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 A.1 outlines the primary potential pathways.[1] 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.

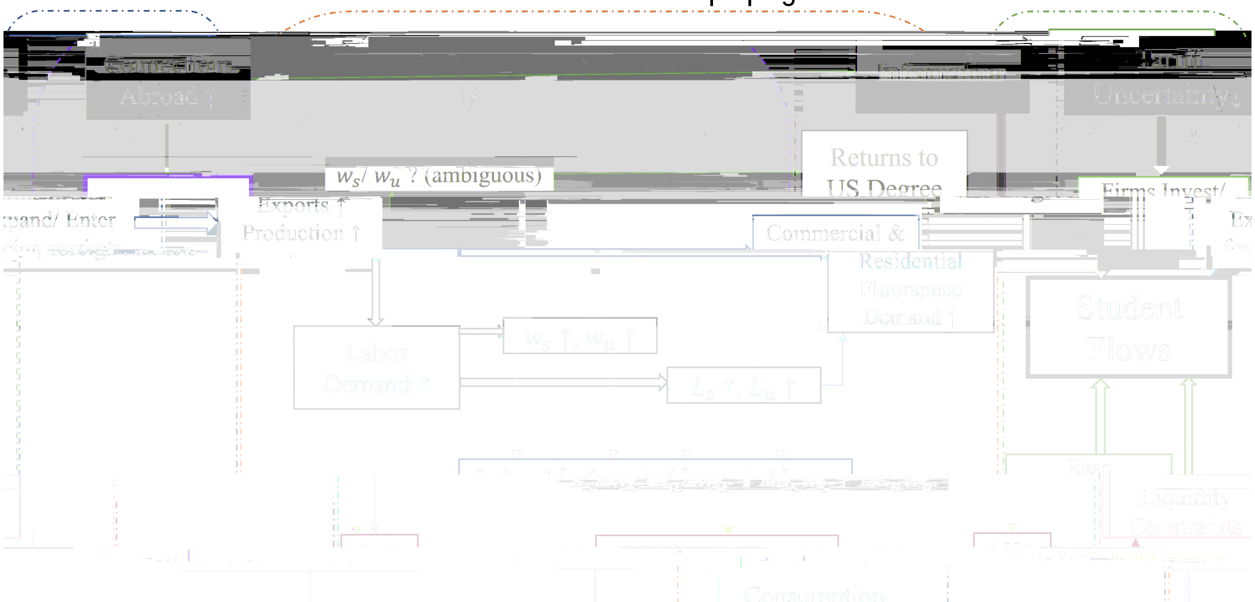
In the next stage of the model, described in Section A.2, we consider how expansions in production affect the local economy. Firm entry and investment lead to an increase in exports, which we consider to be the first step of our empirical analysis (outcomes in orange-bordered boxes are shown empirically).

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 . Increased firm activity raises labor demand locally, which in turn puts

[1] 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.

Figure A.1: A Simple Conceptual Framework

Framework/Concept.png



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.

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 in ux 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 .

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 tari 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 ow of students to colleges. If, however, the industries would bene t 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.

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 rm v produces a variety of product i. As a result, demand for product i produced by rm v is q_v, which depends on consumer prices p_v, in the following manner: $q_v = EP \quad ^1 p_v$, where E denotes total income of the rest of the world, and > 1 is the CES elasticity across products, and $P = \left[\int_v p_v^1 \right]^{\frac{1}{1-}}$ is the CES price index.[2]

As in a standard framework, monopolistically competitive sellers draw a productivity $\frac{1}{!_v}$, and receive $p_v = _i$, as consumers pay tari $_i \geq 1$. Firms choose p_v to maximize their operating pro t $_v = (p_v = _i - !_v) q_v$, and so equilibrium operating pro t is given by:[3]

$$(_i ; !_v) = \sim _i \quad !_v^1 \tag{1}$$

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 < 1. In each period, rms observe the rms active in the previous period, and all tari s and model parameters. If there is no uncertainty in future tari s, the expected value from exporting after entry e is $_e(_i ; !_v) = (_i ; !_v) + \mathbb{E} \sum_t \, ^t \, (_i ; !_v)$.

Let $! \sim G_i(!_v)$. As such, the marginal rm that enters is a rm that draws $!_i$, where the sunk entry cost equals the present discounted value of pro ts:

$$K = \frac{(_i ; !_v)}{1 - } \Leftrightarrow !_i = \left[\frac{\sim}{_i (1 - \quad) K} \right]^{\frac{1}{-1}1} \quad 0 \quad 155 \; 1 \quad 01 \quad 5 \; 5 \quad 1 \quad 0 \quad 0\,111 \quad 1\,551$$

their Appendix AA, $!_i \;\; = !_i U_i$, where $U_i \leq 1$ is the uncertainty factor and depends on the expected distribution of future $\;_i$. As they describe, the uncertainty factor is a function of the di erence between the tari s \threatened" if China's MFN status is terminated and the actually applied MFN tari s. 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 tari rates do not change).

Let us now re-introduce the city c subscript. Export revenue for each rm v is $X_v = p_v q_v = \sim \;\; {}_i^{1} \;\; !_v^{1}$. If N_{ci} are the mass of potential exporters of product i, then the mass of active rms is $N_{ci} \times G(!_i \;)$. Export revenue for product i is:

$$X_{ci} = N_{ci} \int_0^{!_i^{**}} X_v dG(!) = \sim \;\; {}_i^{1} \;\; N_{ci} \int_0^{!_i^{**}} !_v^{1} \;\; dG(!) \tag{3}$$

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

When tari uncertainty changes, tari s $\;_i$ may stay the same, even as $\;\; Ʊ_i \neq 0$. Again, this re ects the fact that the probability of moving to non-MFN tari s on China (or the \threat") is severely reduced. The percent change in city-level exports, would be a function of changing $\;\; Ʊ_i$:

$$\frac{\;\; X_c}{X_c} = \frac{1}{X_c} \sum_i \left(\approx N_{ic} \;\; {}_i \, {}^k \times \;\;\; Ʊ_i \right) = \frac{1}{X_c} \sum_i \left(\approx N_{ic} \;\; {}_i \, {}^k Ʊ_i \times \frac{\;\; Ʊ_i}{Ʊ_i} \right) = \sum_i \frac{X_{ic}}{X_c} \times \frac{\;\; Ʊ_i}{Ʊ_i} \tag{4}$$

As Handley and Limao (2017) argue, MFN status reduced all policy uncertainty ($Ʊ_{i;MFN} = 1$ for all i), whereas, in the non-MFN world, $1=Ʊ_{i;0}$ was directly a function of the ratio of the MFN and non-MFN tari s. As such, $\frac{\;\; Ʊ_i}{Ʊ_i} = 1 - \frac{1}{U_{i;0}} = \frac{1}{x} NTR\ Gap_i$. So the percentage change in the product-speci c uncertainty is a function of the NTR Gap of the product: $NTR\ Gap_i \equiv \ _x \frac{\sigma_i}{\sigma_i}$. These uncertainty changes directly a ect exports, based on the baseline propensity to export. So we de ne $PNTR_c \equiv \sum_i \frac{X_{ic}}{X_c} \times NTR\ Gap_i$.

Together, this motivates our empirical shift-share speci cation for exports: $\frac{\ X_c}{X_c} = \ _x PNTR_c$. 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 tari uncertainty, while the shock is provided by the exogenous change in the uncertainty factor, proxied by $PNTR_c$. Empirically, we provide \Identi cation Checks" in the main paper that check for pre-trends in exports and related outcomes, and we also provide a separate speci cation 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 speci cally 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.07(in)-30s-305(d04(Uamine)-305 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 A.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 , employee compensation W, and real estate income H. For instance, from the above framework in Section A.1, we know $_v = \frac{1}{\ } X_v$, and so a simple rescaling should generate a similar response to $PNTR_c$.[5]

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 $!_v$ to also depend on various factor inputs. In the spirit of tractability, we refer the reader to the middle portion of Figure A.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 higher real wages, it would also change the supply of L^S_{sc} and L^S_{uc}. 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

[5] That is, $\frac{\ _c}{\ _c} \equiv \sum_i \frac{\ _{ic}}{\ _c} = \sum_i \frac{(1= \ )\ X_{ic}}{(1= \ )X_c} = \sum_i \frac{X_{ic}}{X_c} \times \frac{\mho_i}{\mho_i}$.

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.[6]

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 ${}_c$, 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.

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

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 , wage income $W{=}L$, and real estate income H. Let the cost of domestic education (at the origin o) be $_{o}$, and the additional cost of getting a degree from the US be $_{d}$. 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 $_{d}$. Those with a domestic education earn w_o, and if one gets a degree from abroad, they earn a wage premium 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 ($_{d}$ and $_{d2}$) 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.[7]

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: $_{o} + {}_{d}s$. The difference in prices $_{d}$ (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 b. They maximize their two-period utility: $u(c_1) + \; u(c_2)$, where $\; \leq 1$ is a discount factor, and c_1 is the numeraire.

Period 1 consumption depends on wealth Y, the price of education at home $_{o}$, the additional price abroad $_{d}$, 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:

$$
\begin{aligned}
c_1 &= Y - {}_{o} - {}_{d}s + b \\
c_2 &= w + \; s - Rb\,;
\end{aligned}
\tag{5}
$$

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

[7] 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, $b = b$, the rst-order condition with respect to s is:

$$ {}_d\, u'(c_1) = \quad u'(c_2) \tag{6}$$

For reasonable assumptions on $u(:)$, for instance, if $u(c) = \log c$, schooling will respond to income shocks, in the manner $s = \frac{}{(1+\ )\ _d} Y$, for credit constrained households. For non-constrained households, the education decision does not depend on Y.[8]

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 $c = Y - \ _o - \ _d s$. From the rst order conditions, we can derive:

$$s = \frac{Y - \ _o - \ _d \underline{s}}{2\ _d}$$

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

$$= \frac{Y - \ _o - \ _d \underline{s}}{2(Y - \ _o)} = \frac{1}{2} - \frac{_d}{2(Y - \ _o)}\underline{s}$$

If $\underline{s} = 0$, then the demand for services like the US degree would be homothetic, and

[8] 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.

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 $\frac{d}{d(Y \quad o)} > 0$.

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.

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:

$$\ln Y_{ct} = \beta PNTR_c * Post2001_t + \alpha_t + \delta_c + \gamma Z_{ct} + \epsilon_{ct}, \tag{7}$$

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.[9] The coefficient β 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.

[9]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.

The rst three columns in Table B.1 show that comparing the pre-WTO period to the

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 1b) identi ed that two of four known determiunder direct export licenses, which is also measured in 2000.

Input tari s are calculated under standard procedures using import tari s 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 tari s to produce input tari s at this level. The input tari s are a weighted average (given input usage) of the WITS import tari s on the industries used as inputs. We then re-classify input tari s 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 rms that require relationship-speci c investments by the supplier.

As a nal 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 tari s, input tari s, 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 1b and the regional balance checks in Table 2. In the rst 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 $Y_c^?$ and $PNTR_c^?$ are obtained. In the second step, these residuals are then aggregated to the industry level under the form: $\overline{V}_i^? =$

$\frac{\sum_c w_c \quad_{ci} V_c^{\perp}}{\sum_c w_c \quad_{ci}}$. Finally, an equivalent industry-level regression speci cation can be obtained by the general regression equation,

$$\overline{Y}_i^{?} = \quad + \quad \overline{PNTR}_i^{?} + {}^{-?}_{i}; \tag{9}$$

in which $\overline{PNTR}_i^{?}$ is instrumented with the industry shifters $NTRGap_i$, and exposure weights $_i$ 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 $\overline{Y}_i^{?}$, 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 coe cients to replacing the dependent variable in speci cation 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 di erence that we utilize *employment shares* for a given city-industry (ci) pair to construct $_{ci}$. The NTR gaps are identical. Shares are calculated as $_{ci} = \frac{E_{ci}}{\sum_j E_{cj}}$. 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 $_{ci}$ shares across all industries within the city equals 1, as we only use industries where NTR gaps are available.

Table C.1 replicates the speci cations in Table 3 but with the employment shares. Results yield the same qualitative ndings, with more precision (higher t-stats) and somewhat larger magnitudes (inter-quartile e ects) with employment weights.

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:					
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 (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

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 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 ($_{ci}$) — 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.

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 bers; 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.

C.5 Inference Corrections

We now assess the robustness of our results to various inference corrections. We apply recent insights from Borusyak, Hull and Jaravel (2020) and Adao, Kolesar and Morales (2019) to correct for correlations between the shift-share and residuals across cities with similar exposure shares. Additionally, we apply standard corrections for clustering in spatial designs. Finally, we show results are robust to clustering at the more aggregate province level.

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 industry aggregation recommended in BHJ, as described in equation (9). 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 3. 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 1b 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 3. 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 Heterogeneity in Effects of PNTR

Table D.1 examines whether PNTR exposure affected the composition of students. To help inform mechanisms that we examine in Section 6, we study how effects differed by the level and field of study, sources and amounts of funding, and quality of US institutions attended. Panel A was discussed in the main text, and here we discuss the rest of the results.

Panel B of Table D.1 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.[12] 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 D.1 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

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

students received some form of scholarship, grant, or other financial assistance. Estimates indicate that PNTR exposure induced a large shift in student composition toward unfunded students. Panel E assesses growth in the number of students by quartile of their reported personal funds in 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.[13]

[13]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.

Table D.1: Heterogeneity in E ects 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)
E ect as Proportion of Total		.06	.41	.31	.02	.21
Student Proportions in 2002		.02	.06	.41	.49	.02
Change in Proportions						

E Additional Tables and Figures

Table E.1: Summary Statistics

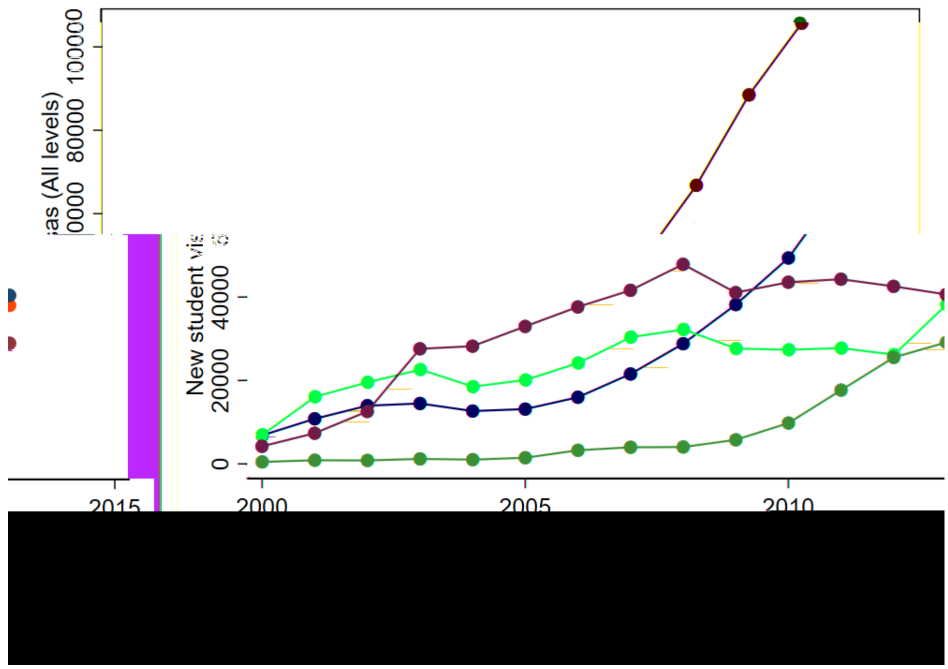
	(1) 2000	(2) 2013
Population (in 000s)	1,093	1,487
	(1,334)	(1,859)
GDP (in 10,000 RMB)	1,852,178	13,447,871
	(3,777,893)	(25,918,510)
GDP per capita (in RMB)	14,537	73,015
	(13,033)	(53,861)
Exports (in 10,000 RMB)	40,911	460,891
	(100,291)	(1,517,142)
Students Entering US Higher Ed Per 1M City Residents	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 ows, 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 E.1: NTR Gaps across Industries

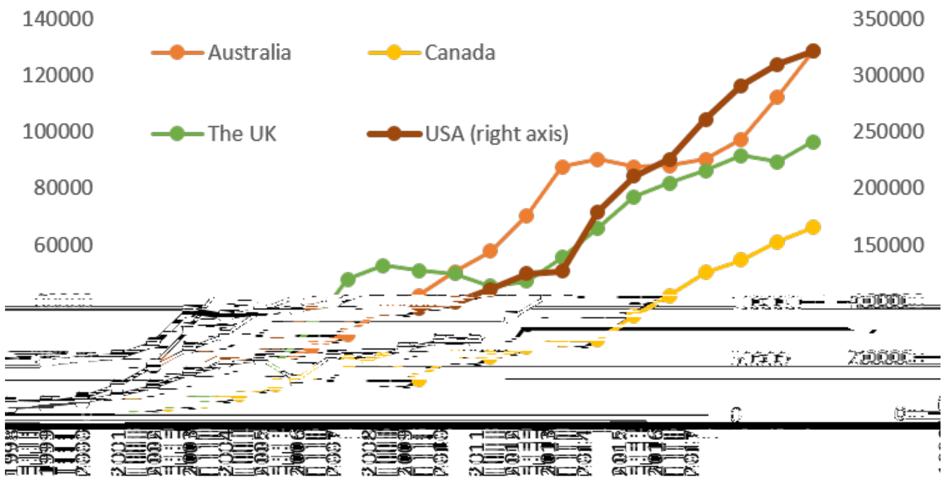
Notes: The gure shows the NTR gaps for each industry. Green bars plot the di erence in NTR and non-NTR tari s shown in Figure 1c. Data on NTR and non-NTR tari rates by industry are from Pierce and Schott (2016).

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



Notes: The gure 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 E.4: Growth in the Number of International Students from China in Top Four Destination Countries



Notes: The gure 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 E.2: The Short-, Medium-, and Long-Run Impacts of PNTR on Student Out ows

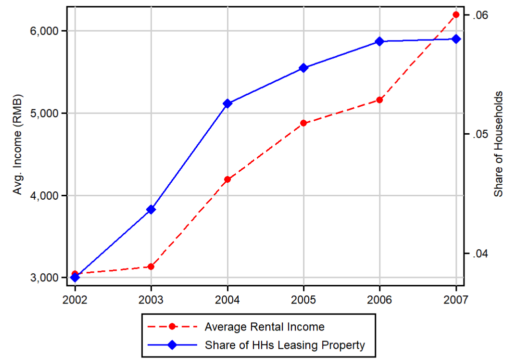
	(1) 2002-07	(2) 2008-10	(3) 2011-13
$PNTR_c$	0.016	0.079	0.152
	(0.013)	(0.028)	(0.051)
Contract Enforcement	0.027	0.046	0.128
	(0.015)	(0.043)	(0.099)
Import Tari s	-0.006	-0.021	-0.010
	(0.017)	(0.034)	(0.066)
Input Tari s	-0.047	-0.151	-0.417
	(0.037)	(0.098)	(0.179)
License Requirements	0.011	0.113	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 e ect of weighted NTR gaps on Chinese student enrollment growth, per thousand city residents, over di erent 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 E.5: The Change in Housing Prices, Rental Income, and Other Income

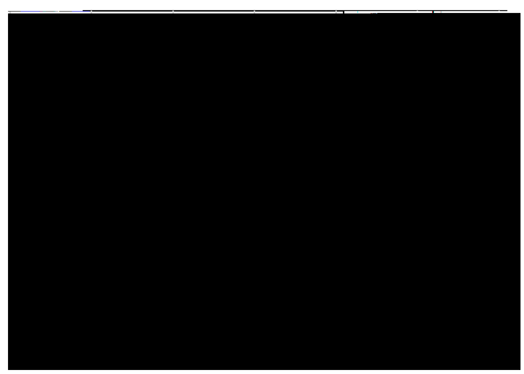
(a) House Prices and Ownership

(b) Rental Income and Leasing Activity



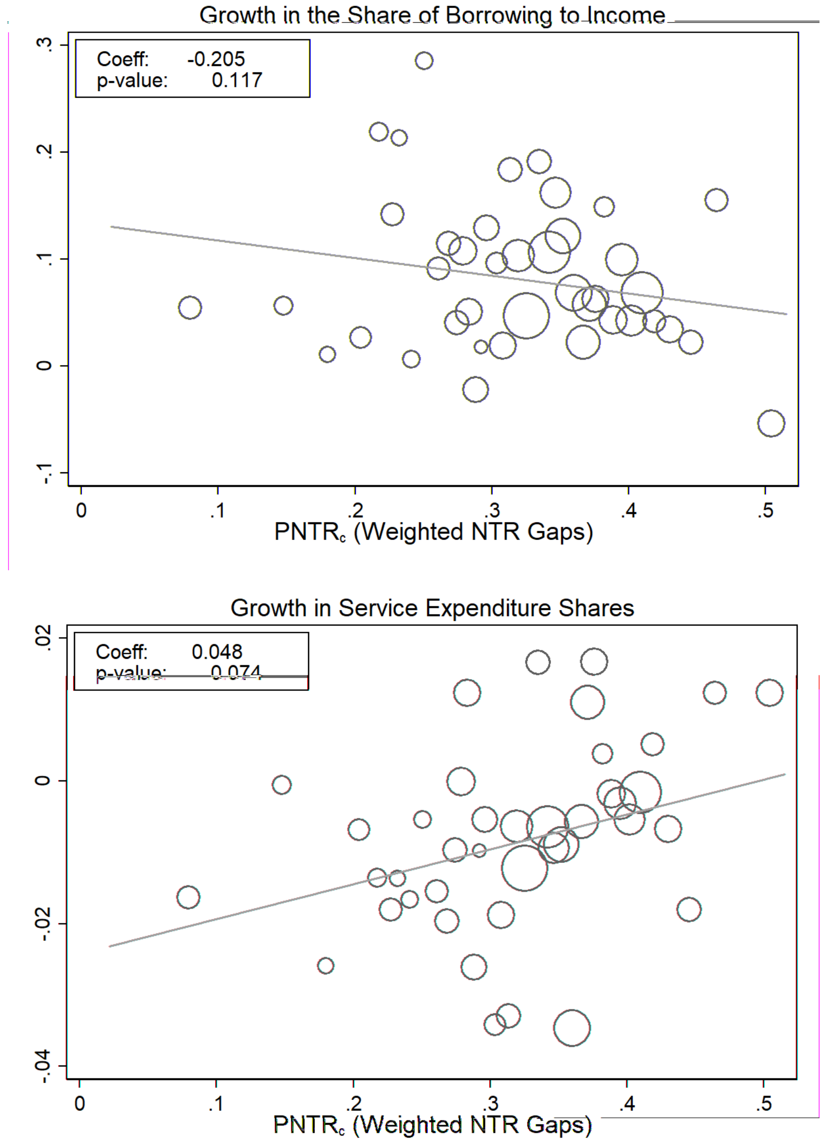
(c) Income by House Ownership

(d) Other Income Sources



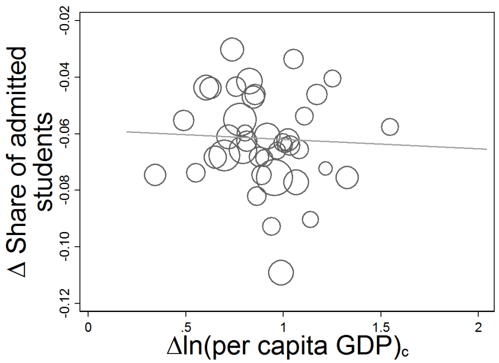
Notes: The figures display information about rental properties in China using micro data from 2002-2007 UHS. For each, we take the average across all households. The top figures show the average number of properties per household along with the share of households who lease properties. The bottom figure 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 E.6: Correlation between PNTR and Household Service Expenditure and Borrowing post WTO

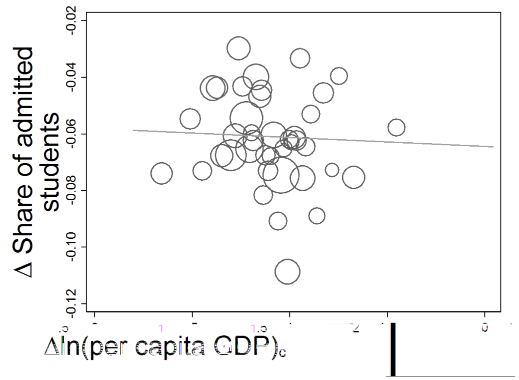


Notes: Figures show binned scatter plots of the relationship between PNTR exposure and post-treatment growth in outcomes. The plots show 40 equal-size bins, weighted by population size in each bin. Data on expenditure on services and borrowing are from the Urban Households Survey, with the outcomes being 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 coe cient and its associated p-value, given heteroskedasticity-robust standard errors, of a regression of the outcome on PNTR exposure.

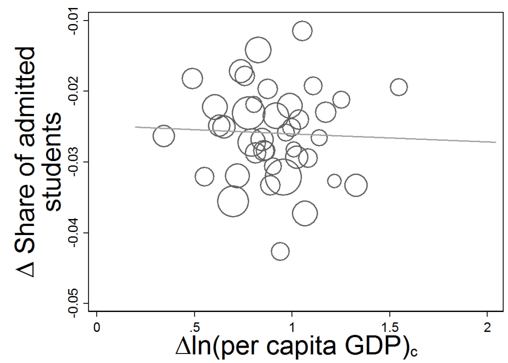
Figure E.7: Correlation between Admission to Elite Universities and per Capita GDP and NPTR Gaps



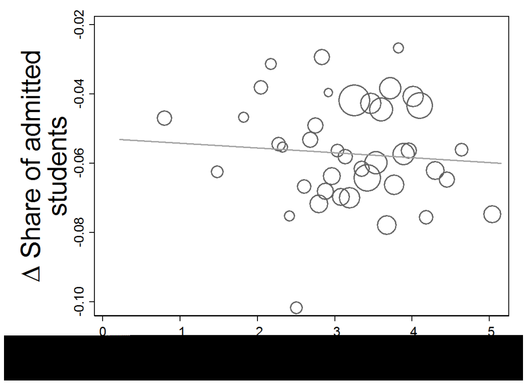
(a) First-tier Universities



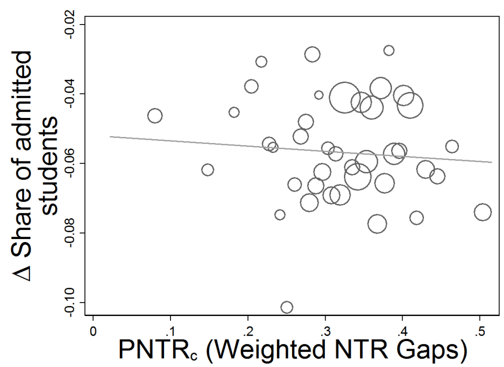
(b) 211 Project Universities



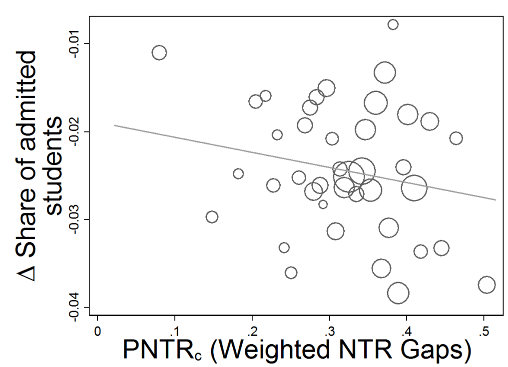
(c) 985 Project Universities



(d) First-tier Universities



(e) 211 Project Universities



(f) 985 Project Universities

Notes: The gure 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 di erence 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-speci c share of admitted students by elite universities.

Table E.3: E ect of PNTR on the Di culty in Entering Elite Chinese Universities

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

Notes: City-level regressions show the e ect 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-speci c share of admitted students by elite universities. All regressions control for region-level xed e ects, where the region is the rst (of four) digit in the prefecture code.

F Intermediary Education Consulting Firms

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, we instead use their pre-2002 geographic distribution to determine to what degree these intermediaries might have facilitated the process.[14] For related reasons, 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 know if their growth captures a reduction in the cost of studying in the US specifically, as would be necessary for the information channel.

We interact the total number of these firms with $PNTR$ exposure in Table F.1, 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.

[14] 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.

Table F.1: Mechanisms: E ect 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 e ect 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. In this table we add to our main speci cation 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). ***$p < 0{:}01$, **$p < 0{:}05$, *$p < 0{:}1$.

G Data Appendix

Table G.1: Variable List with De nition, Notes and Source

Variable	De nition/Notes	Source
S_c	Long di erence (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 tari 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 rm that require relationship-speci c investments by the supplier (with the 1997 United States I-O Use Table).	Nunn (2007)
Import tari s	The applied tari rates by China in 2000, averaged across origins	World Integrated Trade Solution (WITS)
Input tari s	2002 input-output table for China, available for 120 industry groups (\scodes") of which 70 are manufacturing, combined with output tari s during that year	WITS and Annual Survey of Industrial Production (ASIP)
Labor over value-added	Based on rm-level survey, aggregated to the industry level	ASIP
Capital over value-added	Based on rm-level survey, aggregated to the industry level	ASIP
Return on assets	Based on rm-level survey, aggregated to the industry level	ASIP
Return on equity	Based on rm-level survey, aggregated to the industry level	ASIP
Indicators from Table 4	Log Change in: college and middle school enrollment; GDP; employment; FDI ows; 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-speci c high-skill and low-skill speci c 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 rms" from 1990-2001. We categorize rms as agencies with textual analysis from the registration database.	China Firm Administrative Registration Database

G.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.

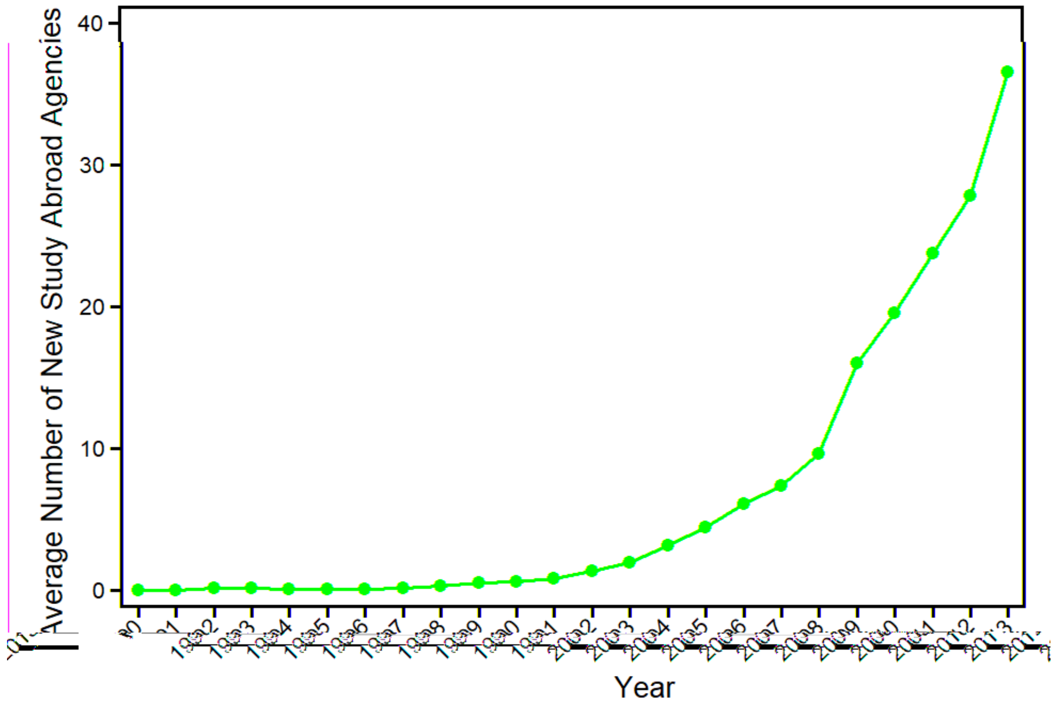
Firm Census Data

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.

Table G.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

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



Local China College Students Admissions Data

The aggregate number of students admitted by universities in each city is computed from the National College Entrance Examination (NCEE) data provided by the China Institute for Educational Finance Research at Peking University. The data covers the universe of students enrolled in Chinese universities and colleges between 2005 and 2011. Other details on the data and the background of the NCEE are discussed in Zivin et al. (2018). We aggregate the micro-level data to obtain the number of admitted students by student's city of origin, university, and year, then we calculate the year-city-speci c share of admitted students by elite universities.

We measure the eliteness of a Chinese university according to its membership in the rst-tier class, 211-Project, and 985-Project.[17] In terms of eliteness, 985-Project universities are typically considered better than the 211-Project universities, followed by the rst-tier universities.

Background: The National College Entrance Examination

The NCEE (i.e., *Gao Kao* in Chinese) is so far the most important channel for higher education admissions in China. In practice, the same subjects are tested in every province, while the testing contents may vary. Each university assigns a predetermined admissions quota to each province before the test, and will admit applicants from the highest to the lowest scores until the provincial quota is lled. 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 di erent prefecture cities within a province will be faced with the same NCEE policy.

0.973 79(NCEtak)-271s-321(dplaarc)273e(admittf(un)27c)273evertserts8(ear.75(Ehirdlass.)-ertsties)-271(in)-270(ertsJ/F

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

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

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

$$IN^T_{d,10-15} = \frac{\sum_{\forall o \neq d} L^T_{od,10-15}}{\sum_{o'} L^T_{o'd,10-15}}, \quad T \in \{S, U\} \tag{11}$$

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.

References

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

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

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

Borusyak, Kirill, Peter Hull and Xavier Jaravel. 2020. Quasi-Experimental Shift-Share Research Designs. Technical report Review of Economic Studies. Forthcoming.

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

Cameron, A Colin, Jonah B Gelbach and Douglas L Miller. 2008. \Bootstrap-based improvements for inference with clustered errors." *The Review of Economics and Statistics* 90(3):414{427.

Chaney, Thomas. 2008. \Distorted Gravity: The Intensive and Extensive Margins of International Trade." *American Economic Review* 98(4):1707{1721.

Conley, Timothy G. 1999. \GMM estimation with cross sectional dependence." *Journal of Econometrics* 92(1):1{45.

Crowley, Meredith, Ning Meng and Huasheng Song. 2018. \Tari scares: Trade Policy Uncertainty and Foreign Market Entry by Chinese Firms." *Journal of International Economics* 114:96 { 115.

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

Erten, Bilge and Jessica Leight. 2020. \Exporting out of Agriculture: The Impact of WTO

Accession on Structural Transformation in China." *Review of Economics and Statistics* pp. 1{46.

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

Feng, Ling, Zhiyuan Li and Deborah L Swenson. 2017. \Trade policy uncertainty and exports: Evidence from China's WTO accession." *Journal of International Economics* 106:20{36.

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

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

Han, Jun, Runjuan Liu and Junsen Zhang. 2012. \Globalization and Wage Inequality: Evidence from Urban China." *Journal of International Economics* 87(2):288{297.

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

Melitz, Marc J. and Gianmarco I. P. Ottaviano. 2008. \Market Size, Trade, and Productivity." *Review of Economic Studies* 75(1):295{316.

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

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

Roberts, Mark J and James R Tybout. 1997. \The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Costs." *The American Economic Review* 87(4):545{564.

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

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