Trade Liberalization and Chinese Students in US Higher Education*

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November 9, 2022

Abstract

We highlight a lesser-known consequence of China's integration into the world economy: the rise of services trade. We demonstrate how the US's trade deficit in goods cycles back as a surplus in US exports of education services. Focusing on China's accession to the World Trade Organization, we show that Chinese cities more exposed to trade liberalization sent more students to US universities. Growth in housing income/wealth allowed Chinese families to afford US tuition, and more students financed their studies using personal funds. Our estimates suggest that recent trade wars could cost US universities around $1.1 bn in annual tuition revenue.

JEL: F16, I25, J24, J61

Keywords: Trade Liberalization, International Students, Service Exports.

*We thank Robert Feenstra for the Chinese trade data from the Center for International Data at UC Davis. We thank Sen Zhou and the China Institute for Educational Finance Research at Peking University for the National College Entrance Examination data. We thank Bingzhao Li for outstanding research assistance. We thank Francesca Antmann, Sam Bazzi, Patricia Cortes, Kyle Handley, Gordon Hanson, Will Olney, Giovanni Peri, Heiwai Tang and seminar participants at the FREIT Empirical Trade Seminar, the Southern Economic Association, APPAM 2020, NEUDC, University of Glasgow Migration and Mobility Workshop, Barcelona GSE, Migration and Development Conference (Madrid), SUFE-IESR Trade Workshop, Queens College, UC Davis, UCSD, Center for Global Development, and Peking University for comments. Mingzhi Xu thanks financial support from the National Natural Science Foundation of China (No.72003003) and Peking University Initiative Scientific Research Program (No.7101302576); Miaojie Yu thanks financial support from National Natural Science Foundation of China (No. 71625007) and Social Science Foundation of China (No. 20ZDA050).

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1 Introduction

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

US higher education has been transformed by marked increases in international enrollment since 2005, driven by Chinese students whose enrollment grew 400% over this period (Figure 1a). Full-fare paying foreign students generated much-needed revenue for universities, often used to the advantage of domestic students (Bound et al., 2020; Shih, 2017).[1] In the same decade after 2005, China's GDP per capita quintupled, from $1,500 to more than $7,500 (World Bank WDI). Rapid economic growth in China increased the affordability of US higher education and expanded the size of college-ready, high-school graduate cohorts. A major driver of this change was China's accession to the World Trade Organization (WTO) in 2001 (Zhu, 2012). In this paper, we demonstrate how this episode of trade liberalization was a crucial determinant of Chinese imports of higher education services from the US.

Detailed, sub-national examination of services trade has been severely constrained due to data limitations. We utilize a novel database of US education exports to international students, obtained through a Freedom of Information Act (FOIA) request, detailing students' city of origin, degree level, university, the field of study, and financial support. This allows

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

us to exploit variation across Chinese prefecture cities in trade liberalization stemming from the reduction in tariff uncertainty with the US during China's 2001 accession to the WTO.

Previously, regular Congressional approval was required to maintain low Normal Trade Relations (NTR) tariffs on Chinese imports. Failure to renew would result in a sudden increase in high non-NTR rates. In 2001, the US made NTR tariff rates permanent. Gaps between NTR and non-NTR tariffs across products help measure the reduction in uncertainty following the conferral of permanent NTR (PNTR) rates. Eliminating tariff uncertainty increased commerce between the US and China and induced export-driven growth in Chinese cities (Figure 1b) (Pierce and Schott, 2016). We develop a city-level exposure measure that is the average gap between NTR and non-NTR rates across products, weighted by the composition of exports by product within cities prior to 2001. This allows us to compare student flows across cities more and less intensely affected by the conferral of PNTR rates.

We find a significant and positive association between trade liberalization and student flows: a 10 percentage point (p.p.) increase in PNTR exposure led to growth in Chinese student enrollment in the US of around 34 students per million city residents.[2] This accounts for 40% of the increase in the flow of Chinese international students by 2013 (relative to the pre-WTO entry). As such, the WTO accession induced substantial student flows externally, and not just internal migration as shown previously (Facchini et al., 2019; Tian, 2020).

Our results inform the consequences of the 2018 US-China trade war. A counterfactual exercise indicates that uncertainty in tariff increases of 20 p.ps could cost US universities a quarter of the current flow of Chinese students at a time that universities are increasingly reliant on revenue from China (Bound et al., 2020), and would eventually reduce total educational exports by 6%.[3]

Our findings are representative of broader implications. While our unique data allows

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

[3]This estimated loss to universities does not account for spillovers on surrounding localities. Institute for International Education (2019) estimates that there were more than one million international students in 2019 (a third of which were from China), and they contributed $45 billion to the US economy.

us to focus on education exports, rising services demand in response to trade liberalization applies to other sectors, such as information and financial services. Although the US goods deficit dominates its services surplus, the global growth of services trade implies that services will soon be sizable enough to shift trade balances (McKinsey Global Institute, 2019).

Alongside increases in scale, we observe changes in the composition of Chinese students. While Chinese students initially tended towards STEM (science, technology, engineering, and mathematics) majors, trade liberalization induced large responses in social sciences and business-related fields. Trade liberalization also increased the share of students at less selective universities. Chinese students traditionally enrolled in Doctoral programs, which typically funded students. Trade liberalization induced a shift towards undergraduate studies, which provides little funding, and often requires full-sticker price tuition payments. As such, we find that PNTR exposure increased the share of students financing their education through personal funds, rather than through scholarships/fellowships.

We outline a simple conceptual framework where firms' decisions depend on the uncertainty of future tariff levels; local labor and housing markets respond to firm expansions, and households make education choices given their income and financial constraints. The framework informs our estimation and potential mechanisms, which we test empirically. Consistent with the growth in self-funded students, we show that trade liberalization increased global demand for Chinese manufactured goods and, subsequently, the income and wealth of city residents. First, PNTR exposure led to an increase in exports of 34% at the city level. Given the relatively high average cost of US tuition, we focus on various sources of wealth and income growth, including real estate appreciation and own-business income. Given limited investment opportunities in China, a meaningful fraction of wealth expansion occurred through housing ownership (Chen and Wen, 2017). We show that trade liberalization increased property values and rental income, contributing to related findings on employment and investment (Cheng and Potlogea, 2017), and wage growth (Erten and Leight, 2020). Expanding income and wealth allowed families with the means to finance the high cost of paying for housing and tuition in the US. We also explore and find a lesser role for other channels, such as changing returns to education, and increased information flows.

Empirical identification of city-level PNTR exposure is derived from industry-level shocks due to the conferral of PNTR, consistent with recent insights on shift-share estimation from Borusyak, Hull and Jaravel (2020). Crucially, we demonstrate that industry NTR gaps appear well-balanced with respect to a variety of industry characteristics prior to WTO, with the exception of mild correlation with import tariffs and export licenses. We then validate our key identification assumption – that PNTR exposure is exogenous conditional on these industry correlates. Regional balance tests show no evidence of differential trends in student outflows and other city-level education measures prior to 2001, no pre-period correlation with city economic indicators (e.g., GDP, Employment, Exports), and no systematic correlation with city demographics or skill/capital intensity (e.g., the share of 18-year-olds, the share of college-educated workers, capital share in output). Our estimates are consistent under a variety of robustness and falsification tests – e.g., excluding large and coastal cities and influential industries, controlling for internal migration, and inference corrections for correlation across cities in baseline industry shares.

We contribute to two strands of the trade literature: the importance of labor reallocation and the role of demand in driving trade patterns. Although the detrimental impacts from Chinese goods imports are well documented (Autor, Dorn and Hanson, 2013; Pierce and Schott, 2016), less is known about services trade, which now accounts for over a third of US trade activity (Eaton and Kortum, 2018).[4] We exploit detailed data on exports of education services to show that trade-driven income growth in China generated strong demand for US higher education, complementing recent findings that trade with China raised non-manufacturing employment (Wang et al., 2018; Bloom et al., 2019; Caliendo, Dvorkin and Parro, 2019). While trade dynamics are driven by relative production costs in previous studies, the operating channel in our empirical findings is an increase in the *demand* for services

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

through greater wealth abroad, consistent with theoretical studies on non-homotheticity in demand (Matsuyama, 1992; Foellmi, Hepenstrick and Josef, 2017; Dingel, 2016; Fajgelbaum, Grossman and Helpman, 2011). As such, our findings indicate that a trade deficit in goods partly cycled back to the US as a surplus in educational services.

We also add to two strands of the human-mobility literature on the inverted-U-shaped relationship between migration and development (Clemens, 2014). The first strand highlights how better prospects at home may result in *out*-migration, as income gains are used to overcome migration-cost barriers.[5] These migration costs are quantifiable for international students as standard tuition and living expenses at US higher education institutions. In contrast, canonical models also show that higher local income may also raise the opportunity cost of emigrating (Angelucci, 2015; Bazzi, 2017). As many international students view the study in the US as a pathway to joining the US labor market (Bound et al., 2015; Shih, 2016), better income opportunities at home may lower the option value of a US degree. As such, it is unclear whether economic growth at home, induced by trade liberalization, would lead to more outflows. We resolve this ambiguity, by showing that income/wealth generation, attributable to trade liberalization, encouraged student flows to the United States.

The second strand of studies offers theoretical justifications for whether migration and trade are substitutes or complements. Although the standard Heckscher-Ohlin model predicts that trade is a substitute for migration, extensions to this model can result in a complementary relationship (Venables, 1999). There is scant evidence in this regard, although studies mostly reject substitutability (Collins, O'Rourke and Williamson, 1997). Our paper provides an unexplored channel for trade and migration as complements. Finally, we speak to recent work on trade and education (Liu, 2017; Li, 2018; Xu, 2020). While prior work has analyzed human capital decisions stemming from changes in the returns to education (Green-

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

land and Lopresti, 2016; Atkin, 2016; Blanchard and Olney, 2017), we highlight the role of trade-induced wealth generation in helping overcome financial barriers to study abroad.

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

2 China's Accession to the WTO

On December 11, 2001, China joined the WTO, importantly converting the uncertain Most Favored Nation (MFN) tariff regime to a permanent NTR tariff regime. Beginning in 1980, the US granted low MFN tariffs to China–subject to yearly Congressional renewal–despite it not having MFN status.[6] The need for annual renewal generated uncertainty over the low-tariff regime's longevity, which inhibited the expansion of commerce between the US and China (Pierce and Schott, 2016; Handley and Limão, 2017). Termination of MFN status would have increased tariffs facing US importers over eight-fold, from an average tariff of 4% (under MFN status) to 35% (Facchini et al., 2019), and affected over 95% of US imports from China (Pregelj, 2001), with the possibility of further retaliation.

The NTR regime made the low MFN tariffs permanent and no longer required Congressional renewal. While not changing actual tariffs, it reduced the uncertainty facing Chinese exporters and US importers, with substantial impacts on trade. China's exports to the US grew by 57% within a year, and by 177% within the first five years of PNTR conferral.[7]

We derive plausibly-exogenous variation in PNTR exposure across Chinese prefecture cities. To quantify the policy treatment, we utilize the potential spike in tariffs under loss

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

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

of MFN status – the gap between NTR and non-NTR tariff rates (henceforth, NTR gap). For each city, we measure PNTR exposure by calculating the sum of the NTR gaps across industries, weighted by the city's industry export shares in 1997, prior to the policy change.

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

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

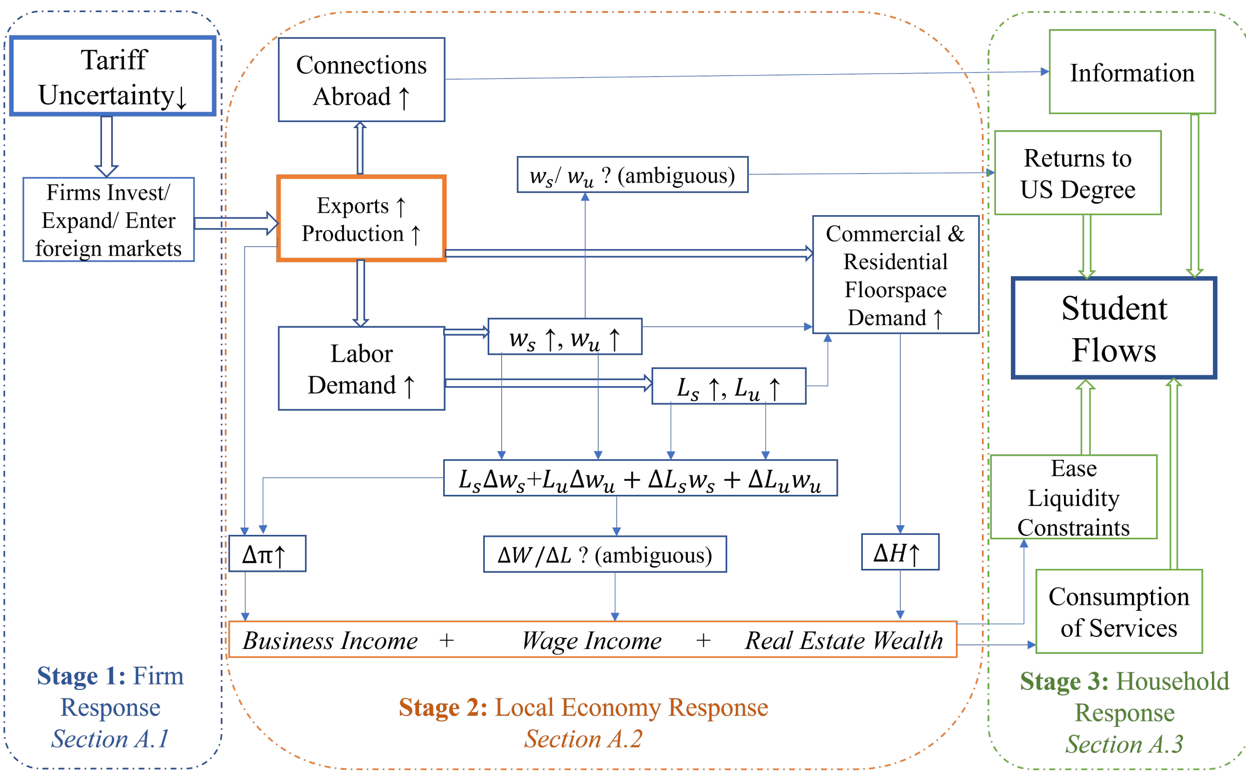
3 Why WTO Entry Affects Student Flows

In this section, we formulate possible mechanisms underlying the relationship between PNTR exposure and Chinese student migration to the US, and use this framework to inform our empirical investigation of the mechanisms in Section 6. While other work highlights complementarities between trade and migration (Venables, 1999), we introduce new channels via which trade generates demand for certain types of services (like higher education), driving the flow of individuals across country borders.

Consistent with the recent trade literature, we view the conferral of PNTR as a trade liberalization shock that reduced uncertainty over future market access. In allowing for the proliferation of exports of Chinese manufactured goods, it also contributed to the structural transformation of China's economy, giving rise to manufacturing and generating substantial economic growth (e.g., Erten and Leight, 2020; Brandt et al., 2017; Manova and Zhang, 2012; Khandelwal, Schott and Wei, 2013; Cheng and Potlogea, 2017). Similar to the development and migration literature, economic growth may have opposing impacts on student outflows, such that the net effect is ambiguous (e.g., Clemens, 2014; Angelucci, 2015; Bazzi, 2017).

Appendix A provides a conceptual framework that elucidates how this structural change may affect student flows. Figure 1 outlines the potential pathways through which a reduction in tariff uncertainty eventually feeds into the household responses that are the mechanisms for student flows that we test empirically. Household responses occur due to changes in the local economy in response to the shock. We provide an intuitive and broad summary of the chain of events in what follows, and leave the detailed discussion to the appendix.

Figure 1: A Simple Conceptual Framework



Note: The diagram summarizes the outline of the conceptual framework covered in Appendix A; w is wage, and L_s and L_u are employment for skilled s and unskilled u workers; H represents house prices, and π is business profits.

In Stage 1 of our conceptual framework (Appendix A.1), a reduction in tariff uncertainty reduces the option value for waiting to invest in export-related activities and induces new firm entry and investment (which we test in a complementary empirical specification in Appendix B). Here, we derive our primary shift-share variable from the firm's optimization exercise. Stage 2 (Appendix A.2) is described in the middle portion of Figure 1. Here, production and exports both increase as a result, which may drive higher business income, wages, capital income, and housing wealth; a rise in information about the US market that is generated through business connections; and an ambiguous change in relative wages between skilled and unskilled labor. As a result, in Stage 3 (Appendix A.3), we delineate four channels through which export-driven economic development potentially influences student flows: (1) income/wealth generation alleviates liquidity constraints associated with financing costs of studying abroad, (2) newly acquired income/wealth is used for consumption of higher-end services, (3) changes in the returns to education raise the value of a US degree, and (4) increased information and networks influence the pool of potential international students. Below we summarize each potential mechanism, with details in Appendix A.

First, income and wealth gains relax financial constraints, increasing the number of households that can afford the cost of US higher education – roughly $30,000 per year for tuition and board during the early 2000s. We formalize a simple theoretical framework in Appendix A.3, which demonstrates that if education is an investment good, then financially constrained households will respond to income shocks by funding their education (in this case, abroad).[8]

Second, if education is a consumption good, increases in income and wealth reallocate expenditures toward high-end services, like education, when preferences are non-homothetic (Appendix A.3 and Linder (1961); Matsuyama (1992)). If the income elasticity of demand for educational services exceeds one (as is estimated for services in Comin, Lashkari and Mestieri, 2019), then growth in income increases the expenditure share on education. Although the growth literature focuses on structural change due to sectoral differences in income elasticities, in an open economy, the demand for educational services can be met by

[8]Sun and Yannelis (2016) causally link credit constraints and the demand for college education.

imports (e.g., sending students overseas) instead of labor reallocation. As a further check for the prominence of income and wealth as a mechanism for the rise in education spending, we explore the evolution of the services expenditure share in liberalization-exposed cities.

What are the sources of income/wealth growth attributable to trade liberalization? Prior work links PNTR exposure to increased wages in China (Erten and Leight, 2020), and employment and investment growth (Cheng and Potlogea, 2017). Interestingly, Bound et al. (2020) illustrate that almost all education costs for Chinese students in the US are financed using family funds, rather than via scholarships or loans. Given the extraordinarily high cost of a US education–one year of tuition is 40-50 times the average Chinese household income–we examine sources of income and wealth generation applicable to high-income groups.

We examine changes to both income (yearly cash flows to households from labor, business, interest, or property leasing) and wealth (household net worth from assets). Although both affect affording US tuitions, and so reflect the same channels in Stage 3 of our model, they manifest differently in the data. Unlike prior work, we explore growth in real estate wealth (i.e., property values) and income (i.e., rents) alongside other sources (e.g., business income, capital gains, etc.). Recent work documents the importance of the real estate sector in China, where, without a developed financial sector, investment growth and capital gains mainly derive from the housing market (Liu and Xiong, 2018; Chen et al., 2017). As upwards of 80% of urban households in our sample own property, property appreciation may comprise a substantial portion of wealth increases among Chinese families.

Other than income and wealth, trade liberalization may affect the returns to a US degree by altering the relative demand for particular skills or relative prices of a US versus Chinese degree. 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. On the other hand, greater outflows of students would occur if trade shocks raised the return to a US degree in the

Chinese labor market. Alternatively, this could occur if the returns to college rise alongside an inelastic supply of higher education within China, raising the relative cost of a degree from a top Chinese university. We empirically assess returns to education 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 work has highlighted the interlinkages between migration and trade networks (Bahar and Rapoport, 2018; Parsons and Vézina, 2018). US universities could become more visible and information on opportunities and admissions procedures clearer to potential Chinese students. In the model in Appendix A.3, this represents a reduced cost of acquiring a US degree. We empirically assess the importance of networks in Section 6, by examining whether prospective students choose universities that have established networks of students from their origin city.

A unique feature of the latter two channels is the pairwise relationship between China and the US, where more connections to the US drive outflows, while the income and wealth channels may drive flows to other destinations. Still, given the US has a large fraction of the world's top-ranked universities, it is likely that a large share of the income-driven student flows would be to the US.

Various other factors likely affected aggregate trends in Chinese students to the US during this period (Bound et al., 2021), including changes to visa policy (Shih, 2016; Chen, Howell and Smith, 2020), increased demand from US universities facing revenue shortfalls (Bound et al., 2020), and the appreciation of the yuan. As our focus is on within-city changes in student flows to the US, we abstract from the influence of such countrywide shocks. In the next section, we describe our empirical approach, and emphasize that it captures relative changes in student outflows across Chinese cities based on their exposure to trade liberalization from the conferral of PNTR.

4 Empirical Strategy and Data

We describe our empirical strategy and data, with additional data details in Appendix E. Although PNTR tariffs were conferred to China as a whole, the impact varied substantially across industries and regions. We leverage the differential policy impact across Chinese prefecture cities based on their pre-2001 industrial activity. PNTR provided larger benefits to some industries, so that cities with existing economic activity in those industries stood to gain much more than cities whose economic activity was concentrated in other industries. We focus on prefecture cities as this geographical administrative unit reflects *hukou* status, thus limiting the scope for endogenous internal migration, and as prefectures can be reasonably identified in the available address information in SEVIS.[9] We develop a city-level measure of exposure to PNTR, and then link this to student outflows to the United States.

4.1 Establishing the Baseline Empirical Specification

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

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

Our primary outcome variable measures growth in the number of students S from city c that matriculate at US institutions. The granularity of our data allows us to examine heterogeneity by the level of study, the attended institution, the amount of funding, and the 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. Because our outcome is long-differenced, we effectively remove the influence of time-invariant city-specific factors, and city-level controls essentially

[9]There are three layers of administrative units: first are provinces, autonomous regions, and centrally-controlled municipalities. Prefecture-level divisions are the second level, mostly consisting of prefecture-level cities. Large prefectures are subdivided into (autonomous) counties and county-level cities. Finally, townships or towns are the third level. Our unit of analysis is the prefecture city. Because sub-municipality trade data are unavailable in the customs data, we include the 4 municipalities, Beijing, Shanghai, Chongqing, and Tianjin, in the analysis. We also provide robustness checks where we drop them.

account for differential trends by city characteristic. We first describe the construction of our outcome and shift-share measures, and then clarify our identifying assumptions.

4.1.1 Growth in the Number of Chinese Students, ΔS_c

We obtain data on Chinese students from the Student Exchange and Visitors Information System (SEVIS) through a Freedom of Information Act (FOIA) request. The data contain records for every foreign student visa by year of matriculation from 2000 to 2013. The information includes the student's permanent address, gender, university, level of study/program type, major field of study, start and end dates, and amount of financial support by source.

We aggregate the individual-level data to city of origin-by-year, and group subtotals by program/funding characteristics. For each city, we calculate the change in the number of students between 2002 and 2013. As cities differ in size, we standardize/divide these changes by the fixed initial (2002) city population of those with non-agricultural *hukou* status, from the China City Statistics Yearbook.[10] As city population is measured in thousands of persons, our dependent variable measures changes in the number of Chinese students per 1,000 city residents (in 2002).

4.1.2 City-Level PNTR Exposure, $PNTR_c$

City-level differences in PNTR exposure are captured by the industrial structure of the city in 1997. We begin by defining a measure of the size of the PNTR policy treatment for each 4-digit International Standard Industrial Classification (ISIC) industry i, as the gap between NTR and non-NTR tariff rates in 1999, using data from Pierce and Schott (2016).[11] Specifically, we define the NTR gap as:

[10] We use the non-agricultural population (i.e., the urban population) for two reasons. First, this ensures consistency with the evaluation of mechanisms, where we use household-level data from the Urban Household Surveys of the National Bureau of Statistics of China. Second, households in agricultural residency status and migrant workers have more difficulty in finding regular jobs in cities, and participate mostly in informal labor markets. Therefore, they are less relevant to the discussion of studying abroad. Nonetheless, we present results where we use the total city population in the denominator as a robustness check of our main results. Robustness tests also examine altering the population in the denominator to that in 2013.

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

$$NTRGap_i = NonNTRrate_i - NTRrate_i \tag{2}$$

NTR gaps do not vary over time as they depend on the non-NTR rates (i.e., the Smoot-Hawley 1930 Tariffs) and NTR rates in 1999 that apply to all WTO trade partners.

Figure 2a illustrates industry-level variation in NTR tariffs and non-NTR tariffs for each 4-digit ISIC product. Some products had a substantial difference between NTR and non-NTR rates. For instance, recorded media faced non-NTR tariffs of nearly 60% compared with an NTR tariff of a 2%. Hence, PNTR eliminated the risk that recorded media exporters might suddenly see tariffs spike by 58 p.ps. In contrast, PNTR had milder impacts on tobacco, which had similarly high non-NTR tariffs but also relatively high NTR rates, and hence, tobacco-producing cities were less impacted by PNTR. NTR gaps are shown in Figure D.1, which reveals substantial variation, with some industries facing almost no gap and others having a gap upward of 60%. The mean NTR gap across industries is 30%.

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

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

To capture existing industrial activity, we measure each industry's share of total city exports, *prior* to the conferral of PNTR, using data on exports by industry and city from the China Customs Database, which were harmonized and generously provided by the University of California, Davis, Center for International Data (Feenstra et al., 2018).[12] We use 1997 as the base year, as it is the earliest year available in the data. Industry export shares are calculated by dividing exports of industry i from city c (X_{ci}^{1997}) by total exports from city c ($\sum_j X_{cj}^{1997}$). Notably, when performing this calculation, we only retain the 119 4-digit ISIC industries that have an associated NTR gap to ensure the export shares sum to 1 and avoid

[12] We utilize information on the quantity and value of exports classified by the Harmonized System for all international transactions from China. Exports are categorized by the destination country and city of origin. The 4-digit city codes provided in the customs data identify a level of geography more disaggregated than the standard prefecture cities in China. Hence, we aggregate city codes in the customs data up to the prefecture level, based on the reported city name. In the end, the original 479 city codes in the customs data are aggregated to 313 prefecture cities, including four municipalities. We do not include exports categorized as process and assembly or process with imported materials.

the "missing shares" issue described in Borusyak, Hull and Jaravel (2020). Industries that are dropped only comprise about 0.17% of the total export value in our sample cities.

The conceptual framework in Appendix A.1 rationalizes our use of export shares given that (like Facchini et al. (2019)) we expect exports as the impetus for the regional economic response to the liberalization. Cities with large export shares in high NTR gap industries have both substantial economic activity and exports of knowledge/infrastructure, which allowed them to capitalize immediately following China's WTO accession. In a robustness check, we construct an alternative exposure measure that uses city-level employment shares by industry in 1990 (again, ensuring shares sum to 1), calculated using data from China's One-Percent Population Census of 1990 of the National Bureau of Statistics (NBS) of China.

As our PNTR exposure measure is a weighted average of NTR gaps, it is informative about the average reduction in uncertainty facing each city. It captures the interaction of how much US tariffs would increase (by industry) if China lost MFN status, with the probability of that event. As the latter probability becomes close to zero post-WTO entry, the exposure proxies for the magnitude reduction in uncertainty per industry, even as applied tariffs are mostly unchanged. This episode reduces entry barriers for Chinese exporters (Handley and Limão, 2017) and raises potential market size.

4.1.3 Descriptive Statistics

Before clarifying and validating our key identification assumptions, we first provide some descriptive statistics of our analysis sample. The resulting sample allows reliable tracking of 268 Chinese prefecture cities over time (see Figure 2b), for which we can measure their exposure to PNTR and growth in the number of students going to the US over 2000-13. Although there are 343 cities in China, our sample comprises over 90% of employment and population, and over 80% of all export activity. As such, our sample cities are broadly representative of the Chinese economy.[13]

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

Table 1 shows summary statistics. Between 2000 and 2013, cities experienced sharp growth in economic activity, with more modest growth in population. In contrast, the average number of Chinese students studying abroad in the United States increased over tenfold. The share of students pursuing undergraduate and master's degrees experienced substantial growth, offset by declines in the share pursuing Doctoral studies. Furthermore, 81% of matriculating students in 2000 pursued STEM degrees, but that share fell to 35% in 2013. The declining share of STEM students was offset by substantial increases in social sciences and arts and humanities. Interestingly, the composition of students by university selectivity, grouped into quartiles by admissions rates, saw large increases in the share of students entering the least selective (tier 4) universities. Notably, the fraction of students that received scholarship funding decreased from 77% to 22%.

Importantly, we assess the descriptive relationship between PNTR and our primary variables of interest: exports and student growth. Figure 3, which provides a scatterplot of log changes in exports from 2000-2013 on PNTR exposure, suggests the policy had a substantial impact on exports after enactment. The coefficient of the best fit lit can be interpreted as: a 10 p.p. higher NTR gap (roughly the-quartile range) increases exports by 34%. Table B.1 in Appendix B further separately examines exports to the US and non-US destinations, showing that only exports to the US exhibit an immediate increase post-WTO in more exposed cities. In sum, the intensity of PNTR appears to be positively correlated with export growth after conferral.[14]

Next, we descriptively examine student emigration. The right panel of Figure 4 illustrates the relationship between PNTR exposure and pre/post-WTO student flows.[15] While there was no correlation with student emigration prior to 2001 (pre-liberalization), PNTR exposure is positively associated with student emigration after enactment (post-liberalization).

[14]In the next subsection, we argue PNTR is exogenous with respect to initial city characteristics and trends, including exports. Along with results in Appendix B, we note that the positive association of PNTR and exports continues to hold under the main specification with all controls included.

[15]The pre-period student flow is measured between 2000-01. The post-period student flow is the average yearly growth–the change between 2000-13 divided by 13. Figure D.2 shows the long-difference (2000-13), rather than the average yearly change.

We then regress year-on-year changes in student outflows on PNTR exposure, and plot coefficients and 95% confidence intervals in the left panel of Figure 4. There is no immediate response in student outflows, and much of the growth in student flows occurs only after 2002, perhaps as income/wealth gains and college decisions take time to materialize. Given the timing of WTO entry, we henceforth focus on student flows over the 2002-13 period.

4.2 Validating Identifying Assumptions

The PNTR exposure measure falls under the broad class of "shift-share" variables that capture local exposure to more aggregated treatments/shocks. Recent advances have clarified how shift-shares may obtain identification from different sources (i.e., exogenous shares or shifters) (Goldsmith-Pinkham, Sorkin and Swift, 2020; Borusyak, Hull and Jaravel, 2020). Following insights from Borusyak, Hull and Jaravel (2020) (henceforth, "BHJ"), we clarify that our PNTR exposure measure obtains identification from shifters: the industry-level NTR gaps. We also note that Jaeger, Ruist and Stuhler (2018) proposes designs ideally should use shifters that embody structural breaks rather than secular trends – in this context, joining the WTO is the break we exploit.

In what follows, we demonstrate that while industry NTR gaps are generally balanced with respect to initial industry-level factors, they exhibit mild correlation with two known determinants of Chinese trade – export licenses (Bai, Krishna and Ma, 2017) and import tariffs (Yu, 2015). Hence, our key identification assumption is that PNTR exposure is exogenous, conditional on these determinants. We then provide substantial evidence in support of this by showing that after conditioning on these determinants of Chinese trade, our PNTR exposure measure is balanced with respect to a variety of city-level pretrends in education, demographics, skill/capital intensity, and other economic indicators.

4.2.1 Shifter (Industry)-Level Identification

Causal identification requires satisfying the following orthogonality condition, with regression weights $w_c = 1/N$ in the unweighted case (for all cities $c = 1...N$):

$$\mathbb{E}\left[\sum_c w_c \cdot PNTR_c \cdot \epsilon_c\right] = 0$$

We then re-express this at the level of the shifters (industries i), thereby obtaining an equivalent shifter-level orthogonality condition. Given $PNTR_c = \sum_i \beta_{ci} \cdot NTRGap_i$, the shifter-level orthogonality condition is,

$$\mathbb{E}\left[\sum_c \sum_i \beta_{ci} \cdot NTRGap_i \cdot \epsilon_c\right] = \mathbb{E}\left[\sum_i \beta_i \cdot NTRGap_i \cdot \bar{\epsilon}_i\right] = 0, \quad (4)$$

where $\beta_i = \sum_c w_c \cdot \beta_{ci}$ and $\bar{\epsilon}_i = \frac{\sum_c w_c \cdot \beta_{ci} \cdot \epsilon_c}{\sum_c w_c \cdot \beta_{ci}}$. Note that in the unweighted case, $\beta_i = \frac{\sum_c \beta_{ci}}{N}$ is the simple average of export shares for a given industry i across all cities c. We follow the convention in BHJ and refer to the β_i as "exposure weights".

Empirically assessing the validity of this orthogonality condition in our context requires first checking whether industry-level NTR gaps (i.e., our shifters) are balanced with respect to other initial industry-level factors. Before continuing, however, it is useful to present descriptive statistics of our industry-level NTR gaps (shifters) and average export shares in 1997 (exposure weights).

The first three rows of Table 2 report summary statistics for the NTR gaps. The distribution of NTR gaps across the 119 ISIC 4 industries shows an average of 0.327 (i.e., the average gap between NTR and non-NTR rates is 32.7 percentage points), a standard deviation of 0.157 and an interquartile range of 0.178. The fourth and fifth rows give descriptive statistics on exposure weights β_i. Importantly, exposure weights must not be so concentrated that only a few industries drive the variation in PNTR exposure. Although the largest exposure weight is 0.113, there is sizable and sufficient variation across industries as shown by the inverse Herfindahl Index (1/HHI$= 1/\sum_i \beta_i^2$), which indicates that our effective sample size is adequate. Our export shares sum to one ($\sum_i \beta_{ci} = 1$) so that we do not face the issue of the missing/incomplete shares described in BHJ.[16]

[16] BHJ demonstrate that if the sum of exposure shares across industries within cities is not constant, this may potentially introduce endogenous variation in the shift-share. We ensure that our export shares sum to one – i.e., $\sum_i \beta_{ci} = 1$. When we calculate β_{ci}, and in particular when we calculate the denominator – i.e., total city exports – we only retain the 119 industries that also have an associated NTR gap in the data. Industries that are dropped only comprise about 0.17% of the total export value in our sample cities.

4.2.2 Industry Balance & Control Variables Z_c

We now assess the balance of our NTR gaps with respect to other industry-level factors measured prior (or as early as possible with available data) to the conferral of PNTR. To do so, we follow the method detailed in BHJ, which involves regressing initial industry-level factors on industry-level NTR gaps, using exposure weights β_i as regression weights (see Appendix C.2 for details). Results from these industry balance checks are in Table 3.

We examine correlations between NTR gaps and factors that have been identified in the literature as strong determinants of Chinese trade. First, prior to China's accession to the WTO, Chinese firms required licenses to export directly, with less than half of all firms reporting having export licenses in 2000. Bai, Krishna and Ma (2017) show that having export licenses had large impacts on productivity growth, so it is reasonable that policymakers would adjust these to stimulate private investment. In case this is related to industry trade uncertainty, we adopt their industry-level measure of restrictiveness in 2000, as a measure of the liberalization impact when China phased out these licenses by 2004.[17] Specifically, we use data on the fraction of export revenues in total exports within an industry that is licensed to export directly in 2000.

Second, we assess balance with respect to the level of tariff rates imposed in 2000 by Chinese imported inputs and final goods, as such tariffs have been shown to affect the productivity of Chinese firms (Yu, 2015). Import tariffs for final goods are the applied tariff rates by China in 2000, averaged across origins, from the World Integrated Trade Solution. Input tariffs are constructed using the 2002 input-output table for China, combined with output tariffs during that year.[18] Given that China's import tariffs pre-WTO are driven by their own non-NTR tariffs, which could have been set with retaliation in mind, there could exist a mechanical correlation with US non-NTR tariffs.

Third, we use data on contract intensity by industry from Nunn (2007). The quality of

[17] For all variables, we provide more specific definitions and sources in Table E.1 in Appendix E.

[18] Industry-level input tariffs are the weighted (by the share on input usage in the I-O table) average of the output tariffs used above, but imposed on the inputs used by each industry.

contract enforcement is shown to increase comparative advantage and exports from industries requiring relationship-specific investment. Demand for higher education could be affected by the growth of such industries utilizing skill-intensive labor as institutions strengthen. The industry-level contract intensity data from 1997 measures the proportion of intermediate inputs employed by firms that require relationship-specific investments by the supplier.

We also examine additional industry-level variables that broadly measure performance, measured from the 2000 Annual Survey of Industrial Production (ASIP). The ASIP is a firm-level survey, which we aggregate to the industry level. We compute the average ratios of labor to value-added and also capital to value-added for each industry, and also the average return on assets and return on equity.

Table 3 demonstrates that industry-level NTR gaps are generally well-balanced with respect to most of these industry-level factors. However, there is a positive and significant correlation between import tariffs and export licenses. This is not surprising given China's early emphasis on industry protection. An interpretation is that China may have retaliated against high non-MFN tariffs on its exports (and hence, likely high NTR gaps) with similarly high import tariffs. With respect to export licenses, it's possible that more licenses were awarded to those industries facing potentially large tariff uncertainty (high NTR gaps). We also note that despite the significant correlation, the magnitudes are relatively small. A 1 s.d. increase in the NTR gap is associated with a 1.5 p.p. increase in the share of export revenue covered under direct export licenses, accounting for less than one-fifth of the overall standard deviation of that measure. Similarly, a 1 s.d. increase in the NTR gap is associated with a 1.6 p.p. larger import tariff, which represents less than one-third of the standard deviation in import tariffs.

Crucially, our identification strategy will need to account for these factors in estimation. To absorb the potentially endogenous influence of these trade-related factors, we construct city-level control variables (Z_c). In particular, we develop shift-share control variables that follow equation 3, but replace $NTRGap_i$ with the appropriate industry variable (e.g., import tariffs, the share of export revenues covered by direct export licenses, etc.) which is interacted with our city-industry export shares (β_{ci}). Although industry NTR gaps are balanced with respect to input tariffs and contract intensity (see Table 3), we construct shift-share control variables for these measures as well given their regular use in the literature. Our preferred specifications Z_c will control for all four of these variables. We note that export shares always sum to 1 in the construction of these shift-share controls to avoid the issue of missing shares. Detailed descriptions of the construction of each of these control variables are provided in the Appendix Section C.1.

4.2.3 Regional Balance

We now provide evidence in support of our key identification assumption. Specifically, we demonstrate that city-level PNTR exposure, conditional on the controls described earlier, is balanced with respect to pretrends in other city-level factors that might relate to student emigration. We follow the method described in BHJ of evaluating regional balance,[19] which is operationally equivalent to regressions that replace the dependent variable in specification 1 with pretrends in city level factors (see Appendix C.2 for details).

Results from these regional balance tests are shown in Table 4. We gather a wide variety of city-level factors, measured during the pre-period, that might plausibly be related to student emigration and organize them into three groups. Column (1) shows results without any controls, while column (2) shows results after including our four primary controls. Column (3) reports the number of cities (observations) underlying the regressions, reflecting the differing availability across the data sources used to measure city pretrends.

The first group in Panel A captures pretrends in city-level educational measures. We

[19] In the first step, city-level pretrend variables (Y_c) and city-level PNTR exposure ($PNTR_c$) are separately regressed on the vector of controls (Z_c), and residuals $Y_c^{\perp}$ and $PNTR_c^{\perp}$ are obtained. In the unconditional case, residuals are obtained from regressions on a constant. In the second step, these residuals are then aggregated to the industry level under the form: $\overline{V}_i^{\perp} = \frac{\sum_c w_c \cdot \beta_{ci} \cdot V_c^{\perp}}{\sum_c w_c \cdot \beta_{ci}}$. Checking regional balance then requires regressing $\overline{Y}_i^{\perp}$ on $\overline{PNTR}_i^{\perp}$, instrumenting $\overline{PNTR}_i^{\perp}$ with the industry shifters $NTRGap_i$, and using exposure weights β_i as regression weights. This is operationally equivalent to using specification 1 and replacing the dependent variable with pretrends in city-level factors, as it produces identical coefficient estimates.

first examine student emigration, our primary outcome, measured from SEVIS data as the change between 2000 and 2001, divided by city population in 2000. Data from the 1997-2000 China Statistical Yearbooks provide other education pretrends (measured as the log change between 1997 and 2000) in the number of students attending college domestically, the number of domestic colleges, domestic students attending secondary schools, and the number of secondary schools. The second group, in Panel B, examines pretrends in general city-level economic factors: the log change between 1997 and 2000 in GDP, employment, FDI flows, real-estate investment, and exports. The final group, in Panel C, provides measures related to city-level demographics (from the 1990 and 2000 Population Censuses) and other measures of skill and capital intensity within the city: the share of 18-year-olds in the population in 1990, the share of college-educated workers in 1990, the share of manufacturing workers in employment in 1994, and the share of capital in output in 1994. We also calculate the growth of these same variables from the initial year in the data to 2000.

Results show that after conditioning on the four other determinants of trade, there is no substantial correlation between city-level factors or their growth and our exposure weighted shocks. Without controls, certain factors, such as the growth in the number of Chinese colleges, appear to be correlated with PNTR exposure. After including our 4 control variables, in column (2), only 1 of 18 coefficients is significant at the 10% level. Taken together, these regional balance checks help substantiate our identification assumption that conditional on the four other trade factors, PNTR exposure is exogenous to other potential city-level factors that might affect student emigration to the US.

5 Results

5.1 Student Flows to US Universities

Figures 3 and 4 reveal a strong positive association between PNTR, exports, and growth in the number of students studying in the US. The sharp growth in student outflows began a few years after the WTO accession. We estimate our benchmark equation (1) in Table 5.

Column (1) excludes controls and shows that PNTR exposure is positively and significantly associated with student emigration. Since we measure long differences in student emigration (2002-13), time-invariant city characteristics and time-varying national trends are accounted for in the estimation. The remaining threats to identification, as discussed in Section 4.2 include city-level exposure to other factors correlated with NTR gaps that might also drive differential trends in student emigration.

To that end, we assess the sensitivity of our results by gradually including our four trade controls. Column (2)-(5) of Table 5 adds controls for import tariffs, export licenses, input tariffs, and contract intensity, iteratively. To get a sense of magnitudes, in the bottom panel, we report the interquartile effect of a rise in PNTR exposure from the 25th to 75th percentiles (about 11 p.ps), in terms of the number of additional students per million city residents/population. We also report the mean of the dependent variable for reference.

Across all specifications, the effect of PNTR exposure remains stable and positive and statistically significant at the 99% level. Coefficient stability to controls lowers the likelihood that confounding omitted variables are biasing our estimates (Altonji, Elder and Taber, 2005). Our preferred estimates come from the model with the full set of controls in column (5), which indicates that moving from a city at the 25th percentile to a city at the 75th percentile – roughly an 11.4 p.p. increase in PNTR exposure – increased student emigration to the United States by 38 per one million city residents. Since the average growth across cities was 146 per one million city residents, the magnitude is about 26% of the mean.

The magnitude of the effect of PNTR exposure can be put into perspective by comparing it with secular trends in Chinese students going to the United States. The 2002-13 period saw the flows of new Chinese students per year at US institutions increase by 86,000 (from 12,500 in 2002 to 98,500). In our specification, the average PNTR exposure across all cities is 0.316, which implies that for the average city, 106 new students per one million residents went abroad per year ($0.337 \times 0.316 \times 1000$) as a response to the liberalization. Given the 327 million persons in the non-agricultural population in 2001, a yearly flow of approximately

35,000 students to the United States can be attributed to the elimination of the NTR gap. As such, the trade shock alone explains about 40% of the increase in the flow of Chinese international students in 2013 relative to the beginning of our sample.

The effect of PNTR exposure on student flows to the US also increases over time, as shown in the left panel of Figure 4 and in Table D.1. When we analyze initial (2002-2007), intermediate (2008-2010), and later (2011-2013) growth, magnitudes grow each period. This is consistent with the gradual accumulation of wealth/income as a predominant mechanism, which we explore in Section 6.

5.2 Robustness of PNTR Exposure

We provide a variety of sensitivity checks in Table 6. We begin with sample refinements in panel A. In column (2), we remove the four largest cities, which also are under the direct administration of the central government – Beijing, Shanghai, Chongqing, and Tianjin. Column (3) excludes capital and coastal cities to ensure that results are not driven by particularly large influential cities or places with stronger access to foreign markets. In order to further test heterogeneity across the size of cities, column (4) reports a specification where we weight the regression by total prefecture population (from the 2005 Census). The coefficient slightly decreases in (2) and (3), and increases in (4), consistent with the effects being slightly greater in the larger cities. Overall, the relationship between student out-migration and trade liberalization is not specific to large cities. We then include region-fixed effects in column (5) to account for any differences in policy, culture, or institutions that vary across regions and over time.[20] The last column includes an additional control for time-varying changes in tariffs – the difference between average city-level tariffs from 2002-2013. Results remain similar to our preferred estimates, reprinted in column (1).

Though our identification is based on exogenous sector shocks derived from industry NTR gaps, we also can evaluate the 1997 export shares used to construct the instrument. Related

[20] Since we estimate a long-differenced regression, we already account for geographic fixed effects. The additional region-fixed effects are akin to including region-by-time fixed effects in a panel regression.

recent papers on shift-share designs have highlighted concerns with lagged shares potentially endogenously affecting future outcomes (Jaeger, Ruist and Stuhler, 2018), and also created useful diagnostics to help establish share exogeneity (Goldsmith-Pinkham, Sorkin and Swift, 2020). To this end, we provide several checks to assess our 1997 export shares.

Jaeger, Ruist and Stuhler (2018) illustrate how lagged shares may embody past shocks that persist over time and continue to impact outcomes during the period under study. We first note the lack of correlation between our measure of PNTR exposure and city-level pre-trends in education, economic conditions, demographics, or skill/capital intensity (as in Table 4). We seek to use shares with longer lags to help reduce any endogenous correlations that may persist over time and into our sample period. While 1997 is the earliest year for export data, we can use employment shares as far back as 1990, consistent with related papers that also use employment shares to construct measures of PNTR exposure at different regional levels (e.g., Erten and Leight, 2020). We construct a similar measure of PNTR exposure using city-level employment by industry in 1990.[21]

Table 6 panel B demonstrates our results are similar when using the PNTR exposure measure created with 1990 employment shares. The first column shows results for the benchmark specification when using this alternative PNTR exposure measure. The estimated effect is similarly positive and significant at the 1% level. While the coefficient appears larger than our export-based PNTR exposure measure, the magnitudes are similar, as the variation in PNTR exposure using 1990 employment shares is on a smaller scale. Moving from a city at the 25th percentile to the 75th percentile – roughly 5.7 p.p. for the 1990-weighted PNTR exposure – increases student emigration by 51 per one million city residents. We note that due to lower coverage in the 1990 Census data, we lose 10 cities from the sample. The remaining columns of panel B repeat the sample refinement checks as in panel A.[22]

[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). As before, we use employment shares for the same 119 industries as the export-based PNTR exposure measure, and ensure the sum of the shares is equal to 1 to avoid the issue of missing shares. Employment shares are calculated from the 1990 Population Census.

[22]In Appendix C.3 we also replicate Table 5 with the alternative PNTR measure that utilizes employment shares (see Table C.1).

We also implement a robustness check introduced by Goldsmith-Pinkham, Sorkin and Swift (2020) to examine the exogeneity of our shares (1997 export shares). We use our PNTR exposure measure, and calculate Rotemberg weights for each industry's export share (Appendix C.4), which capture how important each baseline export share is in the overall identifying variation. Appendix Table C.2 shows the top 30 industry weights. Removing the five industries with the largest Rotemberg weights (described in Appendix section C.4) from our measure of PNTR exposure does not affect our findings (coefficient estimate is 0.513, the standard error is 0.167, and the interquartile effect is 33 per million city residents).

5.2.1 Internal Migration

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

Nonetheless, we examine whether our results are robust to internal migration in panel C of Table 6. In the first three columns, our findings remain robust and stable when controlling for concomitant changes of in- and out-migration rates for both skilled and unskilled workers.[23] In column (4), we use the entire prefecture population (both rural and urban) as the denominator of our outcome variable to account for potential rural-to-urban migration within-prefecture. Results remain robust. In column (5), we divide student growth by the

[23]We use microdata on skilled and unskilled migration from the Chinese Population Census in 2000 and 2015. For both skilled and unskilled workers, we compute the probability of out-migration and in-migration from each city, and then calculate the change from 2000-2015. Each of the first 3 columns includes two measures of internal migration, separately for skilled and unskilled migrants. For details on the Chinese Population Census and the internal migration measures, see Appendix E.

2013 population as it allows our outcome to reflect internal migration over our period. The result, though slightly attenuated, indicates that internal migration alone cannot account for our findings. Notice also that our results are unchanged when excluding large cities that are more likely to attract in-migrants (panel A, column (2)).

5.2.2 Robust Inference

We now assess the robustness of our results to various inference corrections. Recent insights from Borusyak, Hull and Jaravel (2020) and Adao, Kolesar and Morales (2019) suggest shift-share designs may exhibit a correlation between the shift-share and residuals across cities with similar exposure shares. We use the Borusyak, Hull and Jaravel (2020) procedure, of re-estimating our primary specification using an industry-equivalent regression, to estimate exposure-robust standard errors that account for this residual correlation. For further detail on this approach, see Appendix C.5. Column (1) of Appendix Table C.3 re-estimates our primary specification using the BHJ industry-level aggregation. Column (2) further adds in industry-level import tariffs and export licenses – the two factors that failed industry balance tests from Table 3. Note that these are included *in addition* to the city-level controls of our primary estimating equation, and hence the coefficient estimate differs slightly. Our findings remain robust to estimating exposure-robust standard errors.

Borusyak, Hull and Jaravel (2020) also recommend examining the mutual correlation of industry shifters (NTR gaps), which we do by clustering at the industry level more aggregate than the 4-digit ISIC level NTR gaps. Columns (3) and (4) of Table C.3 use the same specification as Column (1), and cluster standard errors at the 3-digit and 2-digit ISIC classifications, respectively. Results from these checks remain statistically significant.

Finally, we examine the robustness of our results to standard corrections for clustering in spatial designs. Columns (5)-(7) use the correction for spatial dependence from Conley (1999), which allows for residual correlation across cities, weighting cities that are defined by a distance threshold. We report results for various distance cutoffs: 50km (the average distance to the nearest city), 100km, and 200km (the median distance to all cities within a province). In column (8) we cluster at the province level. Results remain robust to corrections for spatial clustering of residuals.

5.3 Heterogeneity in Effects by Sub-group and Compositional Changes

Table 7 examines whether PNTR exposure affected the composition of students. We study how effects differed by the level and field of study, sources and amounts of funding, and quality of US institutions attended. Changes to the composition of students help inform mechanisms that we examine in Section 6. For instance, PNTR exposure induced greater increases in full-tuition-paying undergraduate students than subsidized doctoral students, perhaps suggesting that income/wealth growth could underlie our main results.

In Table 7 panel A, we estimate specification 1, altering the dependent variable to be enrollment growth by academic level. We show our main estimates again in column (1). The subsequent columns (2)-(5) reflect how total student growth attributed specifically to the reduction in trade uncertainty is distributed across academic levels. All levels, except doctoral programs, saw significant growth in Chinese students. In the second row, below the coefficient estimates, we report the effect for each academic level as a proportion of the total effect, dividing the academic level coefficients by the coefficient for total students (column 1). The overall PNTR-related growth in students was driven by bachelor's and master's students – 41% and 31% of the total inflow associated with PNTR exposure, respectively. These programs are more likely to be self-funded compared to doctoral programs.

We then compare the proportions of students in 2002, reported in row 3, with the proportion of the effect for each academic level, in row 2. The difference in these proportions is shown in row 4. The last row describes the elasticity: the relative change for each type normalized by baseline value. Although only 6% of Chinese students entering in 2002 matriculated in bachelor's programs, 41% of the inflow generated by PNTR exposure occurred at the bachelor's level, an increase of 35 p.p. In contrast, doctoral students initially accounted for nearly half of all students matriculating in 2002. Since PNTR exposure induced no significant change in doctoral students, the change in proportions is dramatic. While master's students also saw sizable inflows, these were slightly smaller than the proportion in 2002, while the reverse is true for associate degree students.

Panel B of Table 7 examines compositional changes by field of study, separately assessing STEM, arts and humanities, and social sciences in columns (2), (3), and (4), respectively. As they comprise a large fraction of international students, business majors are separately shown in column (5). While all fields saw growth in Chinese students, PNTR exposure shifted the composition away from STEM and towards arts and social sciences. Compared to the baseline proportions, our estimates indicate that PNTR exposure increased the share of students in arts and social sciences by 21 p.ps and 13 p.ps, respectively. Business majors, the most popular social science major among international students, also sustained sizable increases in Chinese students. These patterns again may reflect underlying income/wealth accumulation, as STEM degrees are more likely to receive outside funding than non-STEM fields (e.g., business students rely on their own funds).

In panel C, we examine changes in the composition of students by the quality of the US university they attend, grouped into quartiles based on admissions rates – the 1st quartile represents the most selective schools, and the 4th quartile comprises the least selective.[24] There was an increase in enrollment across the quality distribution. The share of Chinese students grew slightly in the 4th quartile and shrank slightly in the 3rd quartile.

In Table 7 panels D and E, we assess whether PNTR exposure affected the composition of students in terms of the type and amount of funds to finance higher education in the US. Panel D examines the number of students who were funded by scholarships, grants, or other institutional resources ("Has funding") and the number of students who primarily used personal and family income to finance their studies ("No funding"). In 2002, 56% of Chinese students received some form of scholarship, grant, or other financial assistance. Estimates indicate that PNTR exposure induced a large shift in student composition toward unfunded

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

students. Panel E assesses growth in the number of students by quartile of their reported personal funds in 2002. Results indicate compositional shifts among those with substantial personal funds in the 3rd and 4th quartiles. Taken together, this evidence is again consistent with the hypothesis that rising income/wealth helped more students go abroad.[25]

5.4 Policy Counterfactuals: Consequences of a Trade War

Our results inform the recent resurgence in uncertainty in US-China trade relations. Since 2017 the US government departed from PNTR rates, and instituted across-the-board tariffs on goods from China, affecting incomes in China (Chor and Li, 2021). By mid-2019, average tariffs on Chinese goods sustained a nearly 20 p.p rise (PIIE, 2020).[26] Although an agreement in January 2020 (i.e., the phase I deal) modestly reduced tariffs imposed on Chinese goods in exchange for concessions, tariff uncertainty remains significant.

We use our estimates to infer possible changes induced by this recent tariff uncertainty on international student flows and services exports: if Chinese firms currently fear potentially permanent tariffs that are 20 p.ps higher, how will student flows to the US change? Our reduced-form results on the effect of PNTR exposure on student out-migration (Table 5) indicate that a 10 p.p. increase in potential tariffs leads to (eventually) 34 fewer students per million city residents per year. Thus, as a 20 p.p. rise in PNTR for all cities reduces enrollment by 68 students (per 1 million urban residents) per year, this implies 27,948 fewer students per year.[27]

Given the current average tuition at private institutions is $40,000 per year, this implies

[25] We also investigate whether PNTR exposure induced Chinese students to move to high or low human capital localities in the US. This speaks to whether the rise in educational exports exacerbated or dampened the rise in regional inequality in response to trade-induced labor reallocation. PNTR exposure induced a rise in US services exports for all levels of US commuting zones sorted by baseline human capital. This suggests that the reallocation to educational services dampened the growing disparities across regions induced by labor reallocation to other types of services. Results are available upon request.

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

[27] Our analysis captures the change in flows over a 10-year period following the policy change, with the rise in flows materializing gradually. The non-agricultural population at the end of our study period in 2013 is 411 million individuals, implying 27,948 fewer students (68×411) as a consequence of the trade war.

that US institutions would lose \$1.1 billion each year, and since students tend to stay around 4 years, the tuition loss would come out to \$4.4 billion. Our results imply a 6% reduction in the flow of international students to the US per year, and 28% fewer new Chinese students. A sustained reduction in these flows eventually decreases the stock of international students and total educational exports by similar magnitudes, even excluding general equilibrium multiplier effects that reverberate across local economies (Acemoglu et al., 2016).

6 Mechanisms

We explore several explanations for why trade liberalization induced large student flows to the US. In Section 3 and Appendix A, we outlined possible channels. Here, we focus on the possible changes over time across Chinese cities, rather than shocks to the US that should affect all Chinese cities in an equal manner.[28] We examine whether increased student flows to US universities due to PNTR exposure is consistent with (1) income/wealth generation, (2) changing returns to education, and/or (3) information flows and networks.

6.1 Income/Wealth Accumulation

Greater income or wealth may alleviate credit constraints in financing education abroad, and/or may encourage individuals to increase their consumption of education services. As discussed in Section 3 we distinguish between income (annual cash flows to households) and wealth (net worth of assets) since each can affect whether households can afford US tuition, and manifest differently in the data. While they likely have similar impacts on student flows, in distinguishing them we aim to note the comprehensive nature of our investigation as some prior work ignores impacts on housing wealth.

We first establish that trade liberalization raised the fraction of households that could afford a US higher education. We then investigate which sources of income and/or wealth, if any, grew in order to account for this increased affordability. We first examine overall changes

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

in average income, and then real estate income, motivated by literature documenting how Chinese economic growth contributed to tremendous asset price appreciation, particularly in real estate (Chen et al., 2017). Finally, we also analyze non-real estate sources of income such as business, labor, interest, and transfer income.

Recall our earlier results on self-financing of education in panels D and E of Table 7 demonstrated that PNTR exposure had larger effects on enrollment growth among Chinese students without university funding and also among those who have large amounts of personal funds to finance their education. To connect increases in student out-migration with potential changes in income and/or wealth, we first examine whether PNTR exposure raises the share of households that can afford US tuition. To measure tuition affordability, we multiply the average yearly cost of a college of roughly \$27,000 during the 2002-2007 period by 4 years, to get the average cost of a 4-year degree. We then convert this to Chinese currency using the 8RMB-to-1USD exchange rate, yielding the average cost of a 4-year degree for a Chinese family of about 860,000 RMB.[29]

Lacking detailed data on household wealth (including savings, assets, income, etc.), we attempt to proxy for tuition affordability by using data on income from the Urban Household Survey.[30] We define households that can afford US tuition, as those whose total household income accumulated over 10 years meets or exceeds the cost of a 4-year US degree. We then examine changes in the share of households that meet this threshold between 2002-2007, as UHS coverage becomes worse in later years and to also avoid the Great Recession period. Column (1) of Table 8 shows a sizable and statistically significant increase in the share of

[29]We use tuition figures on average total tuition + fees, room and board at private colleges from https://nces.ed.gov/fastfacts/display.asp?id=76. We use private college figures as they are more likely to resemble what international students pay, whereas public college tuitions reflect in-state rates. We average tuition rates during the 2002-07 period that we analyze using UHS data.

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

households that can afford US tuition by 12 p.ps, consistent with our earlier findings on the self-financing of Chinese students.

Given that PNTR exposure led to more families being able to afford US tuition, we seek to understand how family income/wealth changed due to trade liberalization. We begin by examining average income growth in cities in panel A of Table 8.[31] We use data from the Chinese statistical yearbook and examine city changes from 2002-2013 in GDP in column (2), population in column (3), and then average income (i.e., GDP per capita) in column (4). Results indicate that PNTR exposure is associated with large and statistically significant increases in GDP growth, and large but imprecise concurrent growth in population. While impacts on GDP per capita are marginally statistically significant, the magnitudes suggest sizable growth in average income. These findings are consistent with Erten and Leight (2020) who find increases in income in Chinese counties that experienced high PNTR exposure. Additionally, our evidence on population growth in cities, though imprecisely estimated, is consistent with Facchini et al. (2019) and Tombe and Zhu (2019), which show that cities with greater PNTR exposure also saw large in-migration of less-skilled, rural workers.[32]

Given large documented growth in Chinese real estate prices (Chen et al., 2017) we then assess whether the increased ability to pay for US tuition was due to changes in income or wealth from real estate. With respect to income, increasing real estate values alongside the large increases in city population observed in Panel A could result in higher rental prices. As shown by Facchini et al. (2019), cities with high PNTR exposure received inflows of less-skilled, rural workers, which would certainly raise rental income for property owners. Alternatively, higher real estate prices would lead to greater home equity and wealth for homeowners, or increased capital gains from the sale of property.

We explore these various potential changes to income/wealth from real estate in panel B of Table 8 using data from the UHS. Column (1) demonstrates that trade liberalization

[31] The negative effect of import tariffs seen in our results (Table 5) also support the income channel.

[32] We note that Cheng and Potlogea (2017) do not find evidence of changes in wage income, but instead find increases in output, employment and investment growth. They explain that the lack of a rise in local wages resulted from increased population growth in export expansion areas.

increased total income from real estate, which includes rental income and income from the sale of a property. Column (2) demonstrates that the overall gains in real estate income are due to increases in rental income. A 10 p.p. increase in PNTR exposure results in a 30% increase in rental income. There is also an increase in rental income along the extensive margin. In column (3), we show that the fraction of households that collect rental income also rises. Accordingly, rent becomes a larger share of total household income, as shown in column (4). Column (5) shows a positive but imprecise relationship between trade liberalization and self-reported house prices from the UHS. Column (6) also shows a positive and significant increase in commercial property values from the Wind Bank dataset.

Finally, we explore changes in non-real estate-related income sources in panel C of Table 8. These include labor income, business income, capital gains, transfer income, and interest income. While results are imprecisely estimated, coefficient magnitudes suggest possible sizable gains in business income and capital gains, with reductions in income from government transfers. This is consistent with rising income/wealth in cities more exposed to trade liberalization. We note that whereas the UHS is useful in providing these detailed sources of income, the reduction in sample size may contribute to more noise in estimation.

It is quite possible that these gains did not accrue equally to all Chinese families. Panel (a) of Figure D.5 shows that in the early 2000s, slightly more than 80% of families owned a house. Hence, the remaining 20% that did not own and instead rented, all else equal, would not see gains from either rental income or property appreciation. To homeowners, the gains in rental income and property values were sizable. Panel (a) shows average house prices were roughly 80,000-90,000 RMB in the early 2000s and more than doubled by 2007. Our estimates from panel B of Table 8 suggest PNTR exposure may have lifted property values between 30 and 55%, accounting for a third to one-half of the total increase in average prices. The growth was even larger for households owning multiple properties, whose average house price tripled from 2002-2007. Hence, gains in wealth from home equity are likely to have accrued in much greater magnitude to initially wealthier families that owned multiple properties at the onset of China's accession to WTO. Panel (c) of Figure D.5 confirms that multiple property owners are indeed higher up in the income distribution, with total household income about 1.4 times larger than single home owners, and 1.7 times larger than households that do not own property.

Additionally, multiple property owners also benefit from the gains in rental income. Our coefficient estimates from panel B of Table 8 indicate a 10 p.p. increase in PNTR exposure raises rental income by 35%. Panel (b) of Figure D.5 shows that the average rental income was about 3,000 RMB in 2002 and doubled by 2007. Though the fraction of households leasing property was only 4% in 2002, the share of households leasing property grew by just over 2 p.p. from 2002-2007. These gains in rental income disproportionately benefit multiple property owners, who possess additional properties that can be leased.

In sum, our analysis shows that trade liberalization raised the fraction of families that could afford the cost of a 4-year US degree. Greater income/wealth alleviates credit constraints that families face in financing education abroad. Figure 4 shows that the student response is gradual, consistent with the gradual accumulation of wealth required to afford US tuition. Part of the increase in spending power appears to be connected to the large increase in real estate prices, as many households saw higher rental income, and potentially large gains in property values. As we show in the first two columns of Panel A of Table 8, these gains could have been sufficient to help many families overcome the costs of US tuition.

Our theoretical framework in Appendix A suggests that rising income/wealth can lead to greater numbers of students studying abroad through two possible channels: (1) relaxing credit constraints and (2) reallocating consumption towards higher-end services. We provide some suggestive evidence using UHS data on household borrowing and consumption of services in Figure 5. Panel (a) displays a scatterplot across cities of growth in borrowing as a share of household income against PNTR exposure, while panel (b) displays growth in the share of expenditures on services against PNTR exposure. The negative but imprecise relationship between growth in borrowing and PNTR exposure in panel (a) suggests that credit constraints indeed relaxed due to greater income/wealth. The positive and significant relationship in panel (b) indicates that greater wealth/income due to trade liberalization led to a general reallocation of consumption toward services, as the income elasticity of services is greater than that of other goods. Although suggestive, these results confirm that households in cities with greater liberalization behave in ways consistent with rising wealth/income.

6.2 Returns to Education and Access to Local Colleges

Rising returns to education due to trade liberalization could also generate the observed pattern of student out-migration. If capacity-constrained Chinese universities were unable to meet increased demand, students would study overseas. Alternatively, in the absence of capacity constraints at Chinese universities, trade liberalization may have increased the return to a US degree. We explore the likelihood of these scenarios.

We examine whether rising incomes in cities affected capacity-constrained local universities and spilled over into more student emigration. This is less likely in a context where individuals choose a US university over one at home and when there are national markets for university admissions. In Figure D.6, we see no meaningful positive relationship between city-level income growth and admissions of city residents to top universities, nor between PNTR exposure and admissions (the exact numbers are in Table D.2).[33] The lack of this relationship suggests that it is unlikely that (1) local returns to education are rising, and (2) students from growing cities are crowded out from top local universities.

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 explains student flows. We measure industry skill shares from the 2004 Annual Survey of Industrial Production (ASIP) and classify industries as skill-intensive if they are

[33] Details of the data, including the province level quota used in admissions, are included in Appendix E. We measure the eliteness of a university according to its membership in the first-tier class, 211-Project, and 985-Project. Regular colleges and universities can be classified into three tiers according to the admissions process. The first-tier universities are generally considered elite or key universities. In 2011, there were 39 universities on the 985-Project list and 112 universities on 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.

above the median in the ISIC industry data.[34] Using this skill-intensive industry dummy, we construct two new "NTR gap" exposure measures, where the city-level aggregation follows equation (3) but is split into *only* skill-intensive and *only* non-skill intensive industries.[35] Table 9 reports results comparable to our benchmark specification, where each NTR gap measure is constructed using a subset of industries. In the first column, we split industries using skill intensity measures from Chinese industries. In the second column, for robustness, we use a measure from Indonesian industries (Amiti and Freund, 2010). PNTR exposure in *non-skill* intensive industries explains most of the student flows, while cities with greater exposure in skill-intensive industries do not experience relatively higher student emigration.[36]

Overall, it appears unlikely that changes in returns to education play a large role. Our results confirm those in Li (2018), who finds that educational attainment in China declined due to export expansion, as many parts of China had a comparative advantage in low-skill industries.[37] Additionally, although increases in the returns to US degrees could occur, recent evidence from Chen (2020) shows that, all else equal, job applicants with a US degree receive lower call-back rates than Chinese degree holders.

[34]The skill share is the share of skilled workers in the industry, based on the ASIP (only available in 2004). We note that this later year implies skill shares might have changed in response to liberalization, but there is no earlier data available at this aggregation. ASIP surveys all types of firms (state-owned / non-state-owned) whose revenue is more than five million RMB each year in the manufacturing sector. ASIP provides employment at the firm level, which we aggregate to obtain total employment at the city-industry level. Notably, the ASIP industry classification uses the China Standard Industrial Classification (GB/T4754-1994 and GB/T4754-2002) at the 4-digit level. To be consistent with the tariff and trade data, we concord the China Standard Industrial Classification to ISIC Revision three at the 4-digit level, using the crosswalk provided by the NBS of China. 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).

[35]Therefore, the shares sum to one across both measures, but not for each measure. To control for incomplete shares, we control for the sum (across industries) of 1997 export shares of the skill-intensive industries in each city.

[36]That migration was driven by growth in low-skill intensive industries does not imply that these were more liberalized – in fact our regional balance test point to this not being the case – but instead suggests heterogeneous post-WTO effects across sectors of different skill. This could occur for several reasons. For example, if international demand following WTO increased more for China's less-skill-intensive products. In this sense, the PNTR exposure-induced income growth would likely accrue to places where the less-skill-intensive industries were highly exposed to PNTR. Alternatively, demand might have grown equivalently for skilled and less skilled products after WTO, but the beneficiaries of trade-induced income growth in unskilled sectors were those who were previously liquidity constrained and couldn't afford US tuition.

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

6.3 Information

Finally, as detailed in Appendix A, student emigration might occur due to greater flows of information/knowledge regarding US educational opportunities. While directly measuring information flows is empirically difficult, we assess whether prospective students choose universities that have established networks of students from their origin city. Specifically, we include an interaction of $PNTR_c$ with the student flows from city c to the US in both 2000 and between 2000-2003 to increase the sample size. If network effects are important, cities with relatively more student flow to the US before the large influx should continue to see relatively large flows in the 2002-2013 period. From the two separate columns in Table 10A, there is little evidence of this.

Another plausible information channel is learning about the US education market through the process of exporting. However, Figure D.4 shows that the increase in Chinese student out-migration was not confined to the United States only, but rather seen in top destinations across the world (e.g., Canada, Australia, and the UK). This suggests that whatever factors drove the growth in Chinese student flows cannot be explained by US-specific features alone.

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

6.4 Intermediary Education Consulting Firms

Finally, we assess whether intermediary education consulting firms/study abroad agencies play a role in shaping the relationship between PNTR exposure and student out-migration. Such firms professionally assist students in the college application process, and may play an important role in spreading information on US education opportunities. Since it is difficult to separate their growth from the rise in international study more broadly,[38] we instead

[38] We do not view them as part of the mechanisms above as their proliferation likely follows as a response to the interest in studying abroad, and they can be used to go to any destination. For example, we do not

use their pre-2002 geographic distribution to determine to what degree these intermediaries might have facilitated the process.[39] We interact the total number of these firms with $PNTR$ exposure in Table 10B, and do find that the interaction is positive, although not significant at the 10% level. The $PNTR$ coefficient falls relative to the baseline specification, providing some evidence that cities with a larger number of agencies created before liberalization see larger student growth. We interpret these as likely facilitators of studying abroad, with income and wealth gains as the mechanism driving household decisions.

7 Conclusion

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

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

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

know if their growth captures a reduction in the cost of studying in the US specifically, as would be necessary for the information channel.

[39] Our data includes only newly created intermediary education consulting firms by city, so we use the total of these up until WTO entry, normalized by the number of college students in that city.

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

Such declines in international students may hurt universities increasingly reliant on foreign tuition revenues (Bound et al., 2021; Chen, 2021), and the economy more broadly, as foreign students become entrepreneurs (Amornsiripanitch et al., 2021). Education exports added about $44 billion to the US current account, about as large as the combined exports of soybeans, coal, and natural gas (BEA, 2020). Although the conversation on trade with China focuses on the goods deficit, there has been undeservedly little attention on the trade surplus with respect to educational services. We show that these are inextricably linked, as trade-induced income growth in China drove the export of educational services from the US.

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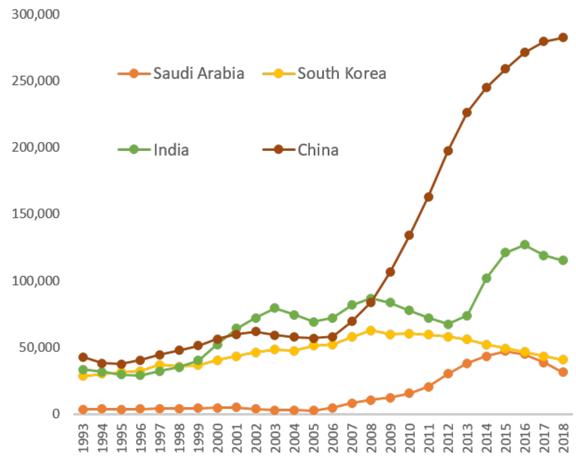
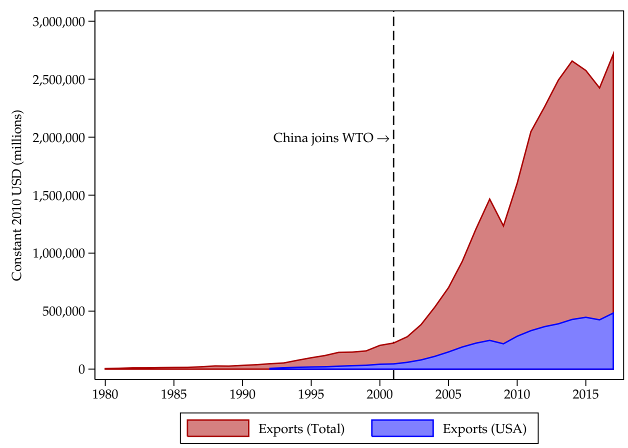
8 Tables & Figures

8.1 Descriptive Figures and PNTR Variation

Figure 1: Growth in the Number of International Students and Exports



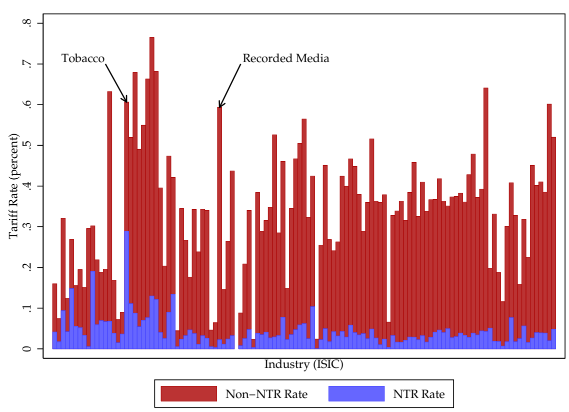
(a) Number of International Students in the United States by Country of Origin



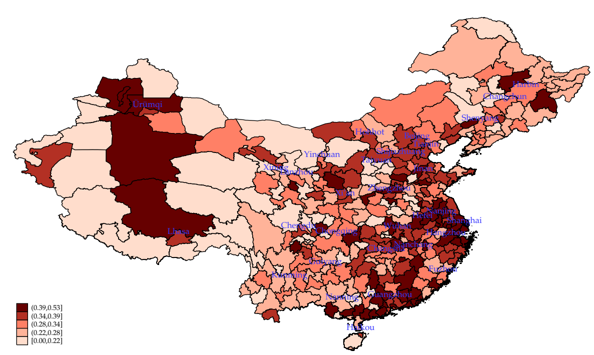
(b) Chinese Exports, 1980-2017

Notes: Figure 1a uses data on enrollment by country of origin from Open Doors, Institute for International Education, 1993-2018, and it includes the sum of graduate and undergraduate students. We show an analogous figure using visa data in Figure D.3. Figure 1b presents Chinese exports to the world as well as exports to the United States only. Data for exports to the United States are from UN Comtrade. Exports to the world are sourced from the World Bank. Both reflect exports in 2010 prices using the US GDP deflator for that year.

Figure 2: Variation in PNTR Exposure across Industries and Space



(a) NTR and non-NTR rates across industries



(b) PNTR exposure across Chinese prefectures

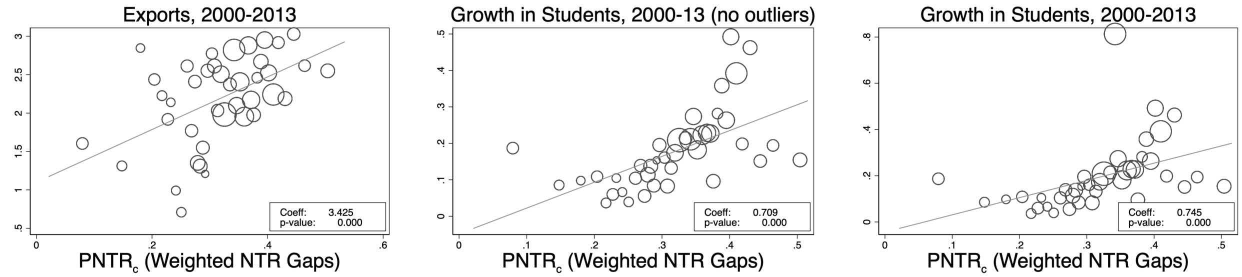
Notes: Figure 2a shows the NTR and non-NTR rates for each 4-digit ISIC industry. The NTR gap is the difference between the two and is plotted in Figure D.1. Figure 2b shows a map of prefecture cities used in the sample, with shading representing the intensity of weighted NTR gaps. We measure city-level exposure as a weighted average of industry-level NTR gaps, weighted by each city's existing activity, as detailed in equation (3). Data on NTR and non-NTR rates by industry are from Pierce and Schott (2016).

Table 1: Summary Statistics

	(1) 2000	(2) 2013
Population (in 000s)	1,093	1,487
	(1,334)	(1,859)
GDP (in 10,000 RMB)	1,852,178	13,447,871
	(3,777,893)	(25,918,510)
GDP per capita (in RMB)	14,537	73,015
	(13,033)	(53,861)
Exports (in 10,000 RMB)	40,911	460,891
	(100,291)	(1,517,142)
Students Entering US Higher Ed Per 1M City Residents	22	365
	(85)	(1,386)
Academic Level:		
Associates	0.00	0.05
	(0.01)	(0.04)
Bachelors	0.02	0.27
	(0.04)	(0.10)
Masters	0.11	0.38
	(0.16)	(0.10)
Doctorate	0.86	0.12
	(0.17)	(0.07)
Other	0.01	0.18
	(0.03)	(0.07)
Field of Study:		
STEM	0.81	0.35
	(0.20)	(0.10)
Social Science	0.14	0.43
	(0.17)	(0.09)
Arts/Humanities	0.05	0.22
	(0.12)	(0.08)
University Admissions Rate:		
Tier 1 - 1st Quartile	0.28	0.18
	(0.22)	(0.06)
Tier 2 - 2nd Quartile	0.26	0.23
	(0.25)	(0.07)
Tier 3 - 3rd Quartile	0.23	0.20
	(0.20)	(0.06)
Tier 4 - 4th Quartile	0.23	0.39
	(0.21)	(0.09)
Scholarship Funding:		
Received Funding	0.77	0.22
	(0.22)	(0.08)
No Funding	0.23	0.78
	(0.22)	(0.08)
Number of Cities	268	268

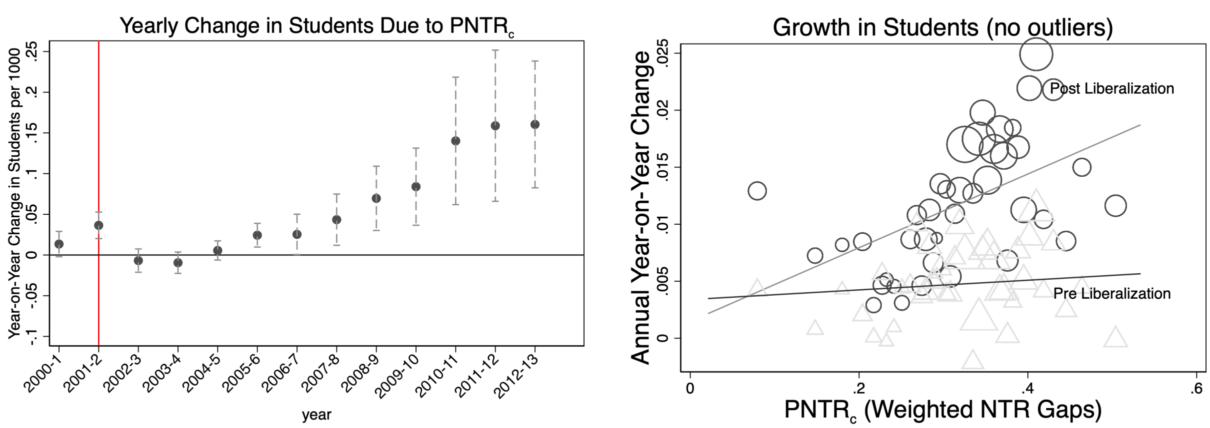
Notes: Data comes from SEVIS individual-level data on student flows, majors of study, and destination universities. 'Students entering US higher education' are measured as a fraction of one million residents in the city. STEM degrees include degrees in Science, Technology, Engineering, and Mathematics.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

Figure 3: Correlation between PNTR_c and Long-Differenced Growth in Outcomes post WTO



Notes: Figures show binned scatter plots of the relationship between the weighted NTR gap (PNTR) and growth in outcomes measured from 2000-2013. The plots show 40 equal-size bins, weighted by population size in each bin. See notes for binned scatter plots details. Export growth (first panel) is measured as the log change from 2000 to 2013, using data from the China Customs Database. Student growth (second two panels) is measured as the change in the number of students from 2000 to 2013, divided by the initial city population (only non-agricultural hukou). The middle figure drops the two cities with the largest student growth (Beijing and Shenzhen) to check for sensitivity to outliers. Coefficients and p-values are based on a regression with no controls, for the full sample available. Data on Chinese students by the city of origin are from SEVIS. Scatterplots showing post- and pre-WTO trends together are shown in Figure D.2.

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



Notes: The left panel shows the year-on-year change in the number of students per 1000 residents of a city as a function of the weighted NTR gap ($PNTR_c$). We divide the yearly change in students by the initial city population in 2000. Each point is from a separate regression. For instance, the final point shows the change in students per 1000 residents between 2012 and 2013 as a function of $PNTR_c$. The right panel shows binned scatter plots of the relationship between the weighted NTR gap (PNTR) and annual (year-on-year) growth in students per 1000 residents. The plots show 40 equal-size bins, weighted by population size in each bin, plotting the mean value within each bin. The right panel drops the two cities with the largest student growth (Beijing and Shenzhen) to check for sensitivity to outliers. Pre-liberalization student growth is measured as the change in the number of students between 2000 and 2001, divided by the initial city population in 2000. Post-liberalization student growth is measured as the change in students from 2002 to 2013 per year (i.e., divided by eleven years), per initial city population in 2002. City population represents the non-agricultural hukou population (in 1000s). Data on Chinese students by the city of origin are from SEVIS.

Table 2: Shock-level (NTR Gap) Summary Statistics

Variable	Statistics
Mean	0.327
Std. Dev.	0.157
IQR (p75-p25)	0.178
Largest importance weight	0.113
1/HHI	23.644
# Shocks	119
# Industries	119

Notes: The table reports summary statistics for our NTR gaps, which vary by industry. We use data on NTR gaps for 119 ISIC 4-digit industries. Additionally, we provide summary statistics of exposure weights, which are a weighted sum of initial city-by-industry export shares. See Borusyak, Hull and Jaravel (2020) for further details.

Table 3: Industry Balance Checks

	(1)
Contract intensity, 1997	0.098
	(0.109)
Import tariffs, 2000	0.159***
	(0.053)
Input tariffs, 2002	0.027
	(0.049)
Export licenses, 2000	0.146*
	(0.079)
Ratio of labor to value-added, 2000	0.021
	(0.222)
Ratio of capital to value-added, 2000	-21.454
	(26.322)
Return on assets, 2000	0.004
	(0.015)
Return on equity, 2000	0.446
	(0.466)
Industries	119

Notes: The table checks whether industry NTR gaps are correlated with any other observed industry-level factors, measured during the pre-period, that might also affect student emigration to the US, which Borusyak, Hull and Jaravel (2020) (BHJ) refer to as industry balance tests. See Appendix C.2 for details on the industry-aggregated regression specification used. We regress various industry-level pre-WTO variables on industry shocks (NTR gaps), weighting by exposure weights. Heteroskedasticity-robust standard errors (in parenthesis). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 4: Regional Balance Checks

	(1) Export Share No Controls	(2) Export Share All Controls	(3) Number of Cities (Obs.)
A: Education Indicators			
Change in Chinese Students/City Pop 2000, 2000-2001	0.004	0.003	268
	(0.004)	(0.006)	
Log Change in Chinese College Students, 1997-2000	0.053	-0.025	182
	(0.284)	(0.359)	
Log Change in Chinese Colleges, 1997-2000	0.455*	0.400	184
	(0.265)	(0.312)	
Log Change in Chinese Middle School Students, 1997-2000	0.902	0.778	246
	(0.912)	(1.066)	
Log Change in Chinese Middle Schools, 1997-2000	0.081	-0.050	219
	(0.115)	(0.141)	
B: Economic Indicators			
Log Change in GDP, 1997-2000	0.020	-0.038	246
	(0.131)	(0.178)	
Log Change in Employment, 1997-2000	-0.509	-0.089	219
	(0.483)	(0.664)	
Log Change in FDI, 1997-2000	0.334	0.475	190
	(0.692)	(1.062)	
Log Change in Real Estate Inv., 1997-2000	-0.012	-0.117	217
	(0.581)	(0.807)	
Log Change in Exports, 1997-2000	-0.123	0.526	268
	(0.843)	(1.019)	
C: Demographics & Skill/Capital Intensity			
Share of 18 y.o. in Population, 1990	-0.000	-0.005	185
	(0.004)	(0.006)	
Share of College Educated Workers, 1990	-0.021	0.002	181
	(0.019)	(0.021)	
Manufacturing Employment Share, 1994	-0.177	-0.048	252
	(0.143)	(0.150)	
Capital Share in Output, 1994	-0.316**	-0.175	251
	(0.134)	(0.131)	
Change in Share of 18 y.o. in Population, 1990-2000	0.020*	0.010	185
	(0.010)	(0.014)	
Change in Share of College Educated Workers, 1990-2000	-0.011	-0.020*	181
	(0.008)	(0.011)	
Change in Manufacturing Employment Share, 1994-2000	0.003	-0.018	245
	(0.096)	(0.124)	
Change Capital Share in Output, 1994-2000	0.222**	0.181	244
	(0.111)	(0.138)	

Notes: The table checks whether our PNTR exposure measure is correlated with any other observed city-level factors, measured during the pre-period, that might also affect student emigration to the US, which BHJ refer to as regional balance tests. See Appendix C.2 for details on the industry-aggregated regression specification used to perform these regional balance tests. This industry-aggregated specification is operationally equivalent to using city-level variation and regressing various pre-WTO city-level variables on our PNTR exposure measure. Column (1) shows results without any controls, while column (2) shows results after including our four primary controls. Heteroskedasticity-robust standard errors (in parenthesis). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

8.2 Main Results

Table 5: Effect of PNTR on Student Outflows

	2002-2013				
	(1) No Controls	(2) +Control for Import Tariffs	(3) +Control for Export Licenses	(4) +Control for Input Tariffs	(5) +Control for Contract Intensity
$PNTR_c$	0.386***	0.443***	0.331***	0.353***	0.337***
	(0.114)	(0.121)	(0.114)	(0.113)	(0.116)
Import Tariffs		-0.209	-0.127	0.027	-0.039
		(0.135)	(0.123)	(0.125)	(0.141)
Export License			0.639**	0.560**	0.395*
			(0.280)	(0.262)	(0.207)
Input Tariffs				-1.061***	-1.035***
				(0.382)	(0.392)
Contract Intensity					0.281
					(0.203)
Interquartile Effect:					
Δ *Students per 1m Pop.*	44	50	38	40	38
Mean Dep Var.	0.146	0.146	0.146	0.146	0.146
Obs.	268	268	268	268	268
R2	0.021	0.024	0.038	0.048	0.056

Notes: City-level regressions show the effect of PNTR exposure on Chinese student enrollment growth between 2002 and 2013 per thousand city residents in 2002. Rows below the coefficients scale up the effect size in terms of students per million residents for a change in the PNTR that traverses its interquartile range (≈10 p.p.). In each column, we iteratively include controls detailed 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. Export licenses refer to the Bai, Krishna and Ma (2017) the fraction of export revenues licensed to export directly. Output tariffs are for the year 2000 (from World Integrated Trade Solution (WITS)), while input tariffs are constructed using WITS tariff data and the 2002 input-output table for China. Contract intensity refers to the Nunn (2007) measure of the proportion of intermediate inputs employed by a firm that requires relationship-specific investments. Heteroskedasticity-robust standard errors reported (in parentheses). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 6: Effect of PNTR on Student Outflows, 2002-2013, Robustness Checks

	(1) Main Effect Col 5 of Table 3	(2) Drop 4 Largest Cities	(3) Drop Capital Coastal Cities	(4) Weighted by Poplation	(5) Control for Region FE	(6) Control for Changing Tariffs
A: Robustness Checks						
$PNTR_c$	0.337***	0.289***	0.302***	0.513***	0.201*	0.341***
	(0.116)	(0.110)	(0.098)	(0.172)	(0.118)	(0.114)
Interquartile Effect:						
Δ *Students per 1m Pop.*	38	33	34	58	23	39
Obs.	268	264	230	267	268	268
R2	0.056	0.051	0.046	0.086	0.091	0.077
B: Employment Weighted PNTR						
$PNTR_c^{1990,EMP}$	0.826***	0.792***	0.706***	0.882***	0.634**	0.767***
	(0.275)	(0.272)	(0.266)	(0.252)	(0.273)	(0.278)
Interquartile Effect:						
Δ *Students per 1m Pop.*	51	49	44	54	39	47
Obs.	258	254	220	257	258	258
R2	0.115	0.103	0.076	0.204	0.151	0.120

	(1) Control for In-Migration	(2) Control for Out-Migration	(3) Control for In- and Out-Migration	(4) Total Population in Denominator	(5) 2013 Population in Denominator
C: Internal Migration Checks					
$PNTR_c$	0.318**	0.270**	0.343**	0.146**	0.224**
	(0.128)	(0.129)	(0.136)	(0.067)	(0.087)
Interquartile Effect:					
Δ *Students per 1m Pop.*	36	31	39	17	25
Obs.	252	252	252	274	275
R2	0.103	0.093	0.138	0.036	0.060

Notes: Regressions show the effect of PNTR exposure on Chinese student enrollment growth between 2002 and 2013 per thousand city residents. The rows below the coefficients scale up the effect size in terms of students per million residents for a change in the PNTR that traverses its interquartile range (≈10 p.p.). We include all main controls. Panel A provides general robustness checks: column (1) reproduces our main estimates from column (5) in Table 5; column (2) drops the four largest cities from the sample; column (3) drops province capitals and coastal cities; column (4) weights the regression by city-wide population; column (5) includes region-level fixed effects, where the region is the first (of four) digits in the prefecture code; column (6) controls for time-varying changes in tariffs at the city-level. Panel B replicates the same specifications as the previous panel but with an alternative construction of $PNTR$. In this case, equation 3 is constructed with industry employment weights from 1990 (where the shifter is unchanged from the benchmark). Panel C assesses endogeneity from internal migration, as Facchini et al. (2019) link PNTR exposure to increases in non-hukou in-migration: column (1) controls for city-level growth in migration rates for skilled and unskilled workers; column (2) for city-level growth in the share of migrants in the skilled and unskilled population; column (3) controls for both migration rates and shares; column (4) normalizes the change in the number of students by the *total* population, including the surrounding agricultural areas; column (5) normalizes the change in the number of students by the 2013 urban population. Heteroskedasticity-robust standard errors reported (in parentheses). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

8.3 Effects by Sub-group and Composition Changes

Table 7: Heterogeneity in Effects of PNTR and Composition Changes, 2002-2013

	(1)	(2)	(3)	(4)	(5)	(6)
A: Level of Study	Total	Associate	Bachelors	Masters	Doctorate	Other
$PNTR_c$	0.337***	0.019***	0.137***	0.103***	0.006	0.071**
	(0.116)	(0.006)	(0.046)	(0.038)	(0.007)	(0.027)
Effect as Proportion of Total		.06	.41	.31	.02	.21
Student Proportions in 2002		.02	.06	.41	.49	.02
Change in Proportions		.04	.35	-.1	-.47	.19
Elasticity	1.49	3.93	12.13	1.35	.05	15.14
B: Field of Study	Total	STEM	Arts	Social Sci.	Social Sci.: Business	
$PNTR_c$	0.337***	0.092***	0.093***	0.151***	0.103***	
	(0.116)	(0.035)	(0.034)	(0.049)	(0.034)	
Effect as Proportion of Total		.27	.28	.45	.31	
Student Proportions in 2002		.61	.07	.32	.22	
Change in Proportions		-.34	.21	.13	.09	
Elasticity	1.49	.61	6.58	2.49	2.6	
C: University Quality	Total	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile	
$PNTR_c$	0.337***	0.083***	0.076***	0.057***	0.121***	
	(0.116)	(0.027)	(0.025)	(0.022)	(0.046)	
Effect as Proportion of Total		.25	.23	.17	.36	
Student Proportions in 2002		.23	.25	.23	.3	
Change in Proportions		.02	-.02	-.06	.06	
Elasticity	1.49	1.64	1.37	1.07	1.79	
D: Funding	Total	Has Funding	No Funding			
$PNTR_c$	0.337***	0.040**	0.297***			
	(0.116)	(0.016)	(0.102)			
Effect as Proportion of Total		0.12	0.88			
Student Proportions in 2002		0.56	0.44			
Change in Proportions		-0.44	0.44			
Elasticity	1.49	.3	3.24			
E: Personal Funds:	Total	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile	
$PNTR_c$	0.337***	0.007	0.048**	0.124***	0.157***	
	(0.116)	(0.007)	(0.020)	(0.041)	(0.054)	
Effect as Proportion of Total		0.02	0.14	0.37	0.47	
Student Proportions in 2002		0.54	0.34	0.09	0.04	
Change in Proportions		-0.52	-0.20	0.28	0.43	
Elasticity	1.49	.05	.68	7.78	26.01	

Notes: Regressions show the effect of weighted NTR gaps on Chinese student enrollment growth between 2002 and 2013 per thousand city residents in 2002. We include all main controls. Column (1) reproduces our main estimates from column (5) in Table 5. The first row below the coefficients documents the effect as a fraction of the total effect in column (1). The second row shows the fraction of students of each type in 2002. 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 2002. In Panel B, STEM degrees include degrees in science, technology, engineering, and mathematics. Social sciences also include business-related degrees, and we separately report effects for business only. Panel C uses IPEDS data to create four quartiles of university selectivity based on admissions rates. In Panel D, 'Has funding' refers to students who reported receiving scholarship funding from the university or other agency, whereas 'No funding' refers to students who finance their education only using personal funds. In Panel E, we divide the students by quartiles of personal funds reported used to fund education, where the fourth quartile includes individuals with the most personal funds, and the first quartile are individuals with the least. Heteroskedasticity-robust standard errors reported (in parentheses). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

8.4 Mechanisms - GDP and Housing Wealth

Table 8: Mechanisms: Effect of PNTR on Household Wealth and Income

Panel A: US College Affordability and Average Income

	UHS 2002-2007	Statistical Yearbook 2002-2013		
	(1) Share of HHs that can afford US tuition	(2) GDP	(3) Population	(4) Avg. Income (GDP per cap.)
$PNTR_c$	0.121^{*}	0.693^{***}	0.273	0.419^{*}
	(0.065)	(0.258)	(0.246)	(0.250)
Obs.	169	267	267	267
R2	0.11	0.10	0.02	0.09
Controls	x	x	x	x

Panel B: Real Estate Income/Wealth

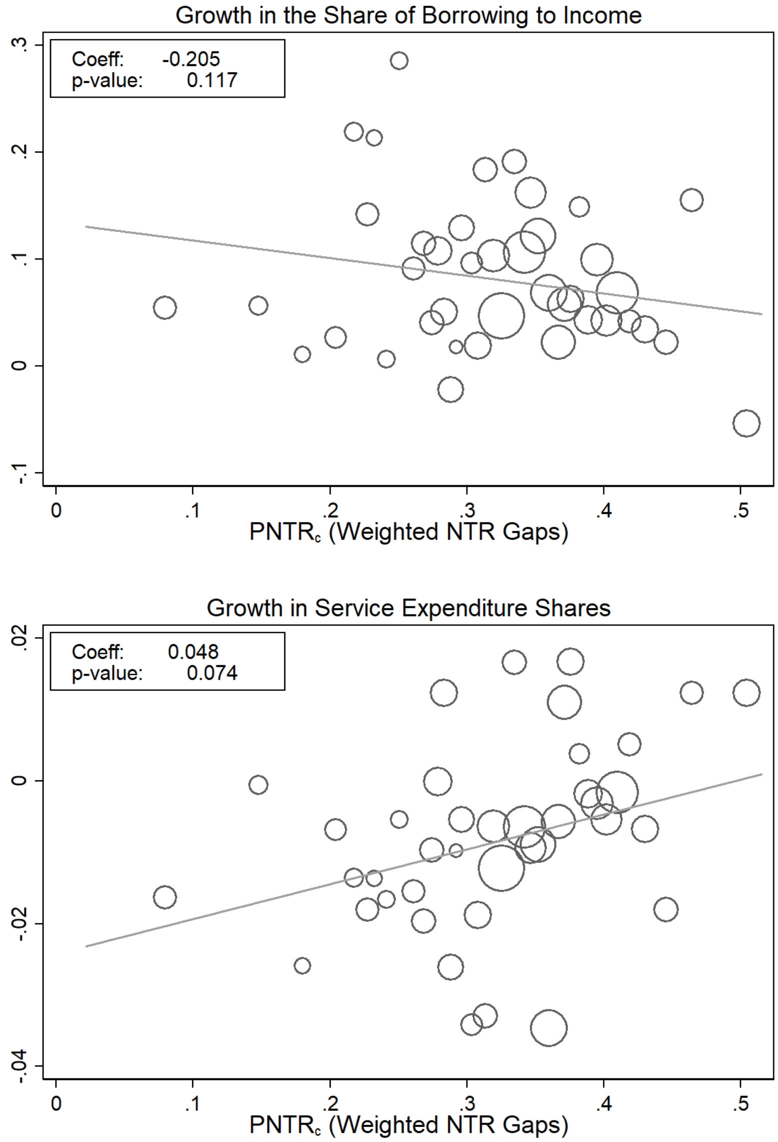
	UHS 2002-2007					Wind Bank 2002-2013
	(1) Real Estate Income	(2) Rental Income	(3) Share of HHs Collecting Rent	(4) Share of Rent in Total Income	(5) House Price (per sqm)	(6) Commercial Price (per sqm)
$PNTR_c$	2.555^{*}	3.466^{**}	0.109^{**}	0.013^{**}	0.297	0.554^{*}
	(1.466)	(1.234)	(0.041)	(0.005)	(0.364)	(0.297)
Obs.	165	149	169	169	169	204
R2	0.02	0.06	0.05	0.03	0.01	0.06
Controls	x	x	x	x	x	x

Panel C: Non-Real Estate Income/Wealth

	UHS 2002-2007				
	(1) Labor Income	(2) Business Income	(3) Capital Gains	(4) Transfer Income	(5) Interest Income
$PNTR_c$	0.106	1.404	0.988	-0.328	-0.791
	(0.149)	(1.209)	(1.128)	(0.269)	(0.636)
Obs.	169	168	167	169	169
R2	0.03	0.03	0.04	0.05	0.04
Controls	x	x	x	x	x

Notes: Panel A shows city-level regressions of weighted NTR gaps on the share of households that can afford US tuition, the log change in GDP, population, and GDP per capita. Data on GDP and population are from the Chinese Statistical Yearbook 2002-13. Data on tuition affordability is from the Urban Household Survey 2002-07 (UHS). We calculate this by converting the average cost of a 4-year college degree in 2002 (roughly \$27,000 per yr $\times$ 4 years) to RMB using the exchange rate of 8 RMB/USD. We then divide this by ten years, which equals about \$86,000 – hence our affordability measure is for those whose accumulated income after ten years is at least equal to the cost of a four-year degree. In Panel B, column (1) examines the log change in real estate income, including rental income and income from the sale of the property; column (2) examines the log change in real estate income that is due to increases in rental income. Data on real estate income is from the UHS. We also examine housing prices (from UHS) and commercial property prices from the Wind Bank dataset, 2002-13. Panel C examines non-real estate income sources, including labor, business, capital gains, transfer, and interest income. Data is from the UHS. Specifications with controls include contract intensity, import tariffs, input tariffs, and export licenses. Heteroskedasticity-robust standard errors reported (in parentheses). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Figure 5: Correlation between PNTR and Household Service Expenditure and Borrowing post WTO



Notes: Figures show binned scatter plots of the relationship between PNTR exposure and post-treatment growth in outcomes. The plots show 40 equal-size bins, weighted by population size in each bin. Data on expenditure on services and borrowing are from the Urban Households Survey, with the outcomes being the change from 2002 to 2007. Service expenditure shares are total service expenditures over household expenditures. Borrowing is measured as total borrowing expenditures over household income. For each plot, we report the coefficient and its associated p-value, given heteroskedasticity-robust standard errors, of a regression of the outcome on PNTR exposure.

8.5 Mechanisms: Returns to Education

Table 9: Mechanisms: Effect of Skill-specific PNTR on Student Outflows

	(1) China Skill Shares	(2) Indonesian Skill Shares
Skilled NTR CHN	-0.016	
	(0.445)	
Unskilled NTR CHN	0.270**	
	(0.112)	
Skilled NTR IND		-0.229
		(0.204)
Unskilled NTR IND		0.197
		(0.245)
Obs.	268	268
R2	.06	.084

Notes: Regressions show the effect of alternative PNTR exposures on Chinese student enrollment growth between 2002 and 2013 per thousand city residents in 2002. As in the baseline specification, we construct the PNTR exposures using (3), but summing across *only* "skill-intensive" and "non-skill intensive" industries. Industry-specific high- and low-skill shares are produced with employment by skill level from ASIP. Given these shares, industries are labeled as "skill-intensive" if above the median across all industries. 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 calculated from the 2004 ASIP. Column (2) repeats this exercise using Indonesia-specific skill shares from Amiti and Freund (2010). In all cases, the high- and low-skill shares sum to the overall PNTR exposure measure. Across *both* measures the shares sum to 1. For that reason, all regressions include as a control the sum (across industries) of 1997 export shares of the skill-intensive industries (to adjust for incomplete shares). All regressions also include the full set of controls. Heteroskedasticity-robust standard errors reported (in parentheses). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

8.6 Mechanisms - Information and Networks

Table 10A: Mechanisms: Effect of PNTR on Student Outflows through Network and Information Channel

	(1) Network Defined as Students in 2000	(2) Network Defined as Total Students from 2000-03
$PNTR_c$	0.194**	0.261***
	(0.093)	(0.094)
$PNTR_c$ X Students in 2000	0.004	
	(0.006)	
Students in 2000	0.000	
	(0.002)	
$PNTR_c$ X Students in 2000-03		-0.001
		(0.001)
Students in 2000-03		0.000
		(0.000)
Obs.	268	268
Controls	x	x

Table 10B: Mechanisms: Effect of PNTR on the Number of Intermediary Study Abroad Agencies

	Intermediary Study Abroad Agencies
$PNTR_c$	0.245*
	(0.129)
# New Agencies (per 10,000 college students), Pre-2002	-0.026
	(0.021)
$PNTR_c$ X # New Agencies (per 10,000 college students)	0.101
	(0.084)
Obs.	254
Controls	x

Notes: Regressions show the effect of PNTR exposure on Chinese student enrollment growth between 2002 and 2013 per thousand city residents in 2002. All regressions include the full set of controls. **Table 10A:** column (1) defines the city-level network as the number of students matriculating in the US in 2000, while column (2) uses the total students matriculating in 2000-03. We interact it with PNTR. **Table 10B** adds to our main specification the accumulated number of new student agencies pre-2002 by city, normalized by the total number of college students in that city (in 10,000s), along with its interaction with $PNTR$. Heteroskedasticity-robust standard errors reported (in parentheses). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix

A A Simple Conceptual Framework

A reduction in uncertainty about the future path of tariffs generates structural change that may affect student flows in different ways. Figure 1 outlines the primary potential pathways.[40] In the first step, detailed in Section A.1, we describe how changes in tariff uncertainty affect firm investment and expansion in production. As uncertainty declines, firms invest in new capacity and enter new markets that will be lucrative for exporting. If export entry requires a sunk entry cost (Roberts and Tybout, 1997), uncertainty generates an option value for waiting to invest in export-related activities (Handley and Limão, 2017). Feng, Li and Swenson (2017) and Crowley, Meng and Song (2018) also find that a rise in uncertainty reduces foreign market entry. Eliminating the threat of non-NTR tariffs will therefore raise investment, which is seen in the entry of new export firms/varieties, and lowers the prices of Chinese-produced goods, raising the demand for such goods in the US, and other destinations. Access to broad foreign markets spurs domestic Chinese production to outpace domestic demand.

In the next stage of the model, described in Section A.2, we consider how expansions in production affect the local economy. Firm entry and investment lead to an increase in exports, which we consider to be the first step of our empirical analysis (outcomes in orange-bordered boxes are shown empirically).

The potential to reach these export markets also encourages firms to invest in expanding manufacturing capabilities, and drives new firm entry and growth. In fact, Appendix B provides empirical evidence for these mechanisms, along with export growth, using pre-WTO data that allows for a two-way fixed effects specification. This may result in higher business income π. Increased firm activity raises labor demand locally, which in turn puts upward pressure on both skilled w_s and unskilled wages w_u. In-migration of skilled L_s and unskilled workers L_u may raise the overall wage bill W, but the change in average wages W/L is ambiguous as an influx of unskilled workers may lower average wages as the composition of the workforce changes. Yet, overall increases in the wage bill may also increase demand for local business activity, once again increasing business income π.

The increases in wages w_s and w_u have an ambiguous impact on the returns to a college degree and to a US degree. If, for instance, the tariff reductions are more toward low-skill industries, then the increase in w_u may lower college returns. Similarly, if the industries require local knowledge and training, they may lower the returns to a US degree. These factors may lower the flow of students to colleges. If, however, the industries would benefit from more knowledge of the US product market, then the returns to a US degree may increase, and raise the flow of students to universities. As such, the impacts on the returns to a US degree are ambiguous.

The increased firm activity, higher wage and business income, and influx of workers, all raise the demand for commercial and residential floor space. For a less than the perfectly elastic supply of floorspace, this raises the value of both commercial and residential floorspace H. Owners of property see a corresponding increase in real-estate wealth.

[40]With the dual aim of tractability and allowing for various mechanisms, in the following subsections we model each broad component of the figure rather than a unified general equilibrium model.

The primary goal of our analysis centers around the final stage of our conceptual framework, described in Section A.3. First, we examine how changes to business income, (aggregate) wage income, and real-estate wealth may improve the purchasing power of households in the region. Households that could not afford a US education may now be able to, as this improved purchasing power **eases liquidity constraints**. Furthermore, as households become richer, they may allocate more of their **consumption to services** like US higher education. For both these reasons, improved purchasing power would increase student outflows.

Second, an increase in exports to the US may, of course, lead to improved connections and information about the US. Better **information about collegiate opportunities** abroad may increase student outflows. Finally, the (theoretically ambiguous) changes to the **returns to a US degree** may drive student flows. If the returns increase, it may increase student outflows to the US, and vice versa.

A.1 Firm Response: Exports and Entry Under Uncertainty

The first part of our conceptual framework builds on Handley and Limão (2017), describes how reductions in tariff uncertainty affect firm entry, expansion, and investment, and derives the first part of our empirical analysis: the change in exports with respect to $PNTR_c$.

The base framework is a standard one of differentiated products and monopolistic competition in entry. We suppress the city c subscript for now. Consumers (across the world) have CES preferences over differentiated goods from different firms, and choose how much to purchase each period to maximize consumer utility. Each firm v produces a variety of product i. As a result, demand for product i produced by firm v is q_v, which depends on consumer prices p_v, in the following manner: $q_v = EP^{\sigma-1}p_v^{-\sigma}$, where E denotes total income of the rest of the world, and $\sigma > 1$ is the CES elasticity across products, and $P = \left[\int_v p_v^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$ is the CES price index.[41]

As in a standard framework, monopolistically competitive sellers draw a productivity $\frac{1}{\omega_v}$, and receive p_v/τ_i, as consumers pay tariff $\tau_i \geq 1$. Firms choose p_v to maximize their operating profit $\pi_v = (p_v/\tau_i - \omega_v)q_v$, and so equilibrium operating profit is given by:[42]

$$\pi(\tau_i, \omega_v) = \tilde{\sigma}\tau_i^{-\sigma}\omega_v^{1-\sigma} \tag{5}$$

Now we depart from the standard framework to introduce policy uncertainty and sunk entry costs, as in Handley and Limão (2017). Firms pay a sunk entry cost K, and continue to potentially export in the next period with exogenous survival probability $\delta < 1$. In each period, firms observe the firms active in the previous period, and all tariffs and model parameters. If there is no uncertainty in future tariffs, the expected value from exporting after entry e is $\Pi_e(\tau_i, \omega_v) = \pi(\tau_i, \omega_v) + \mathbb{E}\sum_t \delta^t \pi(\tau_i, \omega_v)$.

Let $\omega \sim G_i(\omega_v)$. As such, the marginal firm that enters is a firm that draws ω_i^*, where the sunk entry cost equals the present discounted value of profits:

[41] Since each firm v produces at most one product i, we suppress i when using v (multiple v produce varieties of i).

[42] We apply the standard markup over cost $p_v^* = \frac{\sigma}{\sigma-1}\tau_i\omega_v$, and we define $\tilde{\sigma} \equiv \sigma^{-\sigma}\left[(\sigma-1)P\right]^{\sigma-1}E$.

$$K = \frac{\pi(\tau_i, \omega_v^*)}{1-\delta} \Leftrightarrow \omega_i^* = \left[\frac{\tilde{\sigma}}{\tau_i^{\sigma}(1-\delta)K}\right]^{\frac{1}{\sigma-1}} \tag{6}$$

When there is uncertainty in tariffs, firms decide on entry based on a Bellman equation, $\Pi = max\,\{\Pi_e(\tau_i, \omega_v) - K, \delta\mathbb{E}\Pi_e(\tau_i', \omega_v)\}$. The solution to this is an optimal stopping problem that defines an interval of τ_i over which a firm enters. So firms enter when tariffs are low, and the marginal entrant's productivity draw is ω_i^{**}. As Handley and Limão (2017) show in their Appendix AA, $\omega_i^{**} = \omega_i^* U_i$, where $U_i \leq 1$ is the uncertainty factor and depends on the expected distribution of future τ_i. As they describe, the uncertainty factor is a function of the difference between the tariffs "threatened" if China's MFN status is terminated and the actually applied MFN tariffs. Before 2001, there existed a positive probability that China's MFN status would be eliminated. So, one can derive the uncertainty factor as a function of the "NTR Gap", where the *changes* will be determined by *changes in the probability* that MFN status is terminated (given that the non-NTR tariff rates do not change).

Let us now re-introduce the city c subscript. Export revenue for each firm v is $X_v = p_v q_v = \tilde{\sigma}\sigma\tau_i^{1-\sigma}\omega_v^{1-\sigma}$. If N_{ci} are the mass of potential exporters of product i, then the mass of active firms is $N_{ci} \times G(\omega_i^{**})$. Export revenue for product i is:

$$X_{ci} = N_{ci}\int_0^{\omega_i^{**}} X_v dG(\omega) = \tilde{\sigma}\sigma\tau_i^{1-\sigma} N_{ci}\int_0^{\omega_i^{**}} \omega_v^{1-\sigma} dG(\omega) \tag{7}$$

To derive a closed-form gravity equation, we rely on Chaney (2008) and assume productivity is from a Pareto distribution $G(\omega) = (\omega/\bar{\omega})^k$, and $k > \sigma - 1$. This allows us to derive: $X_{ic} = \tilde{\tilde{\sigma}} N_{ci}\tau_i^{-k}\tilde{U}_i$, where $\tilde{U}_i \equiv U_i^{(k-(\sigma-1))}$and $\tilde{\tilde{\sigma}}$ is a function of $\sigma, \delta, k, P, K, E$ and $\bar{\omega}$.

When tariff uncertainty changes, tariffs τ_i may stay the same, even as $\Delta\tilde{U}_i \neq 0$. Again, this reflects the fact that the probability of moving to non-MFN tariffs on China (or the "threat") is severely reduced. The percent change in city-level exports, would be a function of changing $\Delta\tilde{U}_i$:

$$\frac{\Delta X_c}{X_c} = \frac{1}{X_c}\sum_i \left(\tilde{\tilde{\sigma}} N_{ic}\tau_i^{-k} \times \Delta\tilde{U}_i\right) = \frac{1}{X_c}\sum_i \left(\tilde{\tilde{\sigma}} N_{ic}\tau_i^{-k}\tilde{U}_i \times \frac{\Delta\tilde{U}_i}{\tilde{U}_i}\right) = \sum_i \frac{X_{ic}}{X_c} \times \frac{\Delta\tilde{U}_i}{\tilde{U}_i} \tag{8}$$

As Handley and Limão (2017) argue, MFN status reduced all policy uncertainty ($\tilde{U}_{i,MFN} = 1$ for all i), whereas, in the non-MFN world, $1/\tilde{U}_{i,0}$ was directly a function of the ratio of the MFN and non-MFN tariffs. As such, $\frac{\Delta\tilde{U}_i}{\tilde{U}_i} = 1 - \frac{1}{U_{i,0}} = \frac{1}{\beta_x} NTR\ Gap_i$. So the percentage change in the product-specific uncertainty is a function of the NTR Gap of the product: $NTR\ Gap_i \equiv \beta_x \frac{\Delta\tilde{U}_i}{\tilde{U}_i}$. These uncertainty changes directly affect exports, based on the baseline propensity to export. So we define $PNTR_c \equiv \sum_i \frac{X_{ic}}{X_c} \times NTR\ Gap_i$.

Together, this motivates our empirical shift-share specification for exports: $\frac{\Delta X_c}{X_c} = \beta_x PNTR_c$. It is a theoretical foundation for our primary estimation equation, which constructs the city exposure measure. Industry shares of total exports in a city determine its exposure to changes in tariff uncertainty, while the shock is provided by the exogenous change in the uncertainty factor, proxied by $PNTR_c$. Empirically, we provide "Identification Checks" in the main paper that check for pre-trends in exports and related outcomes, and we also provide a separate specification in Appendix B which includes growth in entry and investment rates by $PNTR$ exposure. In the 1997-2006 period, there is a clear relative rise in exports to the US specifically after 2001 in more exposed cities. Similarly, these cities experience relatively higher entry rates in manufacturing along with increased investment rates.

A.2 Local Economy Changes: Profits, Wages, Real Estate Income

Why rely on $PNTR_c$ as the shock to capture China's trading environment, or its gain of market access? Furthermore, why might this be relevant in explaining other broader mechanisms that we examine to explain the rapidly increased demand for U.S. higher education? Erten and Leight (2020) describe a structural shift in China through export-led expansion accelerated after accession to the WTO in 2001. Therefore, this setting provides a unique possibility to study the response to trade liberalization. However, China already faced fairly low applied tariffs, and, for example, guaranteed MFN status from Europe.[43] For this reason, the reduction in uncertainty from the U.S. has been brought forward as an important reason for China's export boom, which accelerates after 2001 (Handley and Limão, 2017). Given the U.S.'s large share of world expenditure, it is plausible that the threat of losing access to that market was an important hindrance to investment and export entry, and that there is a structural break in these after WTO entry. In this case, it would also be industries most exposed to the threat of high tariffs that were "held back", as proxied by the NTR gap.

Trade liberalization can also be viewed as access to a larger market size, with accompanying rises in entry and competition (Melitz and Ottaviano, 2008). Our Stage 1 response in Figure 1 places firm investment and entry into foreign markets as the direct consequence of the drop in uncertainty. Our reduced form specification in the main analysis allows us to pick up the possible effects on the domestic economy as a consequence of the structural changes initiated by a rise in access to foreign markets.

The entry of firms can have substantial impacts on the local economy. As firms enter and produce more, it will increase profits π, employee compensation W, and real estate income H. For instance, from the above framework in Section A.1, we know $\pi_v = \frac{1}{\sigma}X_v$, and so a simple rescaling should generate a similar response to $PNTR_c$.[44]

Similarly, an expansion in production, will increase firm demand for different types of labor (skilled and unskilled), and commercial real estate. For tractability, we had assumed above a single homogeneous input into production, but can consider the cost term ω_v to also depend on various factor inputs. In the spirit of tractability, we refer the reader to the middle portion of Figure 1 to understand how changes in factor input demand would affect the local economy.

A few factors determine changes in prices. First, the relative productivity of each type of labor would affect the demand for skilled L^D_{sc} and unskilled labor L^D_{uc} labor from firms. Cities that have firms that produce more skill-biased products are likely to demand more skilled labor *ceteris paribus*. As demand for such labor increases, it would tend to raise the skilled w_{sc} and unskilled real wage w_{uc}. Yet, as workers migrate to the city in response to

[43] We show in our analysis that the main export response after 2001 is to the U.S. and not to Europe nor other non-US destinations.

[44] That is, $\frac{\Delta\pi_c}{\pi_c} \equiv \sum_i \frac{\Delta\pi_{ic}}{\pi_c} = \sum_i \frac{(1/\sigma)\Delta X_{ic}}{(1/\sigma)X_c} = \sum_i \frac{X_{ic}}{X_c} \times \frac{\Delta\tilde{U}_i}{\tilde{U}_i}$.

higher real wages, it would also change the supply of L_{sc}^S and L_{uc}^S. In a (spatial) labor market equilibrium, the supply and demand for labor in each city, for each type of labor equilibrate.

What happens to average wages in city c? The change in average city real wage is ambiguous as it depends on not just the (labor) demand forces, but also the change in the composition of the workforce. For instance, even though w_{sc} and w_{uc} increase faster in cities with favorable $PNTR_c$, a relatively large influx of low-wage L_{uc} would lower the average wage. This is easy to see if we define average wages as W_c/L_c, where $W_c = w_{uc}L_{uc} + w_{sc}L_{sc}$ is the total wage bill, and $L_c = L_{uc} + L_{sc}$. So the change in average wages is a function of not just the changes in compensation to each skill-type, but also the changing composition of the workforce.[45]

Similarly ambiguous is what happens to the returns to skill $\frac{w_{sc}}{w_{uc}}$ as both the numerator and denominator may increase in cities that have favorable $PNTR_c$.

Finally, the entry of firms and the in-migration of workers would both increase real estate demand. As entering firms look for commercial real estate, the supply elasticity of commercial floorspace will determine the increase in the value of the commercial real estate. This would increase rents H_c^{com}, and incomes of owners of commercial real estate. Similarly, the in-migration of workers L_{sc} and L_{uc} will increase the demand for residential real estate, and once again, the housing supply will determine how rapidly this influx of workers will raise residential rents H_c^{res}. The increase in overall income accruing to owners of real estate H_c is a weighted average of the increases to H_c^{com} and H_c^{res}.

Overall increases in income (GDP) are the sum of the increases in profits Π_c, total wage bill W_c, and real estate incomes H_c. GDP per capita, however, also depends on the change in the composition of the workforce, as an increase in low-wage migration may theoretically lower average wage income.

A.3 Household Response: Liquidity Constraints, Changes in Returns, Expenditure Shares, and Information

Finally, we outline a simple framework that captures the four primary driving forces of our model: how student outflows depend on changes to the information, returns to a US degree, eased liquidity constraints, and shifting one's expenditure share to more services. We keep the framework tractable to derive simple takeaways.

Households begin with household wealth Y. Changes to household wealth may be a consequence of increased profits π, wage income W/L, and real estate income H. Let the cost of domestic education (at the origin o) be κ_o, and the additional cost of getting a degree from the US be κ_d. These additional costs can include the time and effort taken to find out more information about the degrees abroad, and knowing how to apply. These preparations and applications only raise the probability of getting a US degree, as being admitted is not certain. Families can choose how much to invest in improving the probability of getting a US degree s, at a per unit cost of κ_d. Those with a domestic education earn w_o, and if one gets a degree from abroad, they earn a wage premium γ. As such, the expected value of future earnings would be $w_o + \gamma s$.

Changes in Returns and Information: Even in the absence of borrowing constraints

[45] That is, the change in average wage income is $\frac{\Delta w_{uc}L_{uc}+\Delta w_{sc}L_{sc}+w_{uc}\Delta L_{uc}+w_{sc}\Delta L_{sc}}{\Delta L_{uc}+\Delta L_{sc}}$.

or a consumption utility value of a US degree, an increase in exports may affect student flows by changing the returns to a US degree or increasing the information available to potential applicants. Let the additional cost of a US degree be quadratic: $\kappa_o + \kappa_d s + \frac{1}{2}\kappa_{d2} s^2$. To maximize utility in this case, households would simply maximize their lifetime income by choosing how much to invest in trying to get a US degree:

$$\max_s \; Y + (w_o + \gamma s) - (\kappa_o + \kappa_d s + \frac{1}{2}\kappa_{d2} s^2)$$

The first order condition with respect to s suggests:

$$s^* = \frac{\gamma - \kappa_d}{\kappa_{d2}}$$

This equation shows that an increase in the returns to a US degree γ would increase potential outflows abroad. Yet, if the trade expansions actually lowered these returns, there may be fewer students investing in going abroad. Furthermore, better information about US degrees and universities (as a result of trade connections with the US) may lower the costs of getting a US degree (κ_d and κ_{d2}) and raise the share of students investing in going abroad.

The channel described here plays a unique role in that it is about the pairwise relationship between China and the US, where more connections to the US drive flows to the US. The mechanisms below (such as increased incomes), may drive flows to many other destinations.[46]

Liquidity Constraints: Suppose education is an investment rather than a consumption good. In that case, a response to income shocks may imply that households have borrowing constraints to fund their education (in this case, their education abroad). Indeed, as Bound et al. (2020) discuss, almost all the educational expenditures for international students from China are paid by their families, rather than via scholarships or loans. Let us return to the simple cost of a US degree being: $\kappa_o + \kappa_d s$. The difference in prices κ_d (home versus foreign tuition) determines the magnitude of the educational response to income shocks.

Households choose where to invest in education when young, and 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, and c_1 is the numeraire.

Period 1 consumption depends on wealth Y, the price of education at home κ_o, the additional price abroad κ_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:

$$\begin{aligned} c_1 &= Y - \kappa_o - \kappa_d s + b \\ c_2 &= w + \gamma s - Rb \,, \end{aligned} \tag{9}$$

A fraction of households are credit constrained: $b \leq \bar{b}$, where $0 \leq \bar{b} \leq \infty$. For households

[46] Higher incomes may also increase the likelihood of acquiring information (either by easing cost constraints, or consuming more information services). As such, it is a part of the channels described below.

reaching the binding constraint, $b = \bar{b}$, the first-order condition with respect to s is:

$$\kappa_d \, u'(c_1) = \beta\gamma \, u'(c_2) \tag{10}$$

For reasonable assumptions on $u(.)$, for instance, if $u(c) = \log\ c$, schooling will respond to income shocks, in the manner $\Delta s = \frac{\beta}{(1+\beta)\kappa_d}\Delta Y$, for credit constrained households. For non-constrained households, the education decision does not depend on Y.[47]

Consumption Value of Education: Finally, education may not necessarily be considered just to be investment, but may also have a consumption value. In this case, households may consume education as in any other service. We treat services as having a Stone-Geary utility function and again have other consumption be the numeraire:

$$\max_s \ U = log(s + \underline{s}) + log\ c \ \ ,$$

where $c = Y - \kappa_o - \kappa_d s$. From the first order conditions, we can derive:

$$s^* = \frac{Y - \kappa_o - \kappa_d \underline{s}}{2\kappa_d}$$

The expenditure share on a US education is $\Omega \equiv \frac{s^* \kappa_d}{Y - \kappa_o}$. (Note: κ_o is paid by all regardless of any choices, so net wealth is $Y - \kappa_o$).

$$\Omega = \frac{Y - \kappa_o - \kappa_d \underline{s}}{2(Y - \kappa_o)} = \frac{1}{2} - \frac{\kappa_d}{2(Y - \kappa_o)}\underline{s}$$

If $\underline{s} = 0$, then the demand for services like the US degree would be homothetic, and the expenditure share, in this case, would be a constant $\frac{1}{2}$. But non-homotheticity here (when $\underline{s} > 0$) ensures that the expenditure share on such services increases with net wealth $\frac{d\Omega}{d(Y - \kappa_o)} > 0$.

Together, these four possible channels affect how trade expansions affect the decision to try and obtain a US degree. The different channels have different empirical implications as well. For instance, for returns to change, the relative wages of skilled and unskilled must change. Furthermore, if there is something specific about trade with the US specifically driving more information about the US, then trade with other countries should not drive flows. In contrast, changes to incomes and wealth may drive flows to all countries (not just the US) – the US is just unique in the size and quality of its higher education sector, so it will attract a broader share of this increase. Lastly, while we mention both income and wealth in various parts of our analysis, as the conceptual framework shows, they may both play similar roles in easing liquidity constraints and shifting demand to higher-end services. As such, there is little distinction in the roles they play in eventually driving student flows.

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

B Exports and Uncertainty

Our conceptual framework in Appendix A is based on the premise that a reduction in uncertainty about the future path of tariffs generates the entry of new firms and investment growth in anticipation of a larger export market. In the next set of results, we check whether the channels highlighted in theory are present in the data. Since entry and investment data are available starting in 1998, and export data in 1997, for these mechanisms where pre-WTO data exists we run a difference-in-difference two-way fixed effects specification:

$$\ln Y_{ct} = \gamma PNTR_c * Post2001_t + \alpha_t + \alpha_c + \delta Z_{ct} + \epsilon_{ct}, \tag{11}$$

where the outcome is exports, new firm entry, and investment. Given the panel setting with at least 3 years of pre-WTO data, we interact the $PNTR$ measure with a dummy equal to one when the year is 2002 or later. We include year and city-fixed effects, as well as time-varying controls.[48] The coefficient γ represents the relative differences in the outcome after 2001 for cities that vary in exposure. Finally, standard errors are clustered at the city level.

The export specification serves as a robustness exercise for the previous results that showed a larger rise in exports in cities more exposed to $PNTR$. Importantly, we can also differentiate across export destinations. Given that $PNTR$ proxies only for uncertainty with US tariffs, its elimination should be associated with an immediate increase in exports to the US but *not* other destinations. We produce one outcome of exports to the US specifically, an outcome of total exports to Europe, and finally, all non-US destinations. For each of the three destinations, we examine separately a sample of only 1997-2006 along with the full sample. The former sample is comparable to Handley and Limão (2017) and Pierce and Schott (2016), which examine this period immediately after China joins the WTO.

The first three columns in Table B.1 show that comparing the pre-WTO period to the 2002-2006 period results in larger export growth for more exposed cities *only when the outcome is restricted to US exports*. There is a very small and insignificant relative rise in exports to Europe and even all non-US destinations. For the full sample (until 2013), exports grow to all destinations (though still insignificantly so to Europe), but most strongly to the US. Our interpretation is that as firms invest in a market as large as the US, they eventually expand to other markets as well.

In Table B.2, we include new firm entries and investments as outcomes. In Figure 1, a reduction in uncertainty has a direct impact on firm entry and investment as market access increases. Although the impetus for entry is the new export opportunity, our reduced form specification in the main analysis allows for broader economic impacts, which is why we examine total entry and investment in the manufacturing sector (instead of conditioning on exporters).

We mostly rely on ASIP data, although we supplement entry results with the Economic Census, which covers all firms engaged in economic activities.[49] The first two columns display

[48] The controls include the previous time invariant controls (industry contract intensity and export license requirement) interacted with the $Post2001_t$ indicator, along with time varying annual import and input tariffs, and also population.

[49] The ASIP is more comprehensive in terms of firm information, but less representative as it is a survey of

the results for firm entry in the manufacturing sector with each database, and it is clear that after 2001, $PNTR$ exposure is associated with relatively larger entry rates.

The last three columns display results for separate types of investment rates. First, we add investment of fixed capital to annual *changes in value* of firm equity for "total" investment (which is normalized by total sales).[50] Then, we separate these into only "fixed" capital and capital "appreciation". In all cases, there is a relatively higher growth rate of investment rates after 2001 in higher $PNTR$ cities.

firms with more than five million RMB in sales. They are both at the firm level, so we sum all observations in manufacturing to produce city-year observations. See Appendix E for full information on the data used in this subsection and details on the construction of entry and investment rates.

[50]We do not have capital stocks, so we divide investment by total sales. Firm equity is a stock, so we take the first differences to produce the appreciation of the equity value each year. Both values are constructed with the sum of all firms within a city present in ASIP.

Table B.1: Effect of PNTR on Exports by Destination, 1997-2006 and Full Sample

	(1) USA-Pre 2008	(2) EUR-Pre 2008	(3) Non-USA-Pre 2008	(4) USA-All	(5) EUR-All	(6) Non-USA-All
Post*NTRGAP	1.598**	0.643	0.274	1.747**	1.511	1.322**
	(0.765)	(0.796)	(0.517)	(0.857)	(0.968)	(0.640)
Population (millions)	-0.047	-0.033	-0.045	-0.042	-0.034	-0.013
	(0.066)	(0.044)	(0.057)	(0.094)	(0.059)	(0.062)
Annual Import Tariffs	-0.566	0.195	-0.693***	-0.777	-0.355	-1.244**
	(0.457)	(0.514)	(0.233)	(0.631)	(0.918)	(0.554)
Post*Input Tariffs	-1.609	-3.784	-3.840	2.594	-2.436	-3.424
	(4.511)	(3.714)	(2.439)	(4.316)	(4.021)	(2.697)
Post*Contract	1.398	1.115	1.396**	1.861*	1.199	1.462**
	(0.903)	(1.075)	(0.689)	(1.076)	(1.026)	(0.709)
Post*Export Lic	-2.024	-1.084	-0.152	-2.773	-2.604	-0.368
	(1.492)	(1.493)	(0.983)	(1.756)	(1.617)	(1.196)
Interquartile Effect:						
% Change Exports	18	7	3	20	17	15
Mean Dep Var.	16.0	16.3	18.5	16.6	16.9	19.0
Obs.	2,472	2,439	2,472	4,350	4,314	4,350
R2	0.903	0.897	0.941	0.891	0.882	0.928

Table B.2: Effect of PNTR on Firm Entry and Investment Rates, 1998-2008

	(1) New Firms-ASIP	(2) New Firms-Census	(3) Tot Investment (rate)	(4) Capital Apprec. (rate)	(5) Fixed Investment (rate)
Post*NTRGAP	0.092	0.159*	0.151**	0.126**	0.035
	(0.067)	(0.089)	(0.059)	(0.056)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	3,062	3,041	2,625	2,625	2,625
R2	0.725	0.684	0.253	0.137	0.677

Notes: Tables display results using a diff-in-diff specification similar to that in Pierce and Schott (2016). The coefficient of interest is the interaction of city-level $PNTR$ exposure with a dummy for years after 2001. All columns include city and year-fixed effects. For exports as the outcome in Table B.1, we measure log exports for different destinations: USA, Europe, and all non-USA nations. We also separately show results up until 2006 (cols 1-3), and then also for the full sample through 2013 (cols 4-6). In Table B.2 the number of newly created firms is normalized by the "stock" of firms. To get the stock, we first aggregate all newly created firms from 1990-1996. Then starting in 1997, we construct entry rates as: $Entryrate_{ct} = \frac{newfirms_{ct}}{0.5*Stock_{ct-1}+0.5*Stock_{ct}}$. Although ASIP data starts in 1998, we reconstruct the 1990-1996 period using the birth years reported in the set of firms in ASIP. For investment, we normalize all values by total sales. Notice that since the equity value of a firm is given in stocks, we take the first difference to create "Capital Appreciation". "Total investment" is the sum of changes in equity value and fixed asset investment. Due to the first difference, the data starts in 1999 and we keep the same sample for all three columns. In all specifications, we include controls, with a modification since controls used in our baseline specification (Z_{ct}) are time-variant. First, we include import and input tariffs at the annual level, instead of levels before 2002. Second, the contract intensity and export license controls, which are time-invariant, are interacted with the post-2001 dummy. Finally, we add a time-varying population. Standard errors (in parenthesis) are clustered at the city level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

C Shift-share Robustness Checks

C.1 Shift-Share Control Variables

The industry balance tests (see Table 3) identified that two of four known determinants of trade, particularly in the Chinese context, are correlated with industry-level NTR gaps. Specifically, these include industry import tariffs, measured in 2000, and the share of Chinese export revenue covered under direct export licenses, also measured in 2000. Since our primary estimating equation 1 leverages variation across cities, we construct shift-share control variables to account for the potential influence of these industry-level factors. To be conservative, we construct controls for all four of the determinants of trade, even the ones that did not present any pre-WTO correlation with NTR gaps in the industry balance tests – these include industry input tariffs and the measure of industry contract intensity (i.e., the proportion of intermediate inputs employed by firms that require relationship-specific investments by the supplier).

To construct city-level shift share controls, we use a very similar method as in the construction of our PNTR exposure measure, as in equation (3).

$$Z_c = \sum_i \left(\beta_{ci} \times TFi\right), \quad \beta_{ci} = \frac{X_{ci}^{1997}}{\sum_j X_{cj}^{1997}} \, , \tag{12}$$

Equation (12) interacts city-industry export shares in 1997 (β_{ci}) with each of the 4 industry-level trade factors (TF_i). These are: (1) Import tariffs, (2) Export licenses, (3) Input tariffs, and (4) Contract intensity. For import tariffs, we use import tariffs measured in 2000 from the World Integrated Trade Solution–Trade Analysis and Information System. We average import tariffs across origins within an industry, to obtain a single import tariff measure for each industry. For export licenses, we use data provided by Bai, Krishna and Ma (2017) on the fraction of total export revenues for a given Chinese industry that is covered under direct export licenses, which is also measured in 2000.

Input tariffs are calculated under standard procedures using import tariffs and the 2002 input-output table for China from the National Bureau of Statistics. The input-output table is comprised of 70 manufacturing sectors called "scodes" which we concord with HS-level import tariffs to produce input tariffs at this level. The input tariffs are a weighted average (given input usage) of the WITS import tariffs on the industries used as inputs. We then re-classify input tariffs using ISIC concordance. While pre-WTO data would be preferred, they are unavailable, and so we use the earliest available year which is 2002.

Lastly, for contract intensity we use data from Nunn (2007), which measures for each industry the proportion of intermediate inputs employed by firms that require relationship-specific investments by the supplier.

As a final note, none of these measures are confounded by the issue of the missing shares described in Borusyak, Hull and Jaravel (2020). When calculating each control, we ensure the set of city-export shares used sums to 1. Because data on contract intensity cover the same 119 industries as our primary PNTR exposure measure, we use the same city-export shares, which sum to 1. The import tariffs, input tariffs, and export license controls have data available for a larger number of industries (145), and so we calculate city-export shares using this larger set of industries, thereby ensuring they sum to 1.

C.2 Shift-Share Balance Checks

Here we describe how primary estimating equation 1 can be transformed to an equivalent industry-level regression equation, as in Borusyak, Hull and Jaravel (2020), to perform the industry balance checks in Table 3 and the regional balance checks in Table 4. In the first step, the primary explanatory variable (i.e., city-level PNTR exposure $PNTR_c$) and any city-level outcome variables (for regional balance checks) (generically, Y_c) are each individually regressed on the vector of controls (Z_c), and residuals $Y_c^{\perp}$ and $PNTR_c^{\perp}$ are obtained. In the second step, these residuals are then aggregated to the industry level under the form: $\overline{V}_i^{\perp} = \frac{\sum_c w_c \cdot \beta_{ci} \cdot V_c^{\perp}}{\sum_c w_c \cdot \beta_{ci}}$. Finally, an equivalent industry-level regression specification can be obtained by the general regression equation,

$$\overline{Y}_i^{\perp} = \alpha + \delta \overline{PNTR}_i^{\perp} + \bar{\epsilon}_i^{\perp}, \tag{13}$$

in which $\overline{PNTR}_i^{\perp}$ is instrumented with the industry shifters $NTRGap_i$, and exposure weights β_i are used as regression weights.

We note that because the industry balance checks require using industry variables, the dependent variable is simply Y_i – i.e., the industry level measure, rather than $\overline{Y}_i^{\perp}$, the aggregated residuals from the city-level variable Y_c. For the regional balance checks, the dependent variables are the aggregated residuals of the city-level Y_c. Furthermore, the regional balance checks using this industry-level regression yield identical coefficients to replacing the dependent variable in specification 1 with the city-level pre-period variables that we examine.

C.3 Employment Weights

This section explores an alternative strategy that shows that results are similar when using the PNTR exposure measure created with 1990 employment shares instead of exports. This strategy is still closely tied to equation 3, with the difference that we utilize *employment shares* for a given city-industry (ci) pair to construct β_{ci}. The NTR gaps are identical. Shares are calculated as $\beta_{ci} = \frac{E_{ci}}{\sum_j E_{cj}}$. The numerator is the total industry employment in 1990 corresponding to city-industry pair ci. The denominator is the sum total of 1990 employment across all industries within each city. To avoid the "missing shares" issue described in Borusyak, Hull and Jaravel (2020), the sum of these β_{ci} shares across all industries within the city equals 1, as we only use industries where NTR gaps are available.

Table C.1 replicates the specifications in Table 5 but with the employment shares. Results yield the same qualitative findings, with more precision (higher t-stats) and somewhat larger magnitudes (inter-quartile effects) with employment weights.

C.4 Rotemberg Weights

We follow Goldsmith-Pinkham, Sorkin and Swift (2020) and construct Rotemberg weights to get a sense of which industries drive the variation in Normal Trade Relations gaps across cities. Table C.2 details the top 30 industries along with the International Standard Industrial Classification industry name. Not surprisingly, the top industries are textiles and

Table C.1: Main Effect on Enrollment with Employment Weights

	2002-2013				
	(1) No Controls	(2) +Control for Contract Intensity	(3) +Control for Import Tariffs	(4) +Control for Input Tariffs	(5) +Control for Export Licenses
$PNTR_c^{1990}$	1.073***	0.928***	1.011***	0.950***	0.826***
	(0.319)	(0.287)	(0.288)	(0.272)	(0.275)
Contract Intensity		0.613**	0.578**	0.638**	0.385
		(0.277)	(0.282)	(0.300)	(0.280)
Import Tariffs			-0.525*	-0.638**	-0.535**
			(0.293)	(0.279)	(0.260)
Input Tariffs				0.729**	0.671*
				(0.354)	(0.341)
Export License					0.837**
					(0.367)
Interquartile Effect:					
Δ *Students per 1m Pop.*	66	57	62	59	51
Mean Dep Var.	0.149	0.149	0.149	0.149	0.149
Obs.	258	258	258	258	258
R2	0.064	0.085	0.093	0.103	0.115

Notes: City-level regressions show the effect of PNTR exposure on Chinese student enrollment growth between 2002 and 2013, per thousand city residents. PNTR exposure is constructed with 1990 employment shares by industry. 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 ($\approx$ 6 p.p.). In each column, we iteratively include controls. All controls are at the city level, constructed by taking weighted averages of ISIC industries in the same way as the PNTR measure. Notice that the controls are not the same as in the main specification, as now we use employment shares to construct them as well. Contract intensity refers to the Nunn (2007) measure of the proportion of intermediate inputs employed by a firm that require relationship-specific investments. Output tariffs are for the year 2000 (from World Integrated Trade Solution (WITS)), while input tariffs are constructed using WITS tariff data and the 2002 input-output table for China. Export licenses refer to the Bai, Krishna and Ma (2017) measure of the fraction of export revenues licensed to export directly. We report heteroskedasticity-consistent standard errors (in parentheses) at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

apparel. However, outside the top three, there are also chemicals, food, and other miscellaneous industries.

We also conducted a robustness check of our main results by removing the top 5 industries from the construction of our PNTR exposure measure. We thus create a new PNTR exposure measure that is calculated without the top 5 industries. In particular, we drop the top 5 industries from the sample and then construct city-export shares in 1997 (β_{ci}) – in this case, export shares still sum to 1 and are not subject to the issue of the missing shares. We then interact the shares with NTR gaps, as in equation 3, excluding NTR gaps of the top 5 industries. Summing over all industries within the city yields the new PNTR exposure measure that excludes the top 5 Rotemberg weight industries. We then use this as the key dependent variable in regression equation 1. Results yield a coefficient estimate of 0.513 and a standard error of 0.167.

C.5 Inference Corrections

An additional contribution of BHJ is that their transformation of shift-share regression designs from city-to-industrial level variation also includes a new computation of "exposure-robust" standard errors, which account for potential cross-region correlation in residuals. To estimate "exposure-robust" standard errors, we implement our main analysis using the

Table C.2: Rotemberg Weights by Industry, Top 30

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

Notes: The table reports the top 30 industries ranked in terms of Rotemberg weights. Rotemberg weights are calculated using the procedure from Goldsmith-Pinkham, Sorkin and Swift (2020). See Goldsmith-Pinkham, Sorkin and Swift (2020) for further details.

Table C.3: Robustness: Statistical Inference Based on Alternative Specification and Standard Errors

	(1) BHJ Shock-Level Regression	(2) BHJ Exposure-Robust SEs	(3) BHJ Cluster on 3-digit ISIC	(4) BHJ Cluster on 2-digit ISIC	(5) Conley Spatial SEs (50 KM Distance)	(6) Conley Spatial SEs (100KM Distance)	(7) Conley Spatial SEs (200KM Distance)	(8) Cluster on Province
PNTR Exposure	0.337*	0.303**	0.337**	0.337*	0.337***	0.337**	0.337**	0.337**
	(0.170)	(0.151)	(0.160)	(0.179)	(0.119)	(0.140)	(0.169)	(0.162)
Number of Clusters			57	22				30

Notes: Table reports results from inference corrections. The coefficient of column (1) is obtained from the industry-level regressions following BHJ, where we use heteroskedasticity robust standard errors (see regression specification details in Appendix C.2). The previous column has the same coefficient as the main specification, however the correct specification should include the industry-level controls that fail balance tests, which we do in Column (2). We cluster the standard errors at the 3-digit and 2-digit ISIC levels in columns (3) and (4) receptively. In columns (5)-(8), coefficients are obtained from the primary city-level estimating equation (1). We assess Conley Spatial standard errors (Conley, 1999) by using various distance cutoffs: 50 KMs, 100 KMs, and 200 KMs in columns (5), (6), and (7), respectively. In column (8), we cluster at the province level. Standard errors are in parenthesis. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

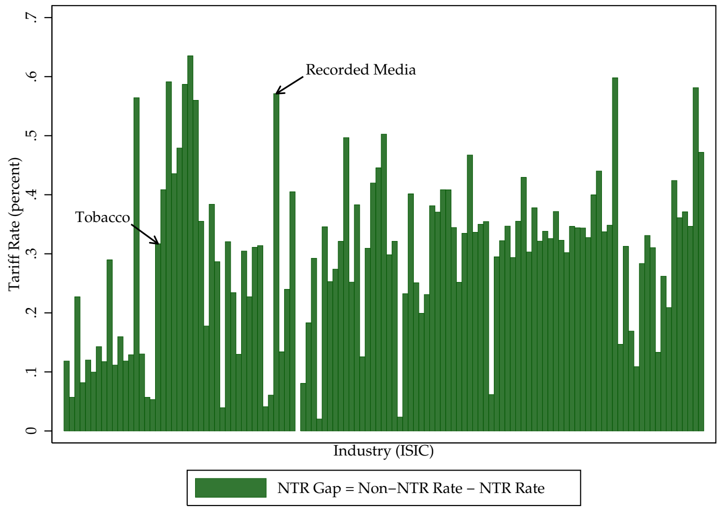
industry aggregation recommended in BHJ, as described in equation 13. Column (1) of Table C.3 shows that the coefficient estimate using the industry-level regression is identical, with standard errors slightly larger than the city-level regression in column (5) of Table 5. Following the suggestion in BHJ, to properly estimate exposure-robust SEs in the next column, we also include in the industry-level regression the two trade-factors that failed industry balance tests in Table 3 as further controls – recall these were the industry-level measures for import tariffs and export licenses. Note that these industry-level controls are included, even after the shift-share controls (Z_c) are partialled-out during the aggregation of variables from city-level to industry level. Hence point estimates in column (2) of Table C.3 differ slightly from the main estimate in column (5) of Table 5. Nonetheless, our results remain significant at the 5% level.

Borusyak, Hull and Jaravel (2020) also recommend examining the mutual correlation of shocks within sectors. To assess this, we use the industry-level regression equation in column (1) and cluster at more aggregate industry levels. Recall our data and design rely on NTR gaps (shifters) at the 4-digit ISIC level. In columns (3) and (4) of Table C.3, we cluster standard errors at the 3-digit ISIC level and also the 2-digit level. Because of the small numbers of clusters at the 2-digit level, we also estimate wild-bootstrap p-values and confidence intervals (Cameron, Gelbach and Miller, 2008), reported at the bottom of the table. Results still remain statistically significant.

Finally, we provide some robustness checks with respect to the spatial clustering of residuals across cities. Here we return to our primary city-level estimating equation (1). In columns (5)-(7) we estimate Conley Spatial standard errors (Conley, 1999). We assess Conley Spatial standard errors by using various distance cutoffs: 50 KMs, 100 KMs, and 200 KMs in columns (5), (6), and (7), respectively. 50km is the average distance to the nearest city in our sample and 200km is the median distance to all cities within a province in our sample. Beyond the cutoff, the correlation between the error terms of two cities is assumed to be zero. Finally, in column (8), we cluster at the province level. Our results remain robust to these checks on spatial clustering.

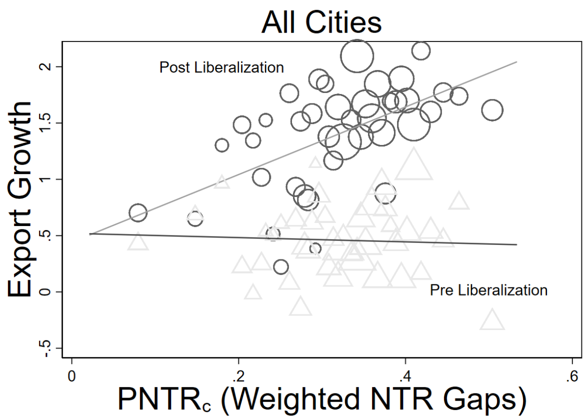
D Additional Tables and Figures

Figure D.1: NTR Gaps across Industries

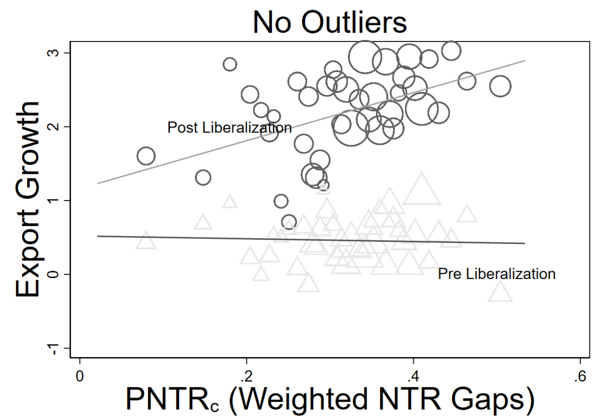


Notes: The figure shows the NTR gaps for each industry. Green bars plot the difference in NTR and non-NTR tariffs shown in Figure 2a. Data on NTR and non-NTR tariff rates by industry are from Pierce and Schott (2016).

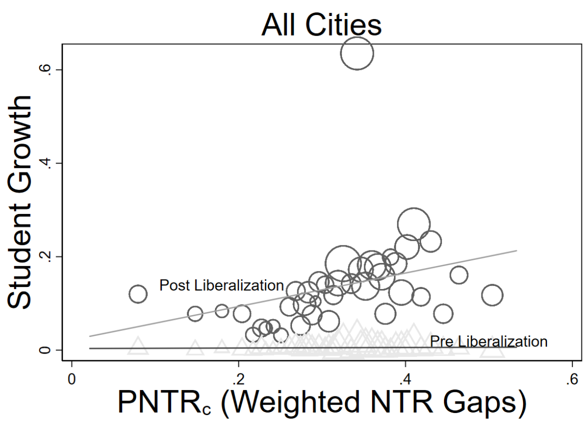
Figure D.2: Correlation between PNTR and Exports and Student Outflows Pre and Post WTO



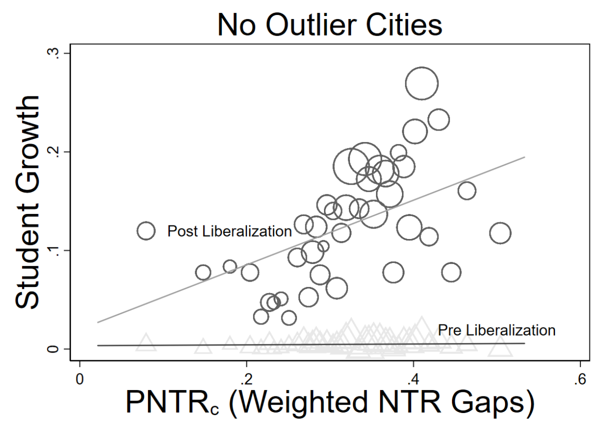
(a) Export Growth for all cities



(b) Export Growth without outliers



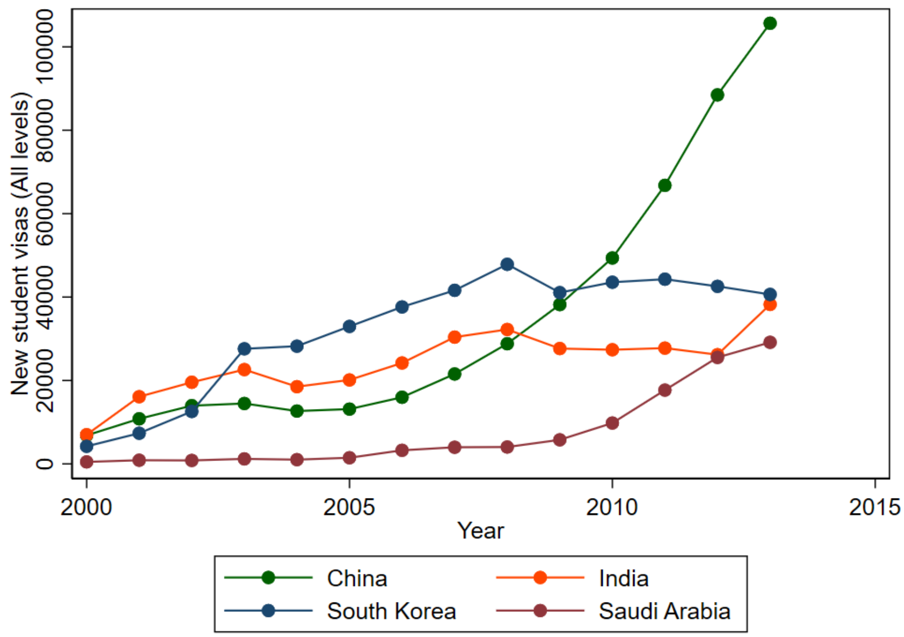
(c) Student Growth for all cities



(d) Student Growth without outliers

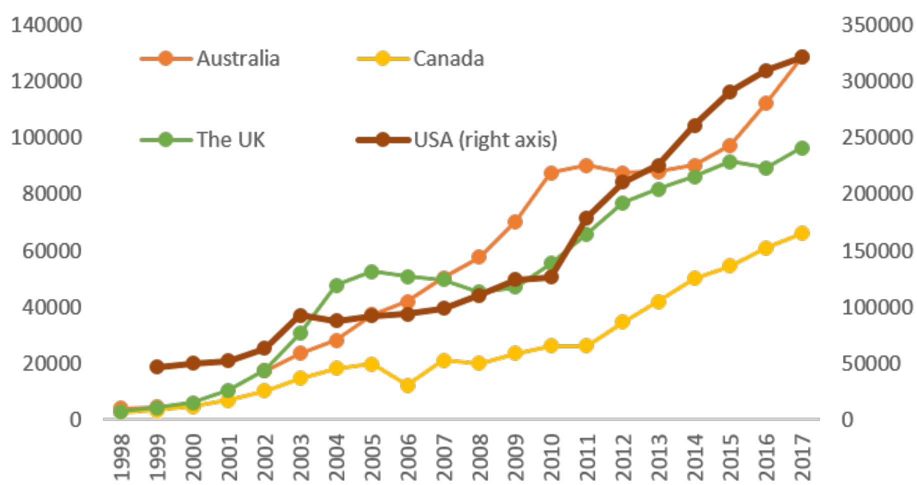
Notes: The figures show binned scatter plots of the relationship between the weighted NTR gap (PNTR) and growth in outcomes. Unlike Figure 4, we show the long-differenced growth (for instance, the total change in students between 2002 and 2013). The plots show 40 equal-size bins, weighted by population size in each bin. The right panels drop two cities with the largest student growth (Beijing and Shenzhen) to check for sensitivity to outliers. Post-liberalization export growth is measured as the log change from 2000 to 2013, using data from the China Customs Database, whereas pre-liberalization export growth is measured as the change from 1997-2000. Post-liberalization student growth is measured as the change in students from 2002 to 2013, divided by the initial city population (only non-agricultural hukou) in 2002. Pre-liberalization growth is from 2000-2001. Data on Chinese students by the city of origin are from SEVIS.

Figure D.3: The Number of New US Student Visas Granted by Country-of-Origin



Notes: The figure shows the number of new US student visas granted to each country of origin. These combine students of all levels (graduate, undergraduate and associate).

Figure D.4: Growth in the Number of International Students from China in Top Four Destination Countries



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

Table D.1: The Short-, Medium-, and Long-Run Impacts of PNTR on Student Outflows

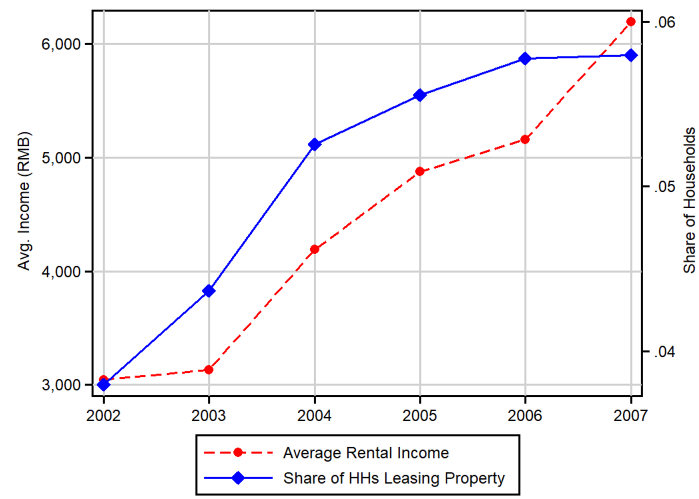
	(1) 2002-07	(2) 2008-10	(3) 2011-13
$PNTR_c$	0.016	0.079***	0.152***
	(0.013)	(0.028)	(0.051)
Contract Enforcement	0.027*	0.046	0.128
	(0.015)	(0.043)	(0.099)
Import Tariffs	-0.006	-0.021	-0.010
	(0.017)	(0.034)	(0.066)
Input Tariffs	-0.047	-0.151	-0.417**
	(0.037)	(0.098)	(0.179)
License Requirements	0.011	0.113**	0.171
	(0.019)	(0.044)	(0.105)
Mean Dep Var.	0.008	0.033	0.066
Obs.	268	268	268
R2	0.020	0.051	0.049

Notes: City-level regressions show the effect of weighted NTR gaps on Chinese student enrollment growth, per thousand city residents, over different periods. We examine a shorter-run time frame in column (1), 2002-07. Column (2) examines a medium-run time frame covering the Great Recession and recovery, 2008-10. Column (3) examines student growth over the longer-run period, 2011-13. We include all the main controls. We report heteroskedasticity-consistent standard errors (in parentheses) at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

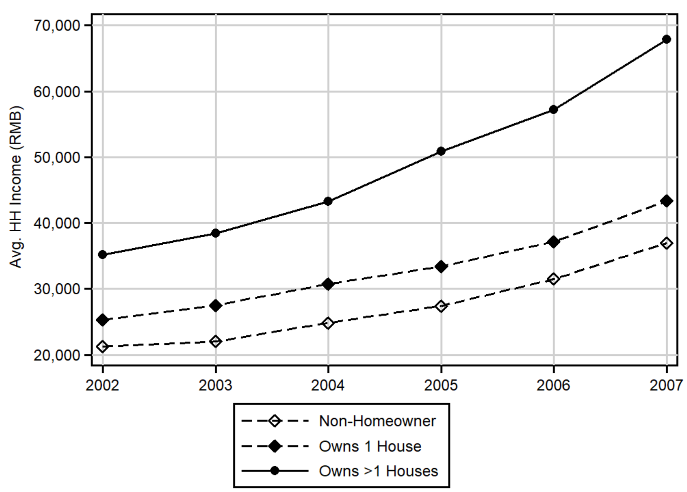
Figure D.5: The Change in Housing Prices, Rental Income, and Other Income

(a) House Prices and Ownership

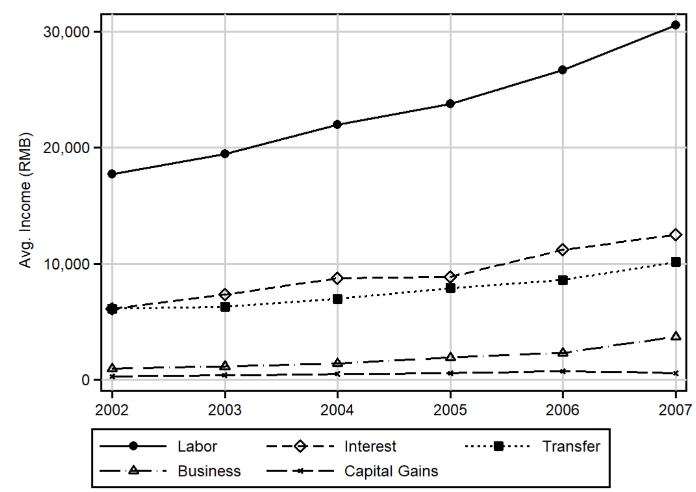
(b) Rental Income and Leasing Activity



(c) Income by House Ownership

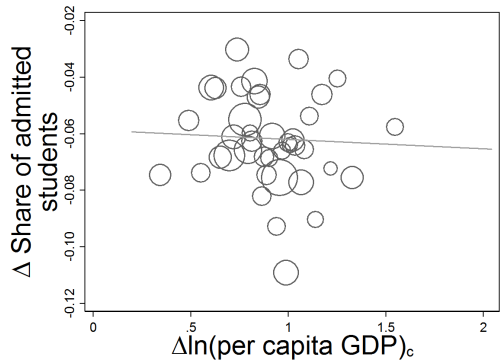


(d) Other Income Sources

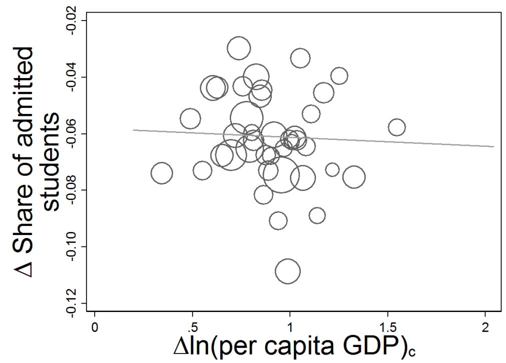


Notes: The figures display information about rental properties in China using micro data from 2002-2007 UHS. For each, we take the average across all households. The top figures show the average number of properties per household along with the share of households who lease properties. The bottom figure shows the average share of income from rents (which is zero for most households) and the rise in household income by year. The figures in the left column construct statistics using all households, while those in the right column are conditional on households that own property.

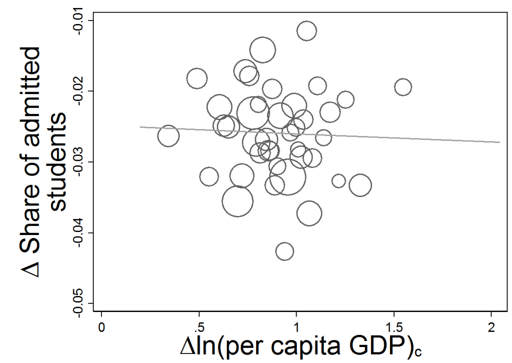
Figure D.6: Correlation between Admission to Elite Universities and per Capita GDP and NPTR Gaps



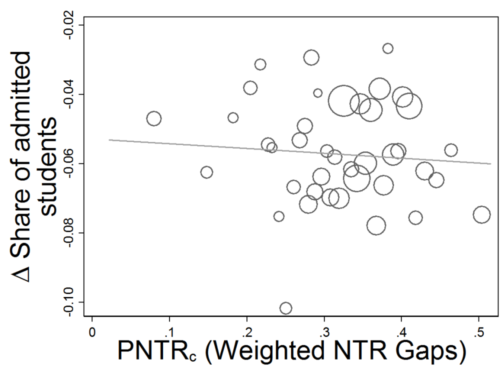
(a) First-tier Universities



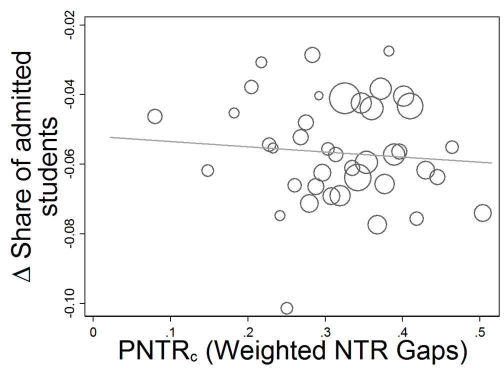
(b) 211 Project Universities



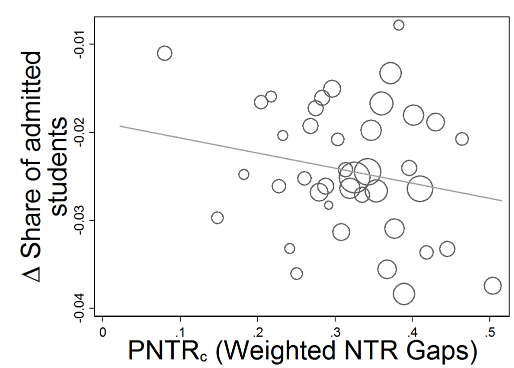
(c) 985 Project Universities



(d) First-tier Universities



(e) 211 Project Universities



(f) 985 Project Universities

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

Table D.2: Effect of PNTR on the Difficulty in Entering Elite Chinese Universities

Dep. 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		211-Project		985-Project	
	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE
$\Delta\ln(\text{GDP})_{c,05-11}$	-0.012	-0.000	-0.011	-0.000	-0.001	0.003
	(0.010)	(0.009)	(0.010)	(0.009)	(0.005)	(0.004)
Region FE	-	Y	-	Y	-	Y
Observations	208	208	208	208	208	208
R-squared	0.005	0.328	0.005	0.318	0.000	0.233
	First-tier		211-Project		985-Project	
	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE
$\Delta\ln(\text{GDP/Pop})_{c,05-11}$	-0.003	-0.000	-0.003	-0.000	-0.001	0.003
	(0.008)	(0.009)	(0.008)	(0.009)	(0.004)	(0.004)
Region FE	-	Y	-	Y	-	Y
Observations	208	208	208	208	208	208
R-squared	0.001	0.328	0.000	0.318	0.000	0.233

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

E Data Appendix

Table E.1: Variable List with Definition, Notes and Source

Variable	Definition/Notes	Source
ΔS_c	Long difference (2002-2013) in Chinese students that matriculate at US Universities per 1,000 city (non-hukou) residents	Student Exchange and Visitors Information System (SEVIS); China City Statistic Yearbooks (CSY)
$PNTR$	Industry (ISIC) gap between NTR and non-NTR tariff rates in 1999	Pierce and Schott (2016)
X_{ci}	Total exports (in 10,000 RMB) by city-industry pairs	China Custom Data
1990 employment	Calculated using data from China's One-Percent Population Census of 1990	1990 Population Census
Pop_c	City-level population (in 1,000s) –various used in the text, which are available annually, for urban and rural.	China CSY
GDP_c	GDP (in 10,000 RMB)	China CSY
Export licenses	Fraction of export revenues in total exports within an industry that is licensed to export directly in 2000	Bai, Krishna and Ma (2017)
Contract intensity	Proportion of intermediate inputs employed by a firm that require relationship-specific investments by the supplier (with the 1997 United States I-O Use Table).	Nunn (2007)
Import tariffs	The applied tariff rates by China in 2000, averaged across origins	World Integrated Trade Solution (WITS)
Input tariffs	2002 input-output table for China, available for 120 industry groups ("scodes") of which 70 are manufacturing, combined with output tariffs during that year	WITS and Annual Survey of Industrial Production (ASIP)
Labor over value-added	Based on firm-level survey, aggregated to the industry level	ASIP
Capital over value-added	Based on firm-level survey, aggregated to the industry level	ASIP
Return on assets	Based on firm-level survey, aggregated to the industry level	ASIP
Return on equity	Based on firm-level survey, aggregated to the industry level	ASIP
Indicators from Table 4	Log Change in: college and middle school enrollment; GDP; employment; FDI flows; real-estate investment. Plus, the share of manufacturing workers in employment and the Share of capital in output in 1994	China CSY
Demographic indicators (Table 4)	Share of 18 year olds in the population and the share of college educated workers in 1990	1990 Population Census
In- and out-migration changes	With data on skilled and unskilled migration, we compute log change (2000-2015) in probability of out-/in-migration by city	2000 and 2015 Population Census
Share of households affording tuition	Change in share of households (2002-2007) whose total household income accumulated over 10 years meets or exceeds the cost of a 4-year US degree	Urban Household Survey (UHS) and authors calculations
Income sources	Real estate income includes rental income and income from the sale of property. Other income sources directly from UHS	UHS
House price	Self reported house valuations	UHS
Commercial price	Commercial house price data starts in 2002.	Wind Bank dataset
Industry skill shares	Industry-specific high-skill and low-skill specific skill shares are produced with employment by skill level. Industries labeled as "skill-intensive" if above the median across all industries. We then produced the $PNTR_c$ using the subset of skilled and unskilled industries separately.	ASIP (China) and Amiti and Freund (2010) (Indonesia)
# of new study abroad agencies	Aggregate entry of newly created "intermediary education consulting firms" from 1990-2001. We categorize firms as agencies with textual analysis from the registration database.	China Firm Administrative Registration Database

E.1 Detail on Sources

USCIS International Students Data

Our primary outcome data comes from an individual-level file of F-1 visa recipients obtained from the U.S. Immigration and Customs Enforcement group of the Department of Homeland Security through a Freedom of Information (FOIA) Request, covering the period 2000 to 2013. These data are not available for previous years. These data identify each student's intended degree, subject of study, post-secondary institution in the U.S., city and country of origin, along with variables indicating cost of attendance, financial support, and the period of study.

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

SEVP requires that students provide their permanent address, which helps determine their prefecture city of origin. We aggregate the individual-level data to obtain total students by year of entry and city of origin, and also group subtotals by program/funding characteristics.

China Customs Database and Tariff Data

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

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

Firm Survey Data

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

Firm Census Data

To measure the number of newly created manufacturing plants by city and year, we use the (second) economic census of China carried out by the NBS in 2008. The data covers all firms in all sectors engaged in economic activities by the end of 2008, including all state-owned and private enterprises spanning all manufacturing and non-manufacturing industries. The data contains rich information on firm characteristics, including the year when the plant was created, in addition to basic firm information, balance sheet information (such as investments, output, value-added), and other information on economic activities. The industry classification in census data uses the China Standard Industrial Classification (GB/T4754-1994 and GB/T4754-2002) at the 4-digit level. We count the number of new firms by city and year based on a firm's year of establishment, which equals the number of firms in city c established in year t.

Information on Study Abroad Agencies

The Ministry of Education of China frequently reported the list of qualified study-abroad agencies in China. However, there are many cases where only the headquarter or main branches of the group are shown on the list.[51] Instead, to obtain the number of study-abroad agencies by Chinese city and year, we apply textual analysis to names of firms in the Firm Administrative Registration Database that is maintained by China's State Administration for Industry and Commerce (SAIC).[52]

In Table E.2, we first summarize the keywords frequently appearing in the name of study abroad agencies based on the list reported by the official website of the Ministry of Education of China, which we use to identify whether an enterprise, in administrative registration data, is a study abroad agency.

With the keywords, we apply the textual analysis to the names of the universe Chinese firms in the administrative registration data, and count the number of firms containing these keywords by city and year. In such a way, we compute the number of newly created study-abroad agencies by city and year. In Figure E.1 we plot the average number of study-abroad agencies per city over time. The average number of study-abroad agencies per city grew from 0.03 in 1990 to 1.42 in 2002 and 36.58 in 2013.

Local China College Students Admissions Data

The aggregate number of students admitted by universities in each city is computed from the National College Entrance Examination (NCEE) data provided by the China Institute for Educational Finance Research at Peking University. The data covers the universe of

[51] For instance, *New Oriental Education & Technology Group* has many branches across Chinese cities, but the list may only report its headquarter in Beijing or the main branch in Zhejiang. For an example of the 2007 list, see http://www.gov.cn/zfjg/content_798542.htm.

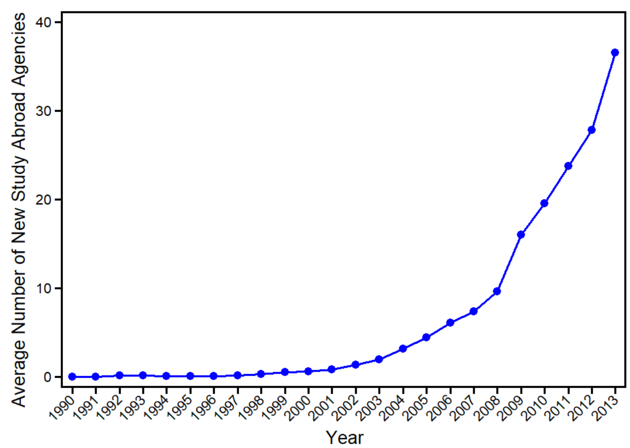
[52] The data reports the administrative information of the universe of enterprises in China. The data contains basic information such as firm name, firm location, industry classification, year of establishment, ownership type, legal representative, shareholders, and registered capital value.

Table E.2: List of Frequent Keywords in Firm Names of Study Abroad Agencies

English Meaning	Chinese Keywords (Pinyin)
study abroad	liu2xue2, chu1guo2fu2wu4, chu1guo2qi3hua4
	chu1guo2zi1xun2, chu1guo2ren2yuan2fu2wu4
education and cultural exchange	jiao4yu4wen2hua4jiao1liu2, jiao4yu4jiao1liu2
	jiao4yu4guo2ji4jiao1liu2, wai4fu2dui4wai4jiao1liu2
	ren2cai2jiao1liu2, ren2cai2ji4shu4he2zuo4
education and cultural consulting	jiao4yu4guo2ji4zi1xun2, jiao4yu4zi1xun2
	jiao4yu4xin4xi1zi1xun2
education and cultural service	jiao4yu4guo2ji4fu2wu4

Notes: Chinese pinyin for each keyword is displayed in the second column.

Figure E.1: Average Number of Newly Created Study Abroad Agencies



students enrolled in Chinese universities and colleges between 2005 and 2011. Other details on the data and the background of the NCEE are discussed in Zivin et al. (2018). We aggregate the micro-level data to obtain the number of admitted students by student's city of origin, university, and year, then we calculate the year-city-specific share of admitted students by elite universities.

We measure the eliteness of a Chinese university according to its membership in the first-tier class, 211-Project, and 985-Project.[53] In terms of eliteness, 985-Project universities are typically considered better than the 211-Project universities, followed by the first-tier universities.

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

Background: The National College Entrance Examination

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

Urban Household Survey Data

The Urban Household Survey (UHS) is conducted by the National Bureau of Statistics of China (NBS), which is similar to the Current Population Surveys in the United States and adopts a stratified and multi-stage probabilistic sampling scheme. The data is a rotating panel where the full sample is changed every three years. The UHS reports household information and economic characteristics, such as the household income of different types. The data have been widely used, and detailed information on the UHS is provided by Han, Liu and Zhang (2012) and Ding and He (2018). The UHS has been used to study wage inequality (Yang, 1999; Ge and Yang, 2014), and we follow their work in making changes in the city's average outcome between 2002 and 2007. This constitutes more than 30,000 households and more than 120,000 individuals each year. This covers between 151-204 cities for the analysis, and we are missing data in the last few years of our student sample.

China Population Census Data

To construct the PNTR exposure measure that uses city-level employment shares by industry in 1990, we use China's One-Percent Population Census data of 1990 to compute city-level employment shares by industry in 1990. As the industry classification in 1990 Population Census uses the China Standard Industrial Classification (GB/T4754-1984), we correspond them to the International Standard Industrial Classification (ISIC) Revision three at the 4-digit level to construct various trade shock measures in practice.

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

$$OUT^T_{o,10-15} = \frac{\sum_{\forall d \neq o} L^T_{od,10-15}}{\sum_{d'} L^T_{od',10-15}}, \quad T \in \{S, U\} \tag{14}$$

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

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

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

China City Statistical Yearbooks

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

Wind-Economic Database

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