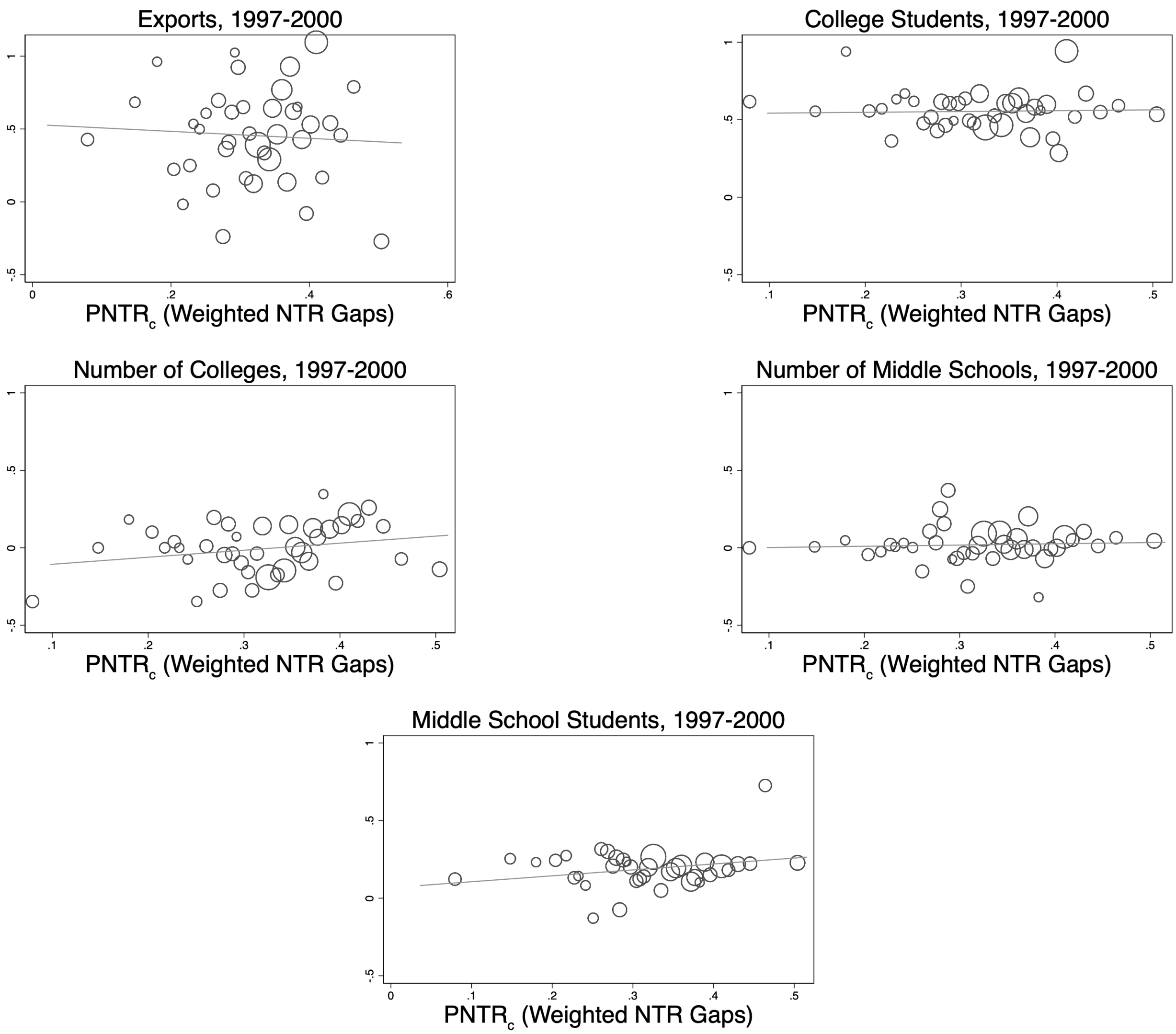
7.4 Identification Checks

Table 2: Identification Checks

	1997-2000					2000-2013
	(1) College Students	(2) Number of Colleges	(3) Middle School Students	(4) Number of Middle Schools	(5) Exports	(6) Exports
A: No Controls						
$PNTR_c$	0.053	0.455	0.152	0.081	-0.236	3.984***
	(0.349)	(0.397)	(0.154)	(0.136)	(0.641)	(0.788)
B: w/ Controls						
$PNTR_c$	-0.025	0.400	0.778	-0.050	0.419	2.881***
	(0.390)	(0.473)	(0.649)	(0.174)	(0.775)	(0.834)
Contract Intensity	-0.054	0.548	2.667*	0.442*	2.562*	1.740*
	(0.434)	(0.464)	(1.486)	(0.254)	(1.339)	(0.981)
Import Tariffs	0.201	0.010	-0.380	-0.074	-2.727**	3.116*
	(0.341)	(0.464)	(1.070)	(0.264)	(1.107)	(1.670)
Input Tariffs	0.412	-0.619	2.490*	1.563	2.536	1.568
	(1.420)	(1.749)	(1.484)	(1.096)	(3.641)	(3.881)
Export License	0.189	-0.401	-3.431	-0.148	-3.660*	-0.998
	(0.984)	(0.976)	(2.261)	(0.378)	(2.148)	(1.713)
Observations	182	184	246	219	275	275

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

Figure 4: Correlation between PNTR Exposure and Pre-trends



Notes: Binned scatter plots of the relationship between weighted NTR gap (PNTR), and pre-trends in outcomes. Plot shows 40 equal sized bins, weighted by population size in each bin. Pre-trend outcomes are measured as the city-level log change between 1997 and 2000. Data on exports come from the China Customs Database. Data on College and Middle School students come from China City Statistical Yearbook.

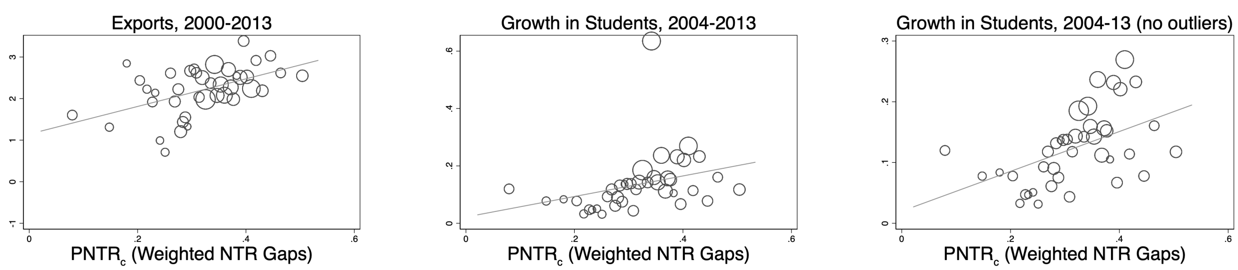
7.5 Main Results

Table 3: Effect on Enrollment, 2004-2013

	(1) No Controls	(2) +Control for Contract Intensity	(3) +Control for Import Tariffs	(4) +Control for Input Tariffs	(5) +Control for Export Licenses
$PNTR_c$	0.358***	0.300***	0.368***	0.380***	0.324***
	(0.104)	(0.104)	(0.106)	(0.105)	(0.106)
Contract Intensity		0.315*	0.337*	0.321*	0.258
		(0.188)	(0.194)	(0.187)	(0.177)
Import Tariffs			-0.265*	-0.111	-0.071
			(0.137)	(0.125)	(0.122)
Input Tariffs				-0.982***	-0.882**
				(0.354)	(0.352)
Export License					0.361**
					(0.178)
Interquartile Effect:					
Δ *Students per 1m Pop.*	41	34	42	43	37
Mean Dep Var.	0.138	0.138	0.138	0.138	0.138
Obs.	275	275	275	275	275
R2	0.023	0.037	0.043	0.054	0.059

Notes: City-level regressions showing the effect of PNTR exposure on Chinese student enrollment growth between 2004 and 2013, per thousand city residents. Rows below the coefficients scale up the effect size in terms of students per million residents, for a change in the PNTR that traverses its interquartile range (≈10 p.p.s). 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 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 parenthesis) at the city level.. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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



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

Table 4: Effect on Enrollment, 2004-2013, Robustness Checks

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

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

Table 5: Effect on Enrollment, 2004-2013, Bartik Checks and Alternative Instruments

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

Notes: City-level regressions showing the effect of trade-shocks on Chinese student enrollment growth between 2004 and 2013, per thousand city residents. We include all main controls: Column (1) reproduces our main estimates from column (5) of Table 3. 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.s). 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 Multifibre Agreement Quotas by using the quota fill rate by industry in 2001 (from Khandelwal, Schott and Wei (2013)). For columns (1)-(5) we report heteroskedasticity-consistent standard errors (in parenthesis) at the city level. In column (6), we report standard errors as outlined by (Adao, Kolesar and Morales, 2019). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

7.6 Migration Elasticities by Sub-group and Composition Changes

Table 6: Migration Elasticities and Compositional Changes, 2004-2013

	(1)	(2)	(3)	(4)	(5)	(6)
A: Level of Study	Total	Associate	Bachelors	Masters	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) of Table 3. The first row below the coefficients document 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 Science also include Business-related degrees, and we separately report effects for Business only. In panel C, we use the IPEDS data to create four quartiles on university selectivity based on admission 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 up by quartiles of personal funds reported used to fund the education, where the 4th quartile uses more personal funds than the 1st quartile. In panel F, we distinguish US commuting zones based on human capital – i.e. the fraction of persons over 25 with a college education (from 1990 decennial census) – and then link students to commuting zones based on the address of the US university. We then construct 4 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 parenthesis) at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

7.7 Mechanisms - GDP and Housing Wealth

Table 7: Log GDP and Population

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

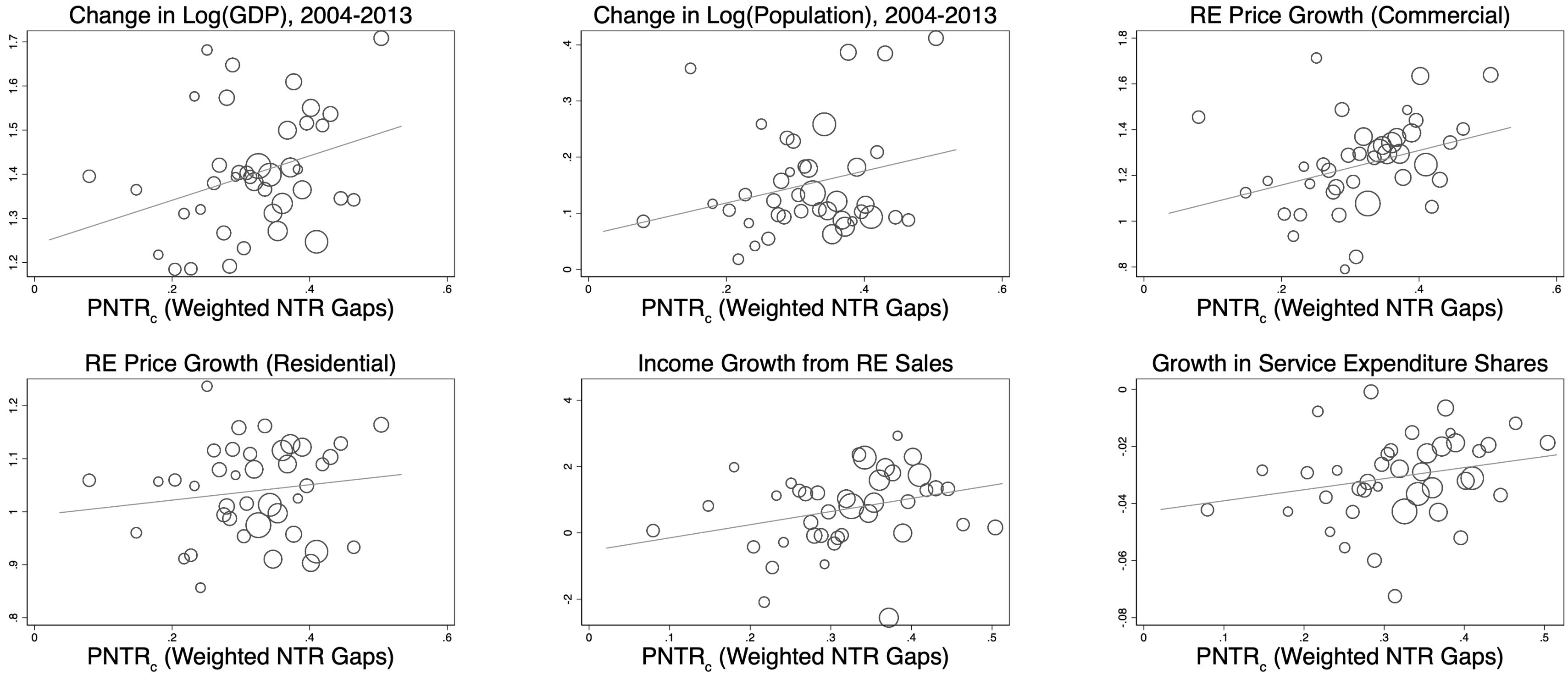
Notes: City-level regressions showing the effect of weighted NTR gaps on logged values of GDP, population and GDP per capita. Even numbered columns include main controls: contract intensity, import tariffs, input tariffs and export licenses. We report heteroskedasticity-consistent standard errors (in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

Table 8: Wealth Shocks and Real Estate (RE) Prices

	RE Price (Residential)		RE Price (Commercial)		Income from RE Sales		Service Exp. Share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PNTR_c$	0.145	-0.023	0.755***	0.554*	3.963*	3.636*	0.039*	0.048*
	(0.175)	(0.175)	(0.285)	(0.297)	(2.057)	(2.036)	(0.022)	(0.027)
Controls		x		x		x		x
Obs.	195	195	204	204	156	156	173	173

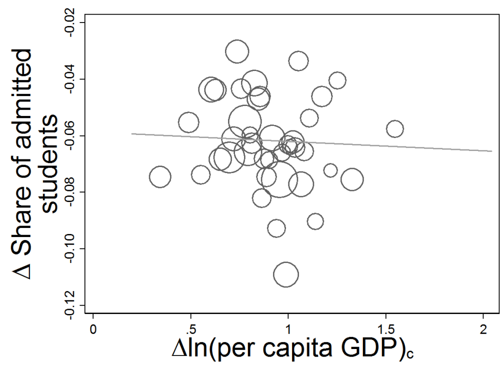
Notes: City-level regressions showing the effect of weighted NTR gaps on growth in real estate prices for both residential and commercial properties, income from real estate sales, and the share of services in exports, all measured in log changes. Even numbered columns include main controls: contract intensity, import tariffs, input tariffs and export licenses. Real estate data from WINDBANK is available from 2002-2013 for commercial propreties, and from 2005-2013 for residential properties. Average income from real estate sales is calculated at the city level from the Urban Household Survey from 2002-2008. Average service expenditures and household incomes are also obtained from the Urban Households Survey. We use the change in the expenditure share for each city from 2002-2008. We report heteroskedasticity-consistent standard errors (in parenthesis) at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Figure 6: GDP and Wealth Shocks

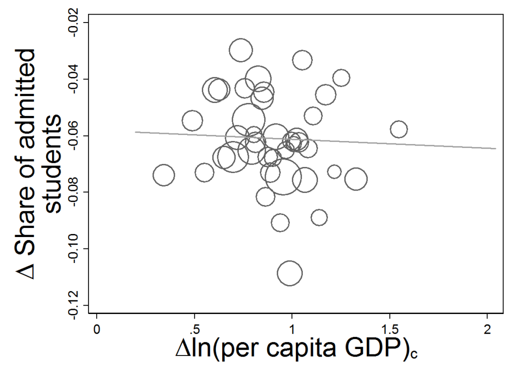


Notes: Binned scatter plots of the relationship between weighted NTR gap (PNTR), and post-treatment growth in outcomes. Plot shows 40 equal sized bins, weighted by population size in each bin. Real Estate data from WINDBANK. Data on GDP and Population by city are from the China City Statistical Yearbook. Average service expenditures and household incomes are also obtained from the Urban Households Survey. We use the change in the expenditure share for each city from 2002-2008.

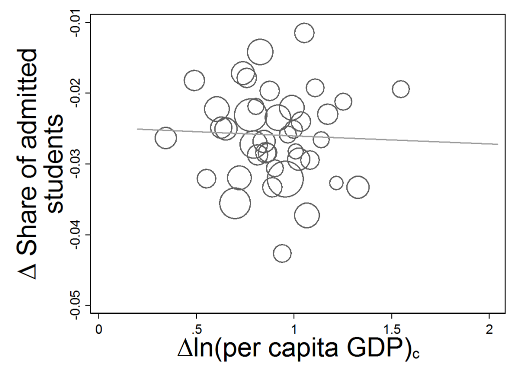
Figure 7: Admission to Elite Universities, Per Capita GDP and PNTR Gaps



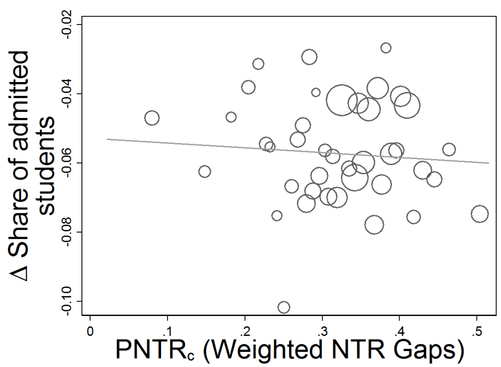
(a) First-tier Universities



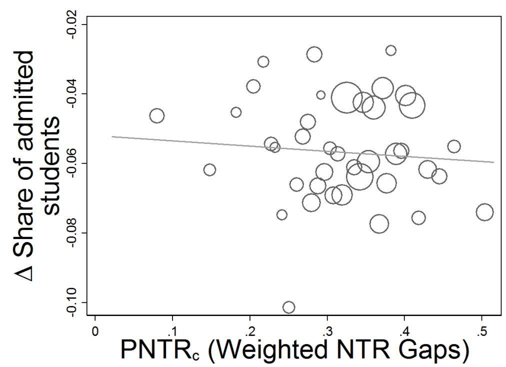
(b) 211 Project Universities



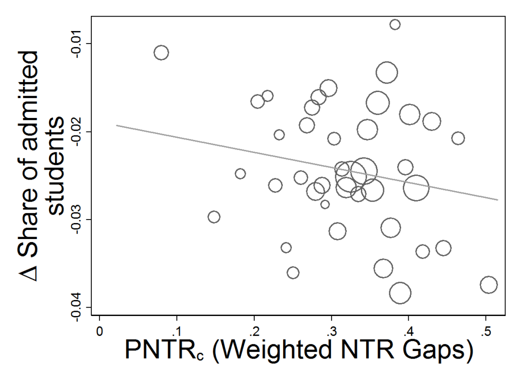
(c) 985 Project Universities



(d) First-tier Universities



(e) 211 Project Universities



(f) 985 Project Universities

Notes: 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 weight. 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, 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.

7.8 Mechanisms - Returns to Education

Table 9: The Effect of Skill-specific Shocks on Student Flows

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

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

7.9 Mechanisms - Information

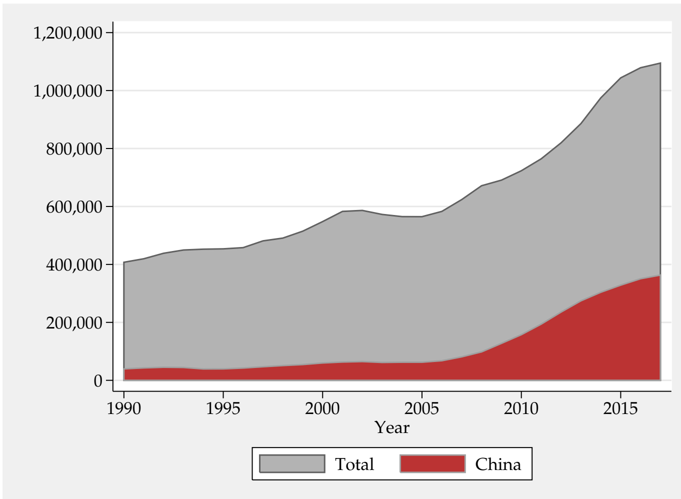
Table 10: Testing Information Flows between China and the US

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

Notes: City-level regressions showing the effect of PNTR exposure on Chinese student enrollment growth between 2004 and 2013, per thousand city residents. Column (1) reproduces our main estimates from column (5) of Table 3. All regressions include the following controls: contract intensity, import tariffs, input tariffs and export licenses. Column (2) shows the first stage, where the outcome of interest is the log change in exports between 2000 and 2013. Column (3) shows two-stage least squares 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 US in the export growth variable. Column (5) once again excludes all exports to the US in the explanatory variable and also the PNTR exposure measure (instrument). We report heteroskedasticity-consistent standard errors (in parenthesis) 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



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

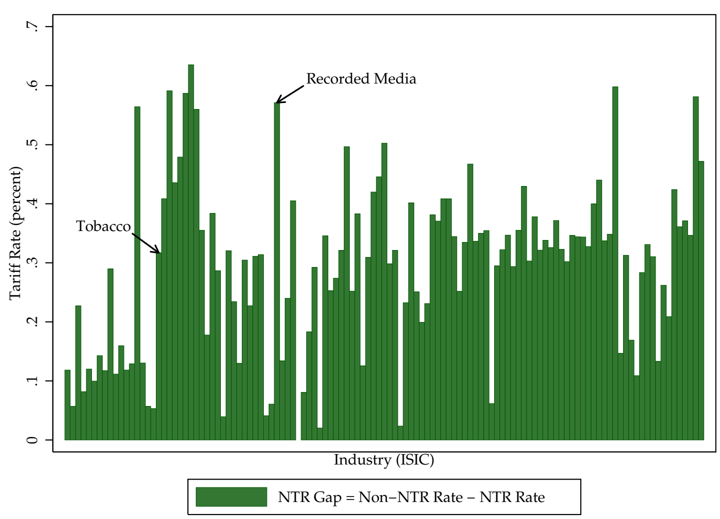
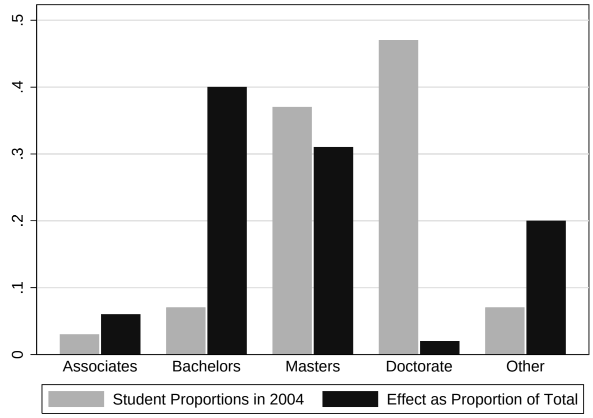


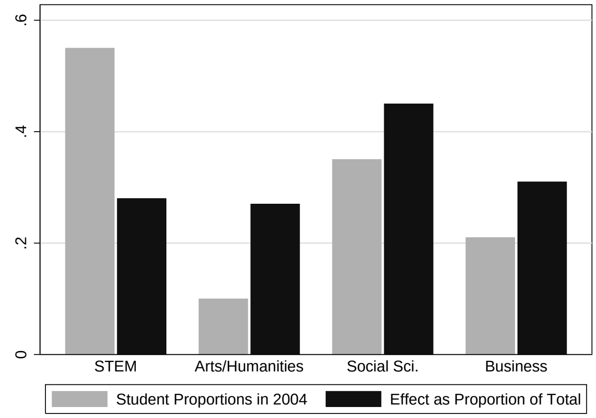
Figure A.2: NTR Gaps

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

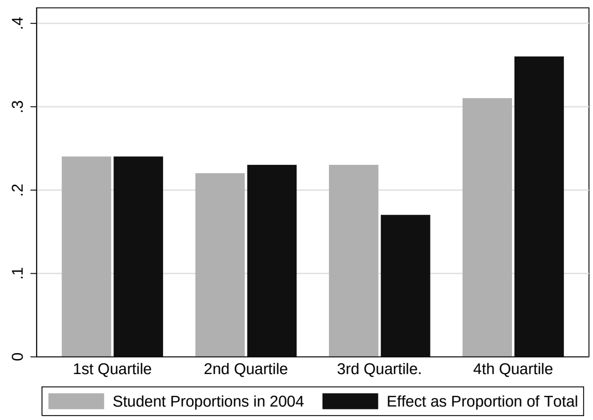
Figure A.3: Changes in the Composition of Chinese Students Attributable to PNTR



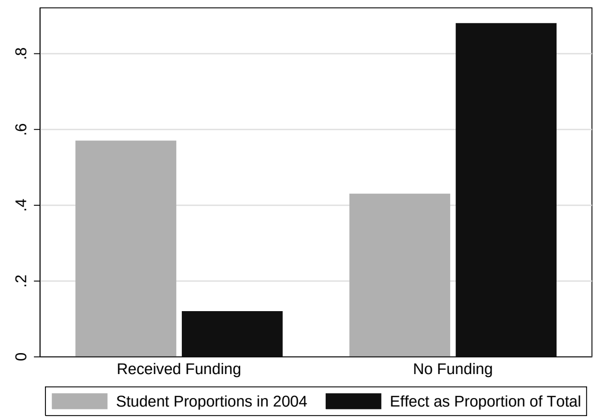
(a) Academic Level



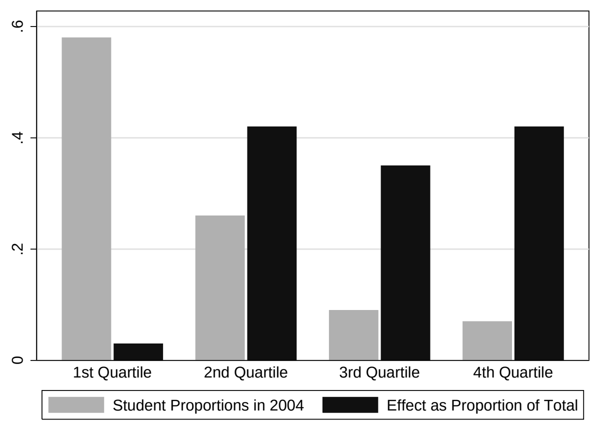
(b) Field of Study



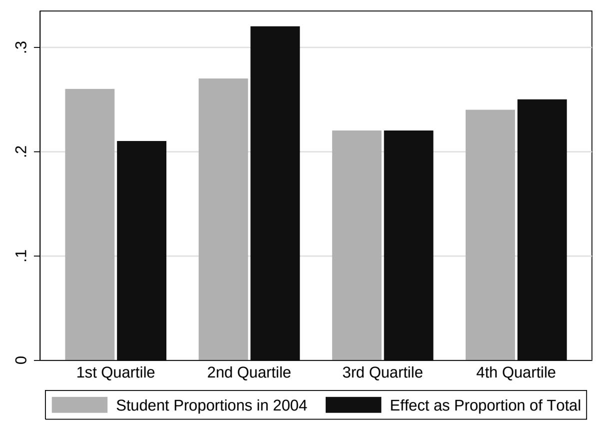
(c) University Selectivity (Admissions Rate)



(d) Scholarship Funding



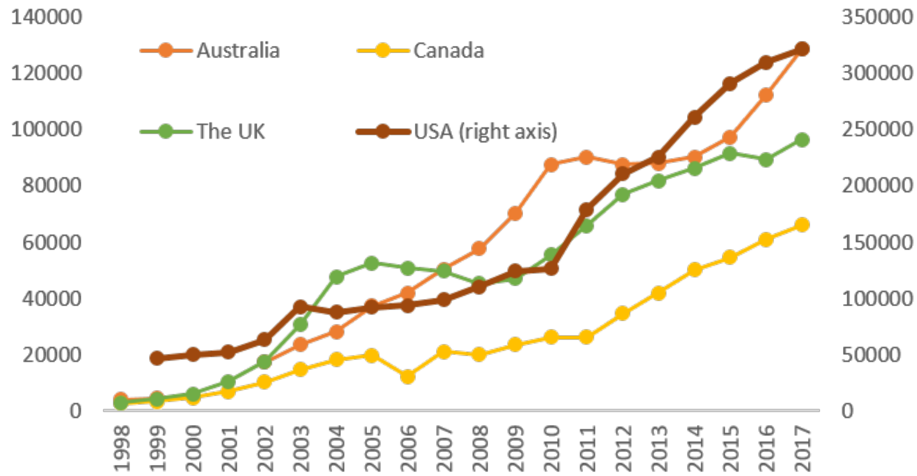
(e) Personal Funding



(f) Human Capital, US Commuting Zones

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

Figure A.4: International students from China in top 4 destination countries



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

Table A.1: Compositional Changes by Degree Level, 2004-2013

	(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 main controls. The first row below the coefficients document 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 Science also include Business-related degrees.

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

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

Notes: City-level regressions showing the effect of weighted NTR gaps on Chinese student enrollment growth, per thousand city residents, over different time periods. We examine a shorter-rrun time frame in column(1), using 2004-2007. Column (2) examines a medium-run time frame, that also covers the Great Recession and recovery, from 2008-2010. Finally, column (3) examines student growth over the longer run period between 2011-2013. We include all main controls. We report heteroskedasticity-consistent standard errors (in parenthesis) at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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

Dept var: Δ Share of admitted college students (05-11)	First-tier (1) OLS	First-tier (2) FE	211-Project (3) OLS	211-Project (4) FE	985-Project (5) OLS	985-Project (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 (1) OLS	First-tier (2) FE	211-Project (3) OLS	211-Project (4) FE	985-Project (5) OLS	985-Project (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 (1) OLS	First-tier (2) FE	211-Project (3) OLS	211-Project (4) FE	985-Project (5) OLS	985-Project (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 (NCEE) 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. (2019) discuss, almost all the educational expenditures for international students from China are from their families, rather than via scholarships or loans. Our model also shows that the difference in prices (home vs. foreign tuition) determine 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.[45]

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

C WID 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 HS level data to ISIC industries.

To construct the WID as our second set of policy treatment, we use the data of world trade flows covering 2000 to 2014. The data is 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 the world demand for imports from China that excludes US imports. To construct the IV based on the change of total world demand, we first calculate the total imports (or exports) of a product at the world level, excluding netting out any trade (exports or imports) that involves either the United States and China. To do so, we aggregate the imports where all other countries (excluding the US and China) are reported and "World" are the source. We then calculate the total exports where all other countries (excluding the US and China) are reported and "World" are the destinations. Then we net out the total imports from the parts exported by the US and China.[46]

$WorldM_{it}$ 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 US. The industry weights are built using past city-level exports as weights.

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

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

[46] 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 import as above. We replace the negative value for the industries where the total adjusted imports (excluding the trade related with the US 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 NTR gaps across cities. Table D.4 below details the top 30 industries along with the ISIC industry name. Not surprisingly, the top industries are textiles and apparels. However, outside of the top 3 there are also chemical, food, and other miscellaneous industries.

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

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

E Other Data

Firm Survey Data

The annual city-industry specific employment sources from the Annual Survey of Industrial Production (ASIP) conducted by the National Bureau of Statistics 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 the employment at the firm level, and we aggregate it up to obtain the total employment at the city-industry level. Notably, The industry classification of ASIP uses 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 International Standard Industrial Classification (ISIC) revision three at the 4-digit level using the crosswalk provided by the National Bureau of Statistics (NBS) of China.

College Students Admission 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.[47] 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, respectively.[48] In terms of eliteness, universities of 985-Project 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 will assign a pre-determined admission 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 in order to be admitted to a university, and they do not compete across

[47] The detailed data information and the background of the National College Entrance Examination are discussed in Zivin et al. (2018).

[48] Regular college and universities can be classified into three tiers according to the admission process. The first tier universities are generally considered as the elite or key universities, whose admission process takes place before the second and third-tier universities (first-tier universities also require higher cut-off scores for admission). The 211-Project refer to the proposal to "enhance the quality of 100 colleges in the 21st century and it is later called the 211-Project. Later 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 ib 985-Project lists are typically considered better than the ones in 211-Project lists. In 2011, there are 39 universities in the 985-Project list, and 112 universities in the 211-Project list.

provinces. Therefore, students from different prefecture cities within a province will be faced with the same NCEE policy.